Is Flood Risk Priced in Bank Returns?

Valentin Schubert*

Job Market Paper

This version: October 18, 2022

Abstract

I quantify the costs of realized flood disasters for banks and create a novel exposure of bank-level flood risk measure using expected flood risk estimates and mortgage lending data. I show that following flood disasters, the profitability and capital ratios of affected banks decrease. The effect holds across different bank subsamples and is persistent over time. Yet, in the cross-section of stock returns, small banks with high exposure to flood risk underperform other banks, on average, by up to 8.7% per year. I continue to find evidence of underperformance when I control for the negative effects of disasters on realized returns or I adjust for investors' aggregated climate change concerns. The findings support regulatory concerns that bank equity is exposed to physical risk from climate change.

Keywords: Banks, Stock returns, Climate change

JEL Classification Codes: E44, G21, G12, Q54

*Department of Finance, Stockholm School of Economics. I would particularly like to thank my advisors Adrien d'Avernas, Mariassunta Giannetti, and Marcus Opp for helpful comments and suggestions, as well as Bo Becker, Alvin Chen, Vincent Maurin, Oliver Rehbein, Riccardo Sabbatucci, Tobias Sichert, Robin Tietz, my discussants Martin Gustavsson, Ivan Ivanov, Yingjie Qi, and Tamas Vadasz and seminar participants at the AREUEA Annual Meeting in Washington, 5th Benelux Banking Research Day, 2022 EEA/ESEM Meeting, IMF RESMF, Nordic Finance Network Ph.D. Workshop, 10th Swedish National Ph.D. Workshop, SSE/SHoF Brown Bag, and 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

1. Introduction

Policymakers are increasingly concerned about the potential effects of climate change-induced disasters on the financial sector. In the United States alone, weather disasters have caused over $2 trillion in property damages since 1980.[1] The widespread consensus is that costs from disasters will likely grow further over the next decades (Intergovernmental Panel on Climate Change, 2015), with climate change increasing the intensity and frequency of storms (National Academies of Sciences, 2016). Central banks have started to conduct climate-related stress tests of the banking sector, and regulators are looking into introducing new climate-related mandatory disclosures (SEC, 2022).[2] Yet, there is limited empirical evidence of how physical risks from climate change affect individual financial institutions or interact with financial stability. In general, it is not clear that physical risks should necessarily affect bank equity. Notably, banks actively manage their risk exposures, for example through diversification and securitization or by adjusting loan terms.[3]

This paper studies how bank equity is exposed to climate risk by quantifying the costs of realized flood disasters for banks and creating a novel bank-level flood risk exposure using expected flood risk estimates and mortgage lending data. Banks exposed to realized floods have a lower return on assets and a lower capital ratio. The estimates are quantitatively similar for large and small banks, which suggests that even larger banks do not fully hedge the costs associated with flooding. However, using the bank-level flood risk exposure, I find that small banks with high exposure to the risk of flooding under-perform compared to non-exposed banks. The effect is sizeable. A portfolio of small

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

[2]The Bank of England published the first climate-related scenario analysis in June 2021, followed by the European Central Bank (ECB) shortly after. More recently financial regulators in Canada and France incorporated climate change analyses in their assessments (Brainard, 2021). In September 2022, the Federal Reserve announced the start of a pilot project to assess climate risk exposures of the six largest U.S. banks (Federal Reserve, 2022)

[3]There is a large theoretical and empirical literature focused on the subject of risk management in firms. More recent examples for banks include Demsetz and Strahan (1997); Loutskina (2011); Cerqueiro, Ongena, and Roszbach (2016); Ouazad and Kahn (2021), or Degryse, Kim, and Ongena (2009) for a broader review of the empirical evidence.

banks with high exposure to flood risk underperforms a portfolio of non-exposed small banks, on average, by 8.7% per year. The flood risk exposure is a robust return predictor and cannot be explained by other standard bank characteristics in cross-sectional regression using pooled OLS. As climate and environmental risks are fundamentally downside risks for most firms (Seltzer, Starks, and Zhu, 2022), exposed banks should, if anything, command a higher expected return, reflecting the higher risk exposure, rather than predicting an underperformance. A negative relation between expected returns and realized returns in equity is not a new phenomenon and has been documented previously.[4] In this setting, while realized disasters do not subsume the result, the underperformance likely reflects a simultaneous combination of unanticipated shocks, such as changes in investor preferences, climate change concerns, and abnormally large disasters.

Measuring firms' exposure to climate risks has proven challenging. To overcome this challenge, I combine flood damage estimates from Sheldus with mortgage-level data to measure the costs of floods for banks. The measure builds on the notion that banks are exposed to floods through their mortgage portfolio and associated collaterals. The measure of flood damage exposure is constructed in two steps. First, I depart from the existing literature and define the bank-level regional weights as the share of originated mortgage amount by a bank in a county relative to its total originated mortgage amount in a given year using mortgage-level location information. As the mortgage portfolio exposes banks to costs from floods, measuring the exposure from banks' assets rather than branch-level information allows me to capture the exposure more closely.[5] Second, the regional weights are matched to the estimated flood damages to calculate a bank-level aggregate flood damage exposure.

Flood disasters significantly decrease bank profitability and increase leverage ratios. The effect on return on assets persists for up to one year. A shock to 1% of the assets is associated with a 1% lower return on assets. Even after one year, equity ratios are still

[4]For example Fama and French (e.g., 2002) or Pastor, Stambaugh, and Taylor (2021) for a more recent example.

[5]For example, Blickle, Hamerling, and Morgan (2022) use branch information and find little effect on profitability.

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

To measure flood risks for banks, I combine expected flood risk estimates from First Street Foundation (FSF) with the bank-level regional weights.[6] A benefit of creating a measure based on lending data as opposed to quarterly reports is that it is not affected by any disclosure concerns. I examine the cross-sectional relation between flood risk exposure and US bank stock returns by running bank-level pooled OLS regressions. Bank-level excess return and flood risk exposure have a strong negative relation, which initially 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 risks from climate not being adequately priced as previously documented for non-bank equities.[7] Unlike other risks that remained relatively constant over the last decades, climate risks have changed in a large way(Oh, Sen, and Tenekedjieva, 2022). The consequence is that these climate risks have proven challenging to adequately assess and price, especially in equities, but also insurance policies or real estate.

Interestingly, banks' stock return underperformance varies with banks' size or reliance

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

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

on mortgage lending. The underperformance is concentrated in the sample of small banks. A one-standard-deviation increase in flood risk exposure is associated with a 3.6 percentage point lower annualized excess return for small banks. Importantly, although these banks have smaller balance sheets, they are not less profitable or less well-capitalized. They are typically also active in a large number of counties and across several states, which renews the importance of capturing the total exposure using a bank's balance sheet information. Additionally, if anything, a higher geographic diversification is linked to less risky banks (Goetz, Laeven, and Levine, 2016) with a lower cost of capital (Becker, 2007), which would imply higher valuations ceteris paribus. However, especially after the 2007 recession, larger banks have been required to disclose more information than smaller institutions, and typically receive more scrutiny from regulators.[8] The additional regulations could have allowed a better assessment of the flood risk exposure of large banks, which partly explains the differing results between the size-sorted samples.

I extend the analysis of flood risk in the cross-section of bank stock returns by sorting banks into portfolios based on their flood risk exposure. A portfolio of banks with high exposure to flood risk exhibits lower future returns than stocks with low exposure. An exposure-weighted portfolio that goes long the top quartile portfolio and shorts the lowest flood risk quartile underperforms by 43 basis points (bps) per month or 5.2% per year.[9] The results are similar for value-weighted portfolios. I confirm the previous result that the underperformance is restricted to the sample of small banks in bivariate portfolio sorts. A long-short portfolio of small banks underperforms, on average, by 77 bps per month, or over 9% annualized, while the alpha on the long-short portfolio of large banks is positive, albeit not significant. Over the period from 2004 to 2020, a portfolio that goes long the top 25% of banks with high exposure to flood risk and short the bottom 25% lost around 50% in the entire sample of banks, or 80% when focusing on small banks. The negative alpha for small banks cannot be explained by a selection of risk factors used in

[8] For example, the Basel III disclosure requirements from the Basel Committee on Banking Supervision.

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

the banking literature, such as the four equity factors from Carhart (1997), and the two bond factors from Gandhi and Lustig (2015).

The underperformance of banks with high exposure to flood risk is puzzling given the correlation between realized floods and bank balance sheet performance. Investors typically require higher expected returns from firms with higher risk exposures. Hence, in expectations, flood-risk-exposed banks should earn a positive premium. However, past return performance may diverge from expected returns for different reasons. Counties with a high flood probability correlate with counties experiencing a larger number of flood disasters. Thus, bank-level flood risk exposure could pick up realized flood disasters, which could explain the estimated lower return performance. As briefly discussed, changes in weather patterns due to climate change complicate the precise forecast of flood disasters. I perform three tests to examine whether negative shock realizations explain the underperformance. First, the flood discount captured by the flood risk exposure prevails in a sample without periods of significant floods and storms. Even when removing all months with floods of any size, the underperformance on the flood risk exposure remains. The magnitudes of the coefficients on the flood risk exposure are slightly smaller (1.5 pp discount versus 2.4 pp in the baseline). Second, the underperformance of flood-risk-exposed banks persists even when explicitly controlling for past disasters using property damage estimates. Third, underperformance prevails when using disaster-adjusted returns as dependent variables. Across the three tests, controlling for past flood disasters reduces the coefficient of flood risk exposure; however, the relation between flood risk and excess returns remains negative and significant. Realized flood shocks explain the underperformance in part, but other drivers likely explain the negative relation. Further, the finding suggests that markets might not have fully adapted to the "new normal" ushered by climate change.

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

Previous literature has found that beliefs about climate change plays an important role in the pricing of climate-risk-exposed assets.[10] Using county-level election data, I find that that the underperformance is stronger for banks mostly lending to counties with a majority of Democratic voter. Further, it is strongest in the years in which a Democratic president was in office (i.e. President Obama). The effects are likely due to negative realizations of regulatory risks in democratic regions. Democratic officials are more likely to introduce new climate policies and regulate business in ways that affect local banks negatively. The explanation holds at the county and federal levels. Therefore the underperformance can be seen as a reaction to policy shocks, rather than an underreaction. Overall, the results are robust to a wide range of controls including flood insurance coverage, local differences in economic growth, or performance of the local real estate market.

This paper is most closely related to the literature investigating the pricing of climate risk, generally in equities. Examples include Bolton and Kacperczyk (2021), Bolton and Kacperczyk (forthcoming), Duan, Li, and Wen (2021), Hsu, Li, and Tsou (2021). While these papers focus on the transition risk from climate change, this study examines the physical risk from climate change, such as Hong, Li, and Xu (2019), Acharya, Johnson, Sundaresan, and Tomunen (2022), Choi, Gao, and Jiang (2020), and Bansal, Ochoa, and Kiku (forthcoming) that focus on heat-related climate risks in non-financial sectors.

[10] Baldauf, Garlappi, and Yannelis (2020) and Bakkensen and Barrage (2022) find that houses at risk of flooding in regions that believe in climate change trade at a discount.

Painter (2020) and Goldsmith-Pinkham, Gustafson, Schwert, and Lewis (2021) analyze climate risks in municipal bonds. This paper analyzes the risk of flooding in the U.S. banking sector.

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

Next, the paper contributes to the literature on natural disasters and bank operations. So far, this literature has only focused on past disasters' effect on banks, while this paper also analyzes the effect of expected risks from climate change. The evidence from the literature suggests that affected banks tend to increase lending in affected areas following disasters (e.g., Cortés and Strahan, 2017; Barth, Sun, and Zhang, 2019; Bos, Li, and Sanders, 2022; Koetter, Noth, and Rehbein, 2020; Brown, Gustafson, and Ivanov, 2021; Ivanov, Macchiavelli, and Santos, 2022). The findings are mostly isolated to certain types of banks and achieved by diverting funds from other parts. Ouazad and Kahn (2021) argue that commercial banks pay attention to climate risk once it hits. They find that following disasters, banks are more likely to load off their mortgages by selling them to the two government-sponsored enterprises (GSE), Fannie Mae and Freddie Mac, while Garbarino and Guin (2021) find that home loan lenders do not adjust their valuation, loan amounts, nor mortgage interest rate following an episode of severe flooding. The findings of this literature flow into the analysis in this paper by looking at securitized mortgages separately.

The effect on bank performance is less clear from the existing literature. Schüwer, Lambert, and Noth (2019) and Blickle, Hamerling, and Morgan (2022) find a negative or insignificant effect on performance, while Noth and Schüwer (2018) provide evidence of a positive effect. The common approach to measure banks' exposure to natural disasters has been to use branch information, either location directly or amount of deposits. This paper extends the empirical approach by using a new exposure measure based on banks' balance sheet data. Specifically, I use banks' mortgage lending activity to map the balance sheet to flood disasters and expected flood risk. I show that using branch location to measure the exposure to floods underestimates the effects compared to using balance sheet information.

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

Finally, my paper contributes to the literature on bank risks. 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 return predictor based on flood exposure.

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

2. Data and Summary Statistics

This section describes the different data sources and introduces the key explanatory variables. The focus of this paper lies on floods and hurricanes among natural disasters. They represent the costliest disasters in the United States (Davenport et al., 2021). Weather disasters have caused over $1 trillion in property damages since 2010, of which almost $300bn in property are attributed to floods and storms (Figure 1).[11] The widespread consensus is that without drastic measures, costs from climate change-related disasters will increase further over the next decades (Intergovernmental Panel on Climate Change, 2015). Sea level rise is to exacerbate the problem even further (Davenport et al., 2021). Some estimates warn that property damages from floods will likely increase by more than 60% over the next 30 years (First Street Foundation, 2021).

As pointed out by the ECB (2019), with increases in frequency and severity of climate disasters, the risk of abrupt value losses of assets in climate risk-sensitive geographical areas increases. Real estate is inextricably linked to its geographic location. Therefore housing in exposed areas is likely to be negatively affected by the expected increase in natural disasters. For financial institutions lending to this area, this implies that collateral and asset values become riskier. Every year, mortgage lenders originate between $200 and $250 billion in new mortgages in flood zones, representing roughly 12.5% of total bank equity (Ouazad, 2020), which means potentially large financial losses.

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

[Place Figure 1 about here]

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

2.1. Bank-Level County Weights

To compute the geographic exposure measure at the bank holding company level, I use data on U.S. mortgages obtained from the publicly available part of the data filed under the Home Mortgage Disclosure Act (HMDA). Federally insured or regulated depository institutions with total assets exceeding $45 million are required to report the received mortgage loan applications and decisions at a yearly frequency.[12] However, as the analysis primarily focuses on publicly listed banks, which typically are large, there is no reason to expect that this threshold and feature of the data should systematically bias the findings.

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

2.2. Flood Damages

Flood disaster shocks are constructed using data from Spatial Hazard Event and Losses Database for the United States (Sheldus) maintained by the University of Arizona.[13]The data provides information on the date, location, and intensity of all presidentially declared natural disasters in the US. For this study, the data is restricted to major floodings and storms. While the National Oceanic and Atmospheric Administration (NOAA) also collects information on non-presidentially declared natural disasters, Sheldus has the

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

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

advantage of estimating dollar damages linked to the different disasters. Additionally, presidentially declared disasters are more likely to be severe and represent significant shocks to banks (Ivanov et al., 2022).

[Figure 2 about here]

Figure 2 plots the total estimated damages from floods in each U.S. county for the years 1980 to 2020. Unsurprisingly, coastal regions have higher estimated flood damages over the sample. Damage estimates are especially high in the Gulf coast regions. However, the map also highlights urban centers due to the simple summing up of total damages, which typically overweights larger and denser areas. For this reason, I measure the intensity of a flood disaster using the total dollar value of property damages in a given county and a quarter scaled by the total personal income in that county.

2.3. Expected Flood Risk

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

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

[Figure 3 about here]

The key variable is shown in Figure 3. It represents the share of properties with a 1% probability of a 1-meter flood by 2050 for each county in the continental United States. Darker shades of blue represent a larger share. Unsurprisingly, coastal regions are expected to be the most affected. Still, counties in lower areas of the Northwest and counties in the Appalachian are also projected to be of high risk.

2.4. Bank Outcomes

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

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

2.5. Measuring Banks' Exposures to Floods and Flood Risk

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

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

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

where $Originated_{b,c,t}$ is the total amount of mortgages originated in county c and year y by bank b. The aim of the weights is to capture general bank lending patterns.

There is some evidence that banks exposed to flood disasters increase the securitization of mortgages and selling originated mortgages to the two government and state-owned enterprises (Ouazad and Kahn, 2021). This reduces the bank's exposure to negative shocks to collateral values. The empirical analysis accounts for this possibility by focusing on non-securitized mortgages in alternative county weight measures. All main results hold if a county weight is defined as the share of retained mortgages. A mortgage is defined as retained if it is not securitized or sold to a third party. The aim is to capture banks' exposure to a county, therefore the focus is on mortgages retained in the banks' portfolios. The benefit of using originated amounts instead of retained amounts is that they reflect a bank's overall business in a region more accurately than only focusing on retained mortgages Giannetti and Saidi (2019). Along the same line, as additional measures, I compute rolling averages of retained and originated mortgages. Rolling averages alleviate concerns that outlier exposures in mortgage lending drive the results. Rolling averages arguable capture underlying lending patterns more closely than yearly flow measures. They are a better proxy for future lending patterns Favara and Giannetti (2017). Therefore, they capture the broad exposure to future profits from lending to a specific county by a given bank.

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

$$\textit{Scaled Damages}_{b,q} = \sum_c (\textit{County Weight}_{b,c,y} \times \textit{Property Damage}_{c,q}). \tag{2}$$

Scaled damages can be viewed as a weighted average of the damages that occurred in quarter q. In the baseline, property damages are normalized by county-level total personal income from the Bureau of Economic Analysis. Alternatively, damages in dollar amounts are normalized by assigning them to the different banks active in a county using county-level market shares.

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

$$\textit{Flood Risk Exposure}_{b,y} = \sum_c (\textit{County Weight}_{b,c,y} \times \textit{Flood Probability}_c), \tag{3}$$

where *Flood Probability* is the flood probability measure from the flood maps produced by FSF. In robustness tests, I alternatively use the county-average risk measure and the share of properties at risk by 2035.

2.6. Summary Statistics

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

[Table 1 about here]

3. The Cost of Flood Disasters

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

3.1. Hurricane Katrina

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

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

$$AR_{b,t} = R_{b,t} - E[R_{b,t}]. \tag{4}$$

The daily expected return is defined as

$$E[R_{b,t}] = \hat{\alpha}_b + \hat{\boldsymbol{\beta}}_{\boldsymbol{b}}' \boldsymbol{F},$$

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:

$$R_{b,t} = \alpha_b + \boldsymbol{\beta}_{\boldsymbol{b}}'\boldsymbol{F} + \epsilon_{b,t}.$$

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.[14] During the hurricane season of 2005, 135 of the 534 counties in the Gulf Coast region were designated to be eligible for FEMA's disaster assistance. A bank is affected by Hurricane Katrina if all its mortgage lending in the previous year (2004) was for properties located in a county eligible for individual and public disaster assistance (the orange region in Figure 4a). The control group consists of banks with all their mortgage lending in counties that received neither individual nor public disaster assistance but are located in the U.S. Gulf region or a neighboring state.[15] These counties are shown in dark blue in Figure 4a. Counties that only received public assistance are excluded. As pointed out in Schüwer et al. (2019), some counties received public assistance because they housed evacuees but were not directly negatively affected by damages. Consequently, nineteen banks are cleanly identified as only active in affected counties, and 27 are located in unaffected counties.

Figure 4b plots the daily cumulative abnormal return of the two value-weighted portfolios from July 2005 to October 2005.

Hurricane Katrina formed on August 24. In the following days, the storm's intensity and trajectory became more apparent. On August 26, it went over the southern tip of Florida, and the trajectory was revised to the Mississippi coast (United States Department of Commerce, 2006). This is seen in the first days of lower negative abnormal returns compared to the control group. On August 28, the National Weather

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

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

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

[Figure 4 about here]

3.2. Shock to the Balance Sheet

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

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

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

[Table 2 about here]

Table 2 reports estimates of equation 5 for bank-level return on assets.

The baseline regression in column (1) estimates a negative and statistically significant relationship between the exposure to flood damages and return on assets. The variable *Scaled Damages* has a t-statistic of -3.8. Further, it has been standardized for ease of interpretation. Therefore, the coefficient of -0.005 suggests that a one-standard-deviation increase in scaled damages results in a decrease in quarterly return on assets of 0.4 basis points. Given an average of 0.4%, this is equal to a 1% decrease in the average return on assets. However, the distribution of flood disasters typically has a large right tail. Hurricane Katrina had a magnitude of almost 100 standard deviations, wiping out the entire income of affected banks. This shows that large shocks are plausible (and likely). A ten-standard-deviation increase in flood shocks is associated with returns on assets of affected banks being 10% lower, consistent with flood damages having a potentially important negative effect on bank performance. This finding is evidence that banks remain exposed to flood disasters, and by extension, to the risk of flooding.

This finding is in contrast to Blickle et al. (2022), who find that bank performance is not negatively affected by natural disasters. Their analysis relies on computing the exposure measures using bank branch information, either by using the number of branches in a county or the share of deposits in a county. I argue that banks are exposed through their asset holdings. An exposure measure to natural disasters should therefore reflect a bank's asset side instead of its liabilities. Furthermore, and more importantly, a bank is assumed to be exposed through its mortgage loan portfolio. Finally, banks typically extend loans outside of their home counties. Hence focusing on physical bank location potentially omits important exposures. Panel B of Table 2 provides evidence of this. The results are obtained from the same regression (equation 5) but using two different exposure measures. In column (4), instead of using mortgage-weighted exposure, county-level flood damages are aggregated using deposits as weights. In contrast, column (5) weighs by physical office locations.[16] The coefficients of interest are insignificant in both cases. This additional test helps reconcile the findings in this study with the findings in prior studies (e.g., Blickle et al., 2022).

The baseline *Scaled Damages* is constructed using damage amounts divided by total personal income and weighted by total mortgage originations. As discussed previously, one might be worried that the results capture underlying differences in securitization. To rule out that this is driving the results, in column (2), the dependent variable is redefined as the property damage estimates weighted by the retained amount of mortgages. In this context, the coefficient is of similar magnitude as in the baseline results, suggesting that wealth differences are not driving the results. Further, the argument can be made that banks with a higher market share, are more likely to be affected by realized floods. Therefore in column (3), damage estimates are first assigned to banks by multiplying by the county-level market share. As previously, the coefficient is of comparable magnitude.

[Table 3 about here]

Table 3 reports the results from equation 5 for a set of balance sheet variables of the publicly traded bank holding companies.[17] All regressions control for time-varying bank characteristics such as leverage, assets, loan ratio, and mortgage ratio. As previously, bank and time fixed effects are included in the regression, while standard errors are clustered at the bank holding company. Column (1) replicates the baseline results for return on assets. The coefficient on *Scaled Damages* has the same sign and very similar magnitude as in Panel A of 2, suggesting that the effect is propagated at the bank holding company. A large flood disaster is associated with exposed banks performing 10% worse than unaffected but otherwise comparable banks. Columns (2) and (3) focus on prudential capital requirements. The estimates show that leverage and capital ratios decrease when flood damages increase. A one-standard-deviation increase in flood damages reduces the ratios by approximately 2 bps. However, given average ratios between 8% and 14%, the effect is small, even for larger episodes. Nevertheless, the coefficients are statistically

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

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

significant, with t-statistics below -2.56. The net stable wholesale funding ratio also declines by 5 bps after a one-standard-deviation increase in flood damages, as reported in column (4). The estimates suggest that banks not only have lower profits but experience losses on their equity. However, the reduced ROA is not matched one-to-one with a reduction in equity, implying that banks manage to offset the majority of the shock without loss on their equity.

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

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

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 *Scaled Damages* in column (5) is negative and significant. The estimate implies that the distance to default is negatively associated with flood disasters and is consistent with flood damages increasing the default likelihood of a bank.

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

3.3. Effect Heterogeneity

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

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

[Table 4 about here]

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

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

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

3.4. Persistent Effects

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

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

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

where h goes from -3 to +4 quarters. I report the coefficients β_1^h on *Scaled Damages* for the two bank performance variables, return on assets and Tier 1 leverage ratio, in Figure 5. 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 5a shows the long-run effect of flood damages on bank-level return on assets. The quarter 1 coefficient is the same as the coefficient in column (1) of Table 2. The plot shows that the drop in return on assets starts in the same quarter as the flood disaster and tapers off over the next year, consistent with the effects of floods having longer-term consequences. Further, the finding indicates that most of the effect on profitability occurs in the same quarter as the flood realizes. The finding is echoed in Figure 5b, which plots the coefficient of Tier 1 leverage on flood damages. Again, most of the effect occurs between the first and the second quarter after the flood disasters. Because the points on the line estimate cumulative effects on the leverage ratio since the shock, the flattening of the line after the second quarter suggests that the flood has little impact on leverage in the second half of the year after the disaster. That leverage remains significantly below its pre-flood level is surprising. Banks might either choose not to or are unable to increase their capital. Either way, it demonstrates that banks are significantly riskier after experiencing major natural disasters, as had also been conveyed by the significantly lower Z-score. This result emphasizes the long-lasting effects of a natural disaster (Noth and Schüwer, 2018). The coefficient estimates in both plots do not show any significant pre-trend.

The evidence in Panel A and B of Figure 5 is consistent with banks experiencing significant losses from floods that require them to offset losses with their equity.

[Figure 5 about here]

Figure 6 conducts a similar analysis using two loan portfolio variables as the outcomes of interest. As seen in Section 3.3, the effect on portfolio performance variables is only seen in the subsample of banks with a high share of mortgage loans on their balance sheet. As previously, the solid line (with circles) presents the point estimates of β_1^h from equation , and the dashed lines (with triangles) give the 95% confidence intervals on this estimate. Standard errors are clustered at the bank level. The flood realizes at time 0. The coefficients are insignificant for the periods before the shock. Figure 6a plots the coefficient from regressing the non-performing loans ratio on flood damages for the sample of banks with a high share of mortgages. Following the shock, the coefficient is positive and implies an increase in non-performing loans within the sample of banks with a high share of mortgages. As previously, the picture suggests that the full effect of the disaster is only registered after some time. The share of non-performing loans increases for three quarters before slowly reverting. Given that non-performing loans are typically measured as loans with missed payments after thirty to ninety days, the insignificant effect in quarter 0 is comforting. It bolsters the identifying assumption that borrowers do not adjust their repayments in anticipation of future adverse weather shocks. Similarly, as shown in Figure 6b, loan charge-offs increase in the quarter following the shock and remain elevated for the next couple of quarters. The increase in loan charge-offs is steeper than the increase in non-performing loans. While NPLs depend on borrowers' behavior, charge-offs are set by lenders. So the difference in slope suggests that lenders partly anticipate the increase in NPL and the ensuing default of a number of borrowers.

[Figure 6 about here]

Taken together, the evidence Figure 5 and 6 is consistent with banks' balance sheets deteriorating significantly after flood disasters and that the effect manifests itself over a relatively long period. In addition, as soon as the flood realizes, banks anticipate the deteriorating economic environment and increase loan charge-offs, which results in an immediate decrease in return on assets. Return on assets and loan charge-offs revert back to the pre-shock level faster than non-performing loans, because of the anticipating behavior of banks.

3.5. The Role of Mortgage Market in Propagating Flood Disasters

The previous sections can be seen as a reduced-form approach, where the bank-level outcomes were directly regressed on the flood damage estimates. Implicitly, the local real estate markets has been assumed to be the connecting link between realized floods and bank performance. This subsection provides evidence of the importance of this channel by first highlighting the relationship between flood disasters and local mortgage delinquency. The second part demonstrates that periods of higher mortgage delinquencies are associated with lower bank performance. To test the first channel, the empirical approach involves regressing county (or Zip) level mortgage performance ratios on flood damages. Formally, I estimate the following equation:

$$\begin{aligned} \mathrm{Y}_{c,t+h} = \quad & \beta_0^h + \beta_1^h \mathit{Flood\ Damages}_{c,t} \\ & + \beta_2^h Y_{c,t-1} + \boldsymbol{\gamma X} + \epsilon_{c,t+k}, \end{aligned} \tag{7}$$

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, *Flood Damages* are calculated by dividing the county-level property damage estimates by the total personal income in a county. The regression includes time (month) and county fixed effects, given by the vector $\boldsymbol{X}$. The county fixed effects ensure that results are unlikely to be driven by unobserved county characteristics, while the time fixed effects alleviate concerns that the results are driven by specific periods. Standard errors are clustered at the state level. Figure 7a 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 before the shock (proxied by the property damages). Following the shock, the coefficient increases to 1 and remains at that level over six months. The coefficient indicates that a 1 percentage point shock leads to a 1 percentage point higher number of foreclosures. Foreclosures are a powerful instrument, imply costly spillovers for a bank (Favara and Giannetti, 2017), and require active intervention from the lender. To avoid any influence by the banks and focus on the behavior of borrowers, Figure 7b reports 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 before 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.

[Figure 7 about here]

Having established a link between residential mortgage performance following natural disasters, the next step involves linking foreclosures and delinquencies to bank performance measures. Formally, the regression is:

$$\begin{aligned} Y_{b,t} = \beta_0 &+ \beta_1 \textit{Market Exposure}_{b,t} + \beta_2 \textit{Capital Ratio}_{b,t-1} \\ &+ \beta_3 \textit{log(Employees)}_{b,t-1} + \beta_4 \textit{log(Assets)}_{b,t-1} \\ &+ \beta_5 ROA_{b,t-1} + \boldsymbol{\gamma X} + \epsilon_{b,t}, \end{aligned} \tag{8}$$

where in the baseline Y_{bt} is the quarterly return on assets 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 are bank-level exposure measures that synthesize the exposure degree to the counties.

[Table 5 about here]

Panel A of Table 5 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 reported in Panel B of Table 5. A 1% increase in the delinquency rate decreases returns on 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 severely affect bank performance.

4. Exposure to Flood Risk

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

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

4.1. Evidence in the Cross-Section of Returns

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

$$\begin{aligned} r_{b,t} - r_{f,t} = \alpha &+ \beta_1 \mathit{Flood\ Risk\ Exposure}_{b,t-1} \\ &+ \beta_2 \mathit{log(Assets)}_{b,t-1} + \beta_3 \mathit{log(BE/ME)}_{b,t-1} \\ &+ \beta_4 \mathit{Leverage}_{b,t-1} + \beta_5 r_{b,t-1} + \epsilon_{b,t}, \end{aligned} \tag{9}$$

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

Column (1) of Table 6 reports the baseline result with the exposure measure based on flood probabilities in 2050 and the share of retained mortgages. The coefficient on the flood risk measure is negative and statistically significant at the 1% level. The effect is also economically significant: a one-standard-deviation increase in flood risk measure leads to a 17-bps decrease in monthly stock returns, or 2% annualized. The estimate suggests that a high flood risk exposure forecasts poor stock performance. Overall, the results imply firms with high flood risk exhibit lower future excess returns net of well-known bank characteristics. This finding is in line with other papers testing whether markets discount physical risk from climate change (e.g., Hong, Li, and Xu, 2019), and highlights differences to studies focused on transition risks from climate change that typically find that investors require higher expected returns from firms with higher risk exposure (e.g., Bolton and Kacperczyk, 2021).

[Table 6 about here]

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

Important is that the different measures all capture a very similar exposure. The last column of Table 6 reports a placebo test, where the exposure measure is intended to capture a different channel. Instead of dividing the number of retained mortgages in a county by the total retained mortgages by a given bank, a bank's retained mortgages are divided by the total aggregate number of originated mortgages in that county (across all lenders). The exposure measure captures the county-level market concentration from the perspective of a single bank. The prediction is that the result from this regression should be insignificant and different from the other results. The coefficient on the exposure measure is positive and insignificant suggesting that a different channel is at work in this scenario.

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

4.2. Heterogeneity of Effects

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

To examine the importance of the heterogeneity for the return predictability, Table 7 presents separate estimates of equation 9 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 7 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 *Scaled Damage* are negative for the two subsamples, but only significantly for the subsample of banks specialized in mortgage lending. The point estimate in column (1) is almost double the magnitude of the point estimate in column (2). For the sample of banks specialized in mortgage lending, a 1-standard-deviation increase in the exposure reduces the excess return by -25 bps, or -3% annualized. However, the interaction in column (3) is not statistically significant either, suggesting that the difference between the two coefficients in columns (1) and (2) is not large enough to warrant largely different conclusions. If anything, the finding is consistent with banks specializing in mortgage lending being more exposed than other banks.

[Table 7 about here]

More interestingly, Panel B of Table 7 reports the estimates for the size-sorted samples. Only the point estimate on *Flood Risk Exposure* for the sample of small banks is negative and statistically significant (with a t-statistics of -3.8). The point estimate is equal to -30 bps, which translates into 3.7% annualized. The coefficient for the sample of larger banks is even positive, albeit insignificant. This suggests that the result does not appear to be due to a lack of statistical power, as the coefficients are not only statistically insignificant but also of a different sign. The difference between the two coefficients is also statistically significant as shown by the interaction term in the last column. Several hypotheses might explain the discrepancy between small and large banks. First, large firms are typically more visible. They attract more scrutiny from investors and analysts but are often also required to disclose more information. This is especially true in the banking industry, where large banks have always been treated differently, but even more so since the Great Recession. The positive (insignificant) coefficient for the sample of large banks is evidence that investors are better able to price the risk exposure to flooding. The opacity and lack of disclosure of smaller banks make the pricing of risk more difficult.

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

4.3. Portfolio-Level Analysis

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

$$r_{i,t} - r_t^f = \alpha_i + \boldsymbol{\beta_i}'\mathbf{F}_t + \epsilon_{i,t}, \tag{10}$$

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

[Table 8 about here]

Table 8 reports the estimates from equation 10. Panel A presents the results for the full sample running from 2004 to 2020. Columns (1) to (4) report the results for the four portfolios. The intercept decreases from 0.38% in poto 0.05%, albeit not monotonically. Column (5) reports the results from running the time-series regression for a portfolio that goes short portfolio 1 and long portfolio 5, i.e., it goes short the portfolio with the lowest exposure and long the portfolio with the highest exposure. The intercept on the

High-Low portfolio has a value of -0.43 and a t-statistic of -3.3. The intercept translates into a 43 bps monthly loss, or -5% annualized.

As in the previous section, small and large banks are analyzed separately. Panel B of Table 8 reports the intercepts of the four flood risk exposure-sorted portfolio for the sample of small banks. The intercepts decrease monotonically as we move from portfolio 1 (in column (1)) to portfolio 4 (in column (4)). The difference between the intercepts in portfolios 5 and 1 is equal to -0.77 and statistically significant at the 1% level. The High-Low portfolio losses 9.6% per month in annualized terms. Finally, Panel C of Table 8 reports the intercepts for the sample of large banks. No discernible pattern in alphas is observed in this last panel. In line with the previous findings, this suggests that the potential role of flood risk exposure is restricted to smaller banks.

4.4. Flood Risk Factor

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

[Figure 8 about here]

Figure 8 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 9. This consistent under-performance of the flood factor cannot be fully explained by exposure to other factors prominent in the asset pricing literature. Column (2) includes the market factor. Columns (3) and (4) add the three Fama and French (1993) and Carhart (1997) four factors. In all cases, the flood factor's alpha (regression intercept) has a very similar magnitude ranging from -0.2 to -0.24 with t-statistics between -1.60 and -1.86. The flood factor's exposures to SMB, HML, and Mom indicate that it is slightly leaning toward larger stocks, growth stocks, and recent winners, although none of the coefficients are statistically significant.

[Table 9 about here]

As size heterogeneity played an important role in the previous analysis, Panel B of Table 9 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 9 constructs the flood factor, but only with the largest 25% of banks. The monthly return difference flips sign and averages 1 bps but is not statistically significant as reported in column (1). Sequentially including the different additional factors does not change the magnitude nor the significance by much. The finding underlines the hypothesis that investors are able to better price the exposure for larger banks. The return differences for the sample of large banks are consistent with the other findings based on bank heterogeneity.

Along the same lines, Figure 9 plots the cumulative return of the flood factor for the two size-sorted subsamples using exposure-weighted and equal-weighted cumulative returns. The time series for the sample of small banks are shown in orange. The solid line plots the exposure-weighted cumulative return of the flood factor based on the sample of small banks. The portfolio loses over 60% over the sample (or almost 100% if we consider the covid-related drop in 2020). The pattern is very similar for the equal-weighted portfolio (dotted line) but less steep. For both portfolios, the cumulative return decreases almost monotonically until 2016 when it increases slightly for a few quarters before decreasing again in 2019. The two return series suggest a steady underperformance of the high-exposure banks that is not solely driven by an outlier. The reason for the flatter curve around 2016 could be due to changes in the regulatory environment. The cumulative return of the flood factor based on the 25% largest banks is flat over the sample. The equal-weighted and exposure-weighted cumulative returns increase until 2016 when they reach around 15%. The equal-weighted cumulative return remains at this level, while the exposure-weighted cumulative return decreases back to 0%.

[Figure 9 about here]

5. Economic Mechanism

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

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

5.1. Realized Flood Disasters

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

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

[Table 10 about here]

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

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

$$\begin{aligned} r_{bt} - r_{ft} = \alpha &+ \beta_1 \mathit{Flood\ Risk\ Exposure}_{bt} + \beta_2 \mathit{Scaled\ Damagess}_{bt} \\ &+ \beta_3 \mathit{Flood\ Risk\ Exposure}_{bt} \mathit{Scaled\ Damagess}_{bt} \\ &+ \beta_4 \mathit{log(Assets)}_{bt} + \beta_5 \mathit{log(BE/ME)}_{bt} \\ &+ \beta_6 \mathit{Leverage}_{bt} + \beta_7 r_{bt-1} + \epsilon_{bt}. \end{aligned} \tag{11}$$

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

[Table 11 about here]

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

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

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

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

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

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

$$r_t^{FF} = \alpha + \beta \mathit{Flood\ Damages}_t + \epsilon_t, \tag{12}$$

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

[Table 12 about here]

The estimates for the full sample of banks are reported in Panel A of Table 12. Again, three different measures of damage exposure are used. Column (1) uses flood-related damages, column (2) is again an indicator variable equal to 1 if the damages are in the top decile, and column (3) aggregates costs across all types of disasters. The variables in columns (1) and (3) are defined as changes because the damages are now summed up across the U.S. every month. The flood realization enters with the expected negative sign in all three specifications. It is also significant in columns (1) and (3). The R-squared is low in all three regressions.

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

Panel B of Table 12 presents the results for small banks. While the sign on flood realization is still negative in all specifications, it is never significant. And the estimated intercept remains negative and significant as in the results from the previous sections.

5.2. Climate Change Concerns

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

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

Second, I use the monthly version of the Media Climate Change Concerns (MCCC) index based on climate change-related newspaper articles introduced by Ardia et al. (2022).[18] 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

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

benefit of their data is that an index is available for an array of different components. While the focus is on the aggregated measure, the results for an index focused on flood-related concerns, climate summits, and global warming are shown separately. This allows for disentangling concerns about physical risks from transition risks.

The estimates from these regressions are reported in Table 13. 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.

[Table 13 about here]

Panel A of Table 13 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 13. The coefficients on *Flood Risk Exposure* are always negative and significant with t-statistics below -3.2. The magnitude on ΔCC for the full sample and the sample of small banks are also very similar for the different measures.

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

5.3. Regulatory Risks

Climate change and beliefs about climate change have become strongly political in the United States. Typically, Republican voters believe that climate change is real to a lesser extent than Democratic voters (Pew Research Center, 2016). Elected officials from the Democratic party are more likely to introduce new climate legislation and regulate business activities, which negatively affects banks in Democratic counties or States. Therefore, the pricing of flood risk exposure might differ, depending on which party controls legislation and the location of banks. I test this using election data to estimate the following regression:

$$\begin{aligned} r_{b,t} - r_{f,t} = \alpha &+ \beta_1 \mathit{Flood\ Risk\ Exposure}_{b,t} + \beta_2 \mathit{Political\ Indicator}_{b,t} \\ &+ \beta_3 \mathit{Flood\ Risk\ Exposure}_{b,t} \mathit{Political\ Indicator}_{b,t} \\ &+ \beta_4 \mathit{log(Assets)}_{b,t} + \beta_5 \mathit{log(BE/ME)}_{b,t} \\ &+ \beta_6 \mathit{Leverage}_{b,t} + \beta_7 r_{b,t-1} + \epsilon_{b,t}, \end{aligned} \tag{13}$$

where *Political Indicator* is either based on county-level presidential election results or simply captures the party affiliation of the current President. In the first case, county-level vote shares are aggregated at the bank level using the mortgage share. If the majority of counties voted Republican, the indicator variable is equal to one. For the second measure, the indicator variable is simply equal to one if the sitting President is republican (i.e. during the terms of President Bush and President Trump).

[Table 14 about here]

The results from the regression are tabulated in Table 14. Columns (1) to (3) use the county-level election outcomes as the indicator variable for i) all banks, ii) small banks, and iii) large banks. In all three specifications, the flood risk exposure has a negative coefficient, suggesting that banks active in mostly democratic counties underperform, no matter the size. The estimates on the interaction between flood risk exposure and political indicator are surprising. The coefficient is positive and significant in the first and third columns. This suggests that banks in Republican counties underperform to a lesser extent, and even outperform other banks in the case of large banks. The finding can be reconciled with the explanation that Democratic-controlled counties and states were more likely to introduce new regulations which negatively affected the stock prices of exposed banks.

In columns (4) to (6), the indicator variable reflects the views at the Federal level. Again, the coefficients suggest that the underperformance is strongest in years in which a Democratic president was in office. During these years, general attention to climate risks and the probability of climate-related policies were higher than during the terms of President Bush and President Trump. Along the same line, Panel A in Table 15 separately investigates the control of the House of Representatives, the Senate, or the presidency. As previously, the underperformance is insignificant if Republicans control Congress or the presidency. As the measures correlate, Panel B in Table 15 estimates the regression using three orthogonal indicator variables: Republican control of Congress, only Senate, or only the House of Representatives. The effect is strongest if Republicans control either no house or only Senate. The control of Congress nullifies the coefficient on flood risk exposure. This finding is explained by the House of Representatives and the President being the two major instances at the Federal level to introduce new climate legislation.

Overall, the evidence in this section supports the view that regulatory shocks (mostly) introduced by Democratic party-affiliated officials lead to the underperformance of assets more exposed to climate risks.

6. Robustness

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

6.1. Flood Insurance

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

In the United States, the standard home insurance contract covers some natural disasters such as fire, but it explicitly excludes floods (Oh et al., 2022).[19] Flood insurance has to be taken separately and is provided federally by the National Flood Insurance Program (NFIP). Flood insurance is technically required by law for most mortgage borrowers in FEMA-designated flood zones. However, there are a couple of important caveats. Federal flood insurance only covers mortgages up to $250,000 in flood damage, and virtually no private insurers are available for the remaining coverage. Further, insurance contracts are short-dated with yearly renewals, leading to many borrowers dropping out. And flood insurance is only mandatory in officially designated flood zones, leaving many properties at risk. The NFIP has, on average, 5 million active contracts compared to 15 to 36 million homes that are estimated to be exposed to disaster risk.[20] An additional reason for the diverging numbers between the insured and at-risk homes is that climate change has led to significant changes in the underlying risk and increased risk-sensitive regions. So keeping up with these changing patterns is important if insurance coverage should match actual risks. While FEMA is mandated to update its maps at a five-year interval, most of them are older. This results in a mismatch of insured and exposed homes.

To test the effect of flood insurance formally, I use the flood insurance policy data from NFIP published by FEMA. The data is available in two separate files. The first file

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

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

includes information on active policies and is available from 2009 to 2022. It includes information such as the coverage and premium of individual policies. On average, the data includes around 4 million active policies compared to the estimated 15 million homes at high risk of flooding. The total insured amount is $1 trillion, with building coverage of roughly $750 billion, while around $250 billion in content is covered. The number of active policies has slightly decreased in recent years. As expected, coastal regions in the Gulf have the highest number of active policies. The second file from the NFIP includes information on policy claims. And similarly to before, claims are concentrated around the Gulf.

[Table 17 about here]

Columns (1) and (2) of Table 17 report the estimates of the cross-sectional regressions that include the variables for flood insurance penetration. In column (1), *Flood Policies* is the retained mortgage-weighted average of the number of active flood policies from the NFIP, which reduces the potential fallout from future floods for exposed banks. The control in column (2) is based on policy payouts for insured buildings and captures flood realizations. Through the three samples of banks, controlling for flood insurance does not alter the magnitude nor significance of the estimate on the flood risk exposure. Small flood risk exposed banks underperform by about 30 bps per month. Exposure to more or fewer flood insurance policies does not seem to have any predictive power, which alleviates concerns that differences in flood insurance take-up might be driving the negative risk premium. Flood claims load significantly negatively. However, this effect is reassuring, because flood claims are also highly correlated with flood disasters and the intensity of a disaster.

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

6.2. Mortgage Delinquencies

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

Columns (3) and (4) of Table 17 test this conjecture by controlling for banks' exposure to foreclosures or defaults. Again, through the different samples, the baseline results persist: in the full sample and for small banks, flood risk exposed banks underperform with a monthly flood discount of 20 to 30 bps. Defaults load negatively in the three samples, suggesting that poor real estate performance is associated with lower future returns as hypothesized.

6.3. Regional shocks

To rule out the possibility of other shocks, I control for additional regional measures. The estimates are collected in Table 18. Column (1) includes state-level macroeconomic variables, such as $log(GDP)$, inflation, income per capita, and unemployment rate. The state-level variables are aggregated at the bank level using the same method as for the county-level flood probabilities presented in Section 2.5. Each state-level measure is weighted by the dollar amount of mortgages retained by a bank in that given state. Column (2) includes 50 state indicator variables. For a given bank, a state indicator takes on the value of 1 if the bank has originated a mortgage in that state. This approach can be viewed as a form of manually including state-fixed effects. Column (3) interacts the state dummies with year dummies. Finally, column (4) includes HQ-state-fixed effects.

Across the four specifications, the coefficient on the *Flood Risk Exposure* is negative, ranging from -0.24 to -0.12, suggesting that the finding is not driven by unobserved regional characteristics. The results from Table 18 are evidence that the baseline finding is not driven by unobserved regional characteristics captured by the *Flood Risk Exposure*.

[Table 18 about here]

7. Conclusion

Climate change-related disasters are projected to increase and become considerably more extreme. While policymakers are increasingly concerned that these disasters could negatively affect financial stability, the literature lacks clear evidence of the interaction between physical risks from climate and bank equity.

Focusing on flood disasters, in this paper, I provide evidence that flood shocks negatively affect banks' loan performance and equity. The first contribution is constructing a bank-level flood risk exposure measure that combines up-to-date flood risk maps with bank mortgage lending data. Previous literature has focused on the physical location of banks to measure their exposure to shocks, but this paper shows that the balance sheet composition matters. I document that banks' return on assets is significantly lower following a flood disaster. Not only is the initial shock relevant, but the effects are also long-lasting with return on assets being lower for up to one year after the flood. Floods affect bank performance in part through the banks' mortgage portfolio. Non-performing loans and loan charge-offs are significantly higher. Furthermore, I find that disasters significantly negatively impact household delinquencies and foreclosures, which directly spill over to bank operations. Together with the projected increase in the severity and frequency of flood disasters, this suggests that the negative impact of floods will worsen.

The second contribution is to assess whether these risks are priced 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 predicts a return underperformance. The negative predictability is restricted to the sample of smaller banks and is sizeable. On average, a one-standard-deviation increase in exposure results in a 3.6 percentage point lower annualized excess return. Consistent with previous findings on different physical risks from climate change 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 77 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, flood risk exposure only predicts the stock returns of smaller banks.

I shed light on how the flood risk exposure negatively relates to the bank stock returns. The underperformance is most likely driven by a combination of different unanticipated shocks. First, past flood disasters cannot fully explain the negative predictability. While flood disasters lead to weaker stock performance, the negative relation of flood risk exposure decreases but persists. Second, the effect is not driven by investor attention or knowledge about climate change. Using the MCCC index from Ardia et al. (2022) and search data from Google, I find that climate change concern has negative predictability for bank stock returns regardless of the bank's exposure to flood risk. Still, the negative predictability of flood risk exposure persists. In a final exercise, I find that the underperformance is concentrated on banks active in Democratic-leaning counties, specifically in the years under President Obama.

The results suggest that banks are negatively affected by flood realizations but that investors do not directly or entirely pay attention to physical risks from flooding, which highlights the concerns that markets might not have fully adapted to the "new normal" ushered by climate change. Further, investors are more worried about climate policy risks rather than pure physical risks in line with findings from Ardia et al. (2022). This could also explain the lower predictability from 2016 to 2019 as regulatory changes were lower during the Trump presidency. The negative return predictability of the flood risk exposure for smaller banks suggests that investors withdraw from this segment of the market, while 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.

Bakkensen, Laura A, and Lint Barrage, 2022, Going underwater? Flood risk belief heterogeneity and coastal home price dynamics, *The Review of Financial Studies* 35, 3666–3709.

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.

Bansal, Ravi, Marcelo Ochoa, and Dana Kiku, forthcoming, Climate change and growth risks, *Climate Change Economics: The Role of Uncertainty and Risk* .

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

Becker, Bo, 2007, Geographical segmentation of US capital markets, *Journal of Finance* 151–178.

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.

Blickle, Kristian, Sarah Ngo Hamerling, and Donald P. Morgan, 2022, How bad are weather disasters for banks?, Federal Reserve Bank of New York Staff Reports 990.

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

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

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

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

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

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

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

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

Cerqueiro, Geraldo, Steven Ongena, and Kasper Roszbach, 2016, Collateralization, Bank Loan Rates, and Monitoring, *The Journal of Finance* 71, 1295–1322.

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

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

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

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

Degryse, Hans, Moshe Kim, and Steven Ongena, 2009, Managing risks in the banking firm, in *Microeconometrics of Banking: Methods, Applications, and Results*, 164–173 (Oxford University Press).

Demsetz, Rebecca S., and Philip E. Strahan, 1997, Diversification, Size, and Risk at Bank Holding Companies, *Journal of Money, Credit and Banking* 29, 300–313.

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

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

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

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

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

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

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

Fama, Eugene F., and Kenneth R. French, 2002, The equity premium, *The Journal of Finance* 57, 637–659.

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

Federal Reserve, 2022, Federal Reserve Board announces that six of the nation's largest banks will participate in a pilot climate scenario analysis exercise designed to enhance the ability of supervisors and firms to measure and manage climate-related financial risks, https://www.federalreserve.gov/newsevents/pressreleases/other20220929a.htm.

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

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

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

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

Giannetti, Mariassunta, and Farzad Saidi, 2019, Shock propagation and banking structure, *The Review of Financial Studies* 32, 2499–2540.

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.

Goetz, Martin R., Luc Laeven, and Ross Levine, 2016, Does the geographic expansion of banks reduce risk?, *Journal of Financial Economics* 120, 346–362.

Goldsmith-Pinkham, Paul, Matthew T Gustafson, Michael Schwert, and Ryan C Lewis, 2021, Sea level rise exposure and municipal bond yields, Working Paper.

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

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

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

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

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

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

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

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

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

Loutskina, Elena, 2011, The role of securitization in bank liquidity and funding management, *Journal of Financial Economics* 100, 663–684.

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

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

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

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

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

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

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

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

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

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

Painter, Marcus, 2020, An inconvenient cost: The effects of climate change on municipal bonds, *Journal of Financial Economics* 135, 468–482.

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

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

Pew Research Center, 2016, The policitcs of climate, Technical report.

RealtyTrac, 2016, Housing news report .

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

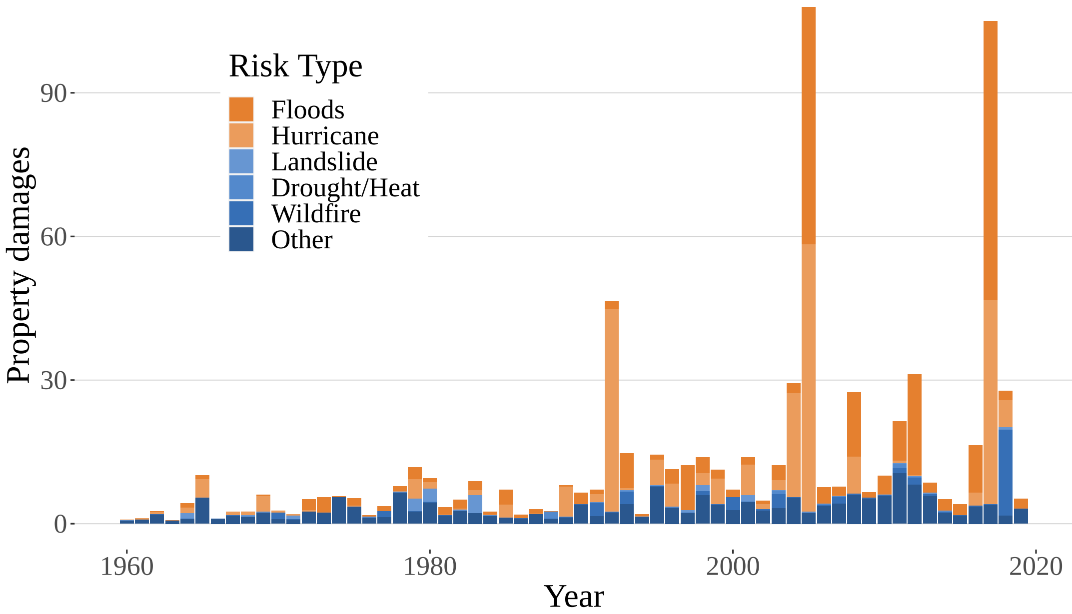
Schüwer, Ulrich, Claudia Lambert, and Felix Noth, 2019, How do banks react to catastrophic events? Evidence from Hurricane Katrina, *Review of Finance* 23, 75–116.

SEC, 2022, The enhancement and standardization of climate-related disclosures for investors, Proposed Rule 87 FR 21334.

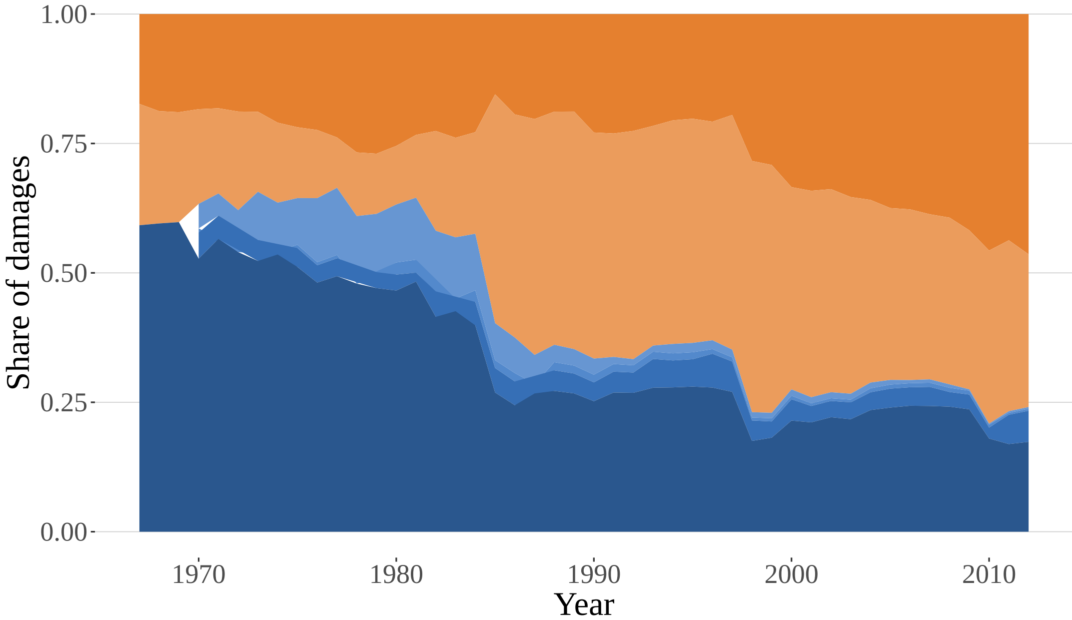
Seltzer, Lee, Laura T Starks, and Qifei Zhu, 2022, Climate regulatory risks and corporate bonds, *Federal Reserve Bank of New York Staff Reports* 61.

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

8. Figures



a) Property Damage Estimates



b) Share of Damage Estimates

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

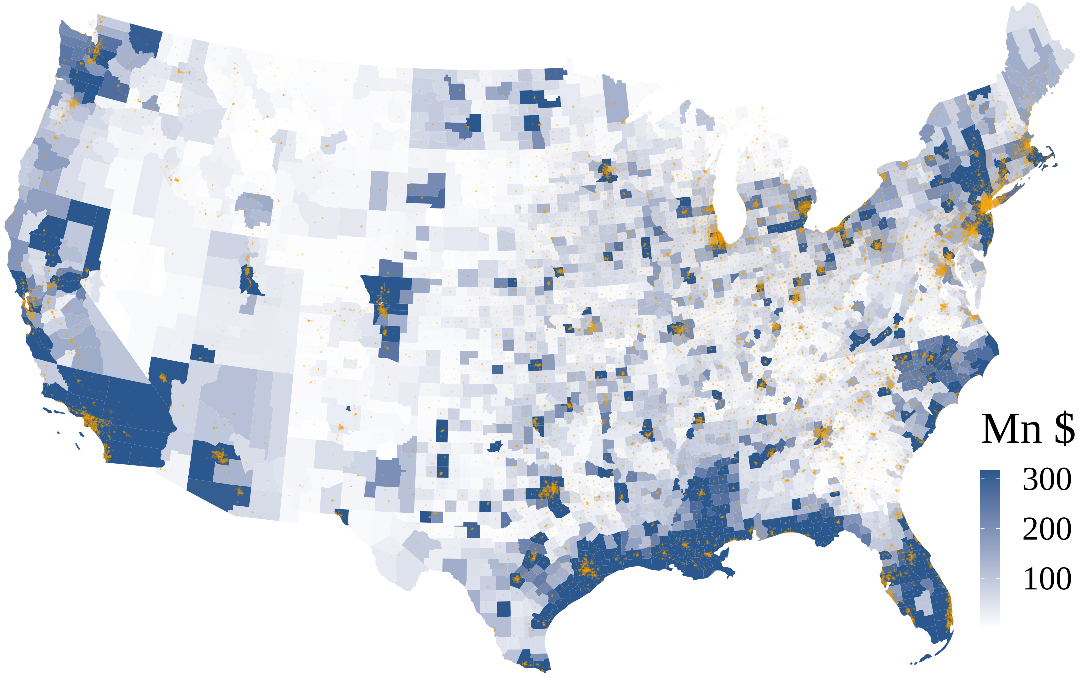


Figure 2: Flood Damage Map. This figure plots the county-level property damages from floods for the years 1980 to 2020 in shaded blue. The estimates come from Sheldus. The orange dots represent bank branches and are obtained from FDIC Summary of Deposits for the year 2020.

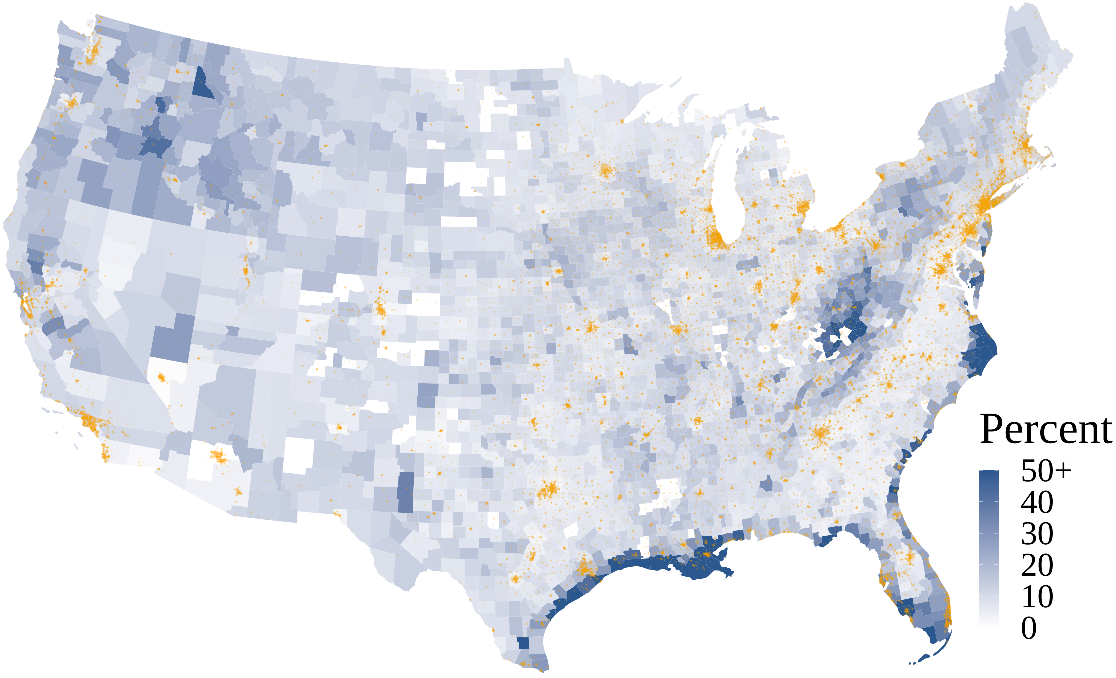
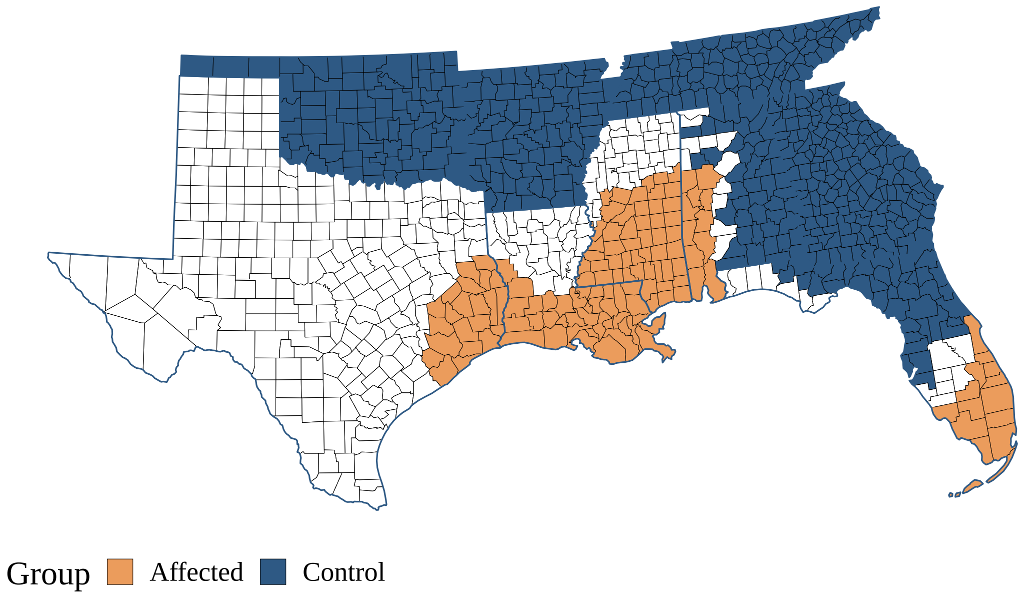
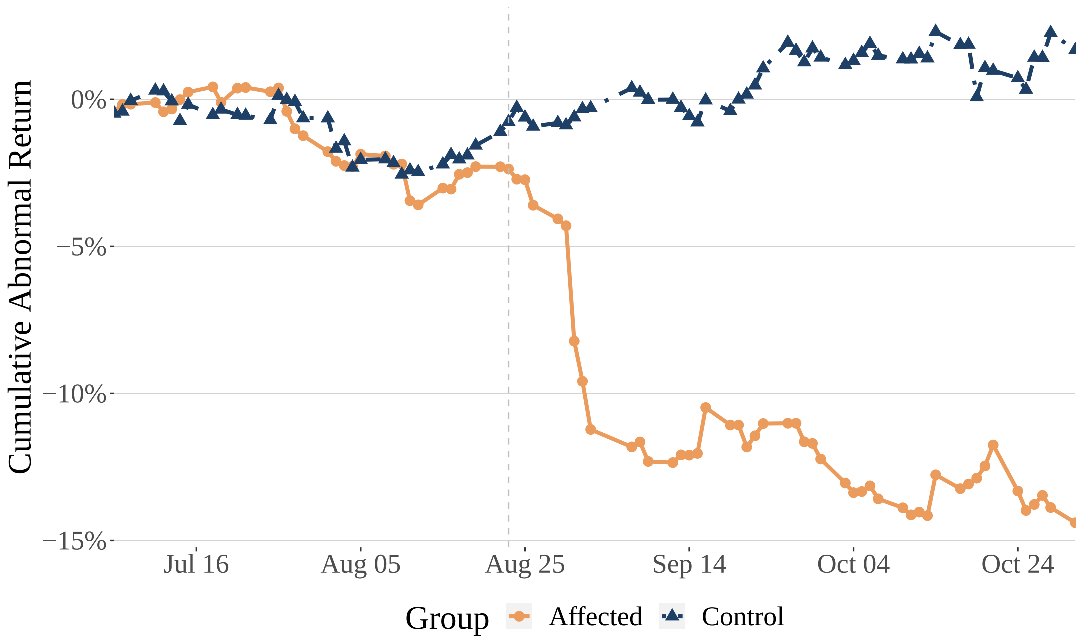


Figure 3: Flood Risk Map. This figure plots the county-level flood risk. The data comes from First Street Foundation and shows the number of properties with a 1% probability of flooding by 2050.

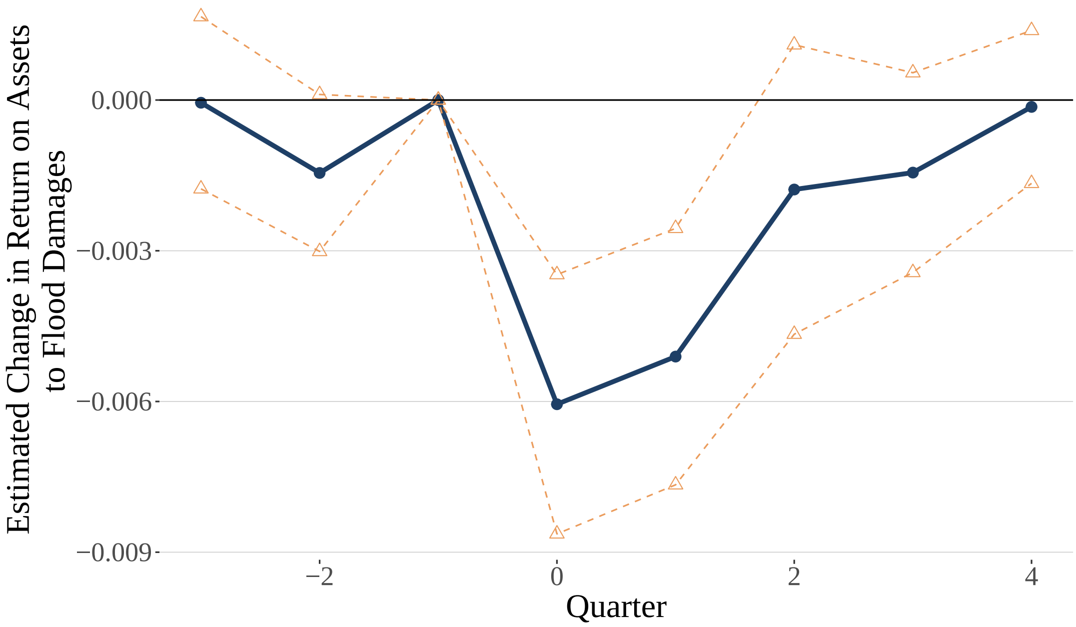


a) Affected Areas

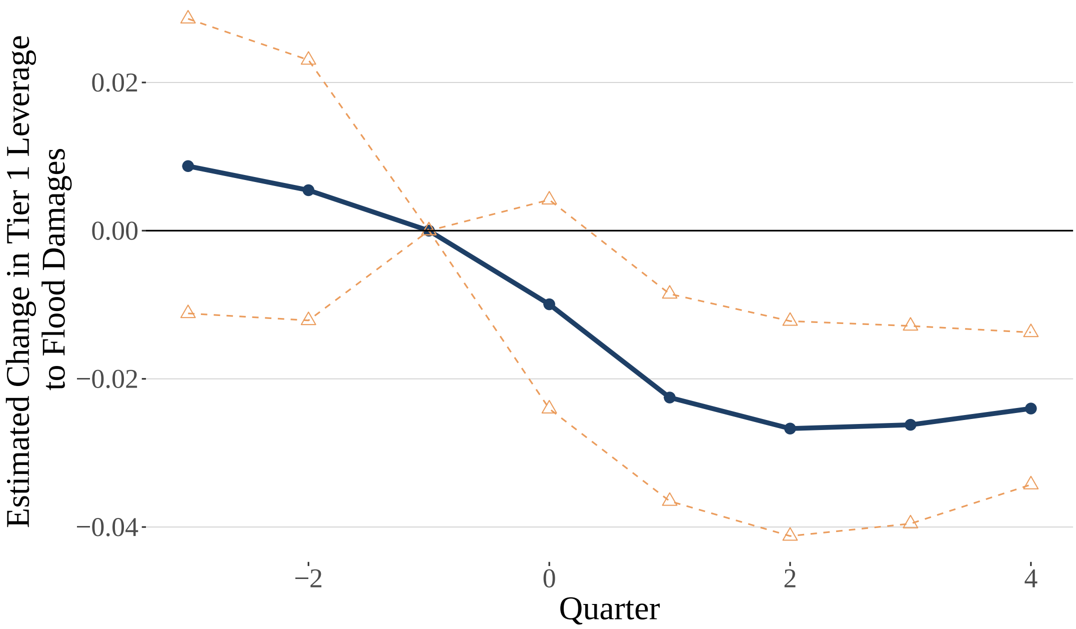


b) Cumulative Abnormal Return

Figure 4: Stock market response to Hurricane Katrina. This figure presents the stock market response to Hurricane Katrina in August 2005. Banks active in counties that received individual disaster relief from the Presidential Declaration Disaster Relief program are defined as treated. The counties are shown in orange in Panel A. Banks active in blue-shaded counties (that received neither individual nor public relief, but are located in the Gulf) are the control group. Panel B reports the cumulative abnormal return of treatment (orange circles) and control group (blue triangles).

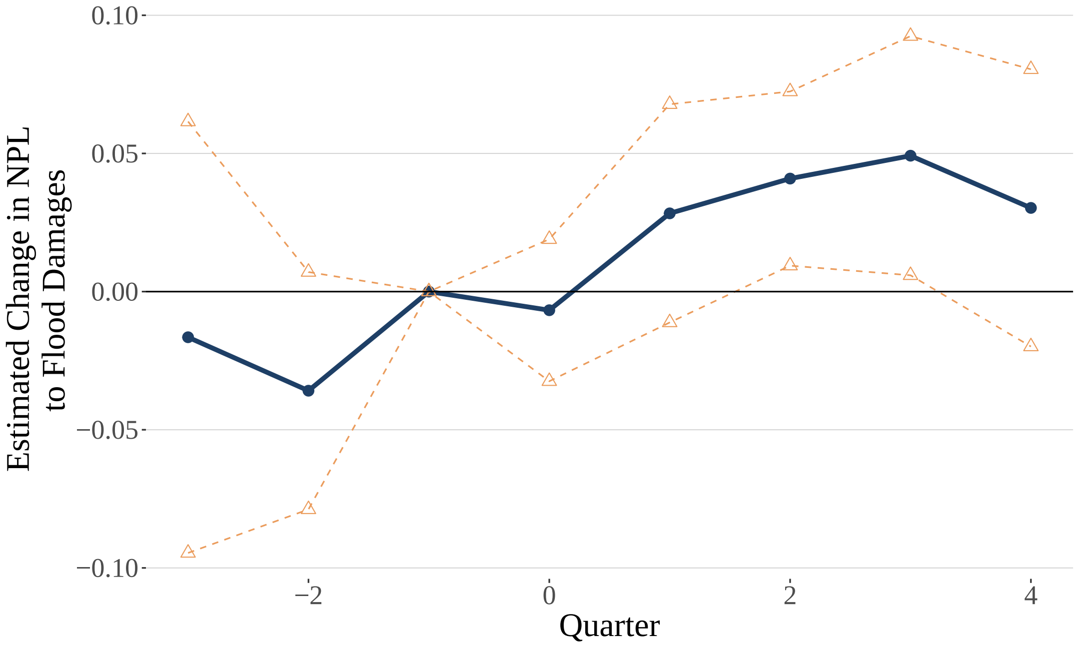


a) Return on Assets

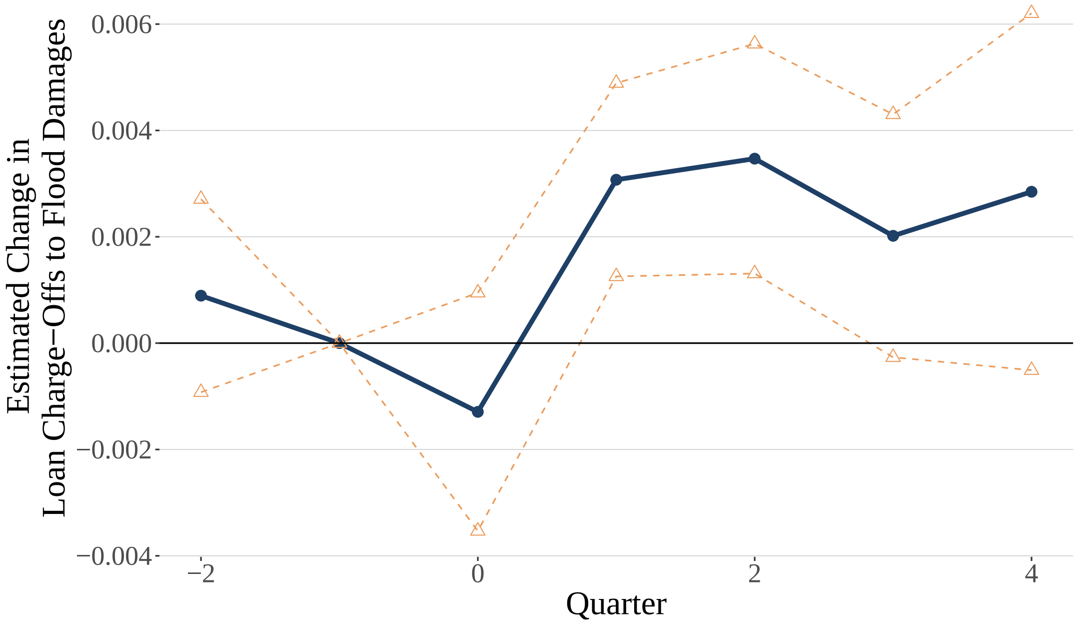


b) Tier 1 Leverage Ratio

Figure 5: Effect of flood disasters on bank performance. This figure presents the relation between bank-level exposure to current flood damages and returns on assets (Panel A) and Tier 1 leverage ratio (Panel B). This figure is estimated by regressing the bank variable in $t+h$ on the exposure to current (t) flood damages, where h runs from -3 to +4 quarters. All regressions are run including *Tier 1 leverage*, *log(assets)*, and the *Mortgage lending ratio*, as well as bank and quarter fixed effects. Standard errors are clustered at the bank level. The solid line presents the point estimates for *Scaled Damages*. The short dashed lines present 97.5% confidence intervals on this estimate.

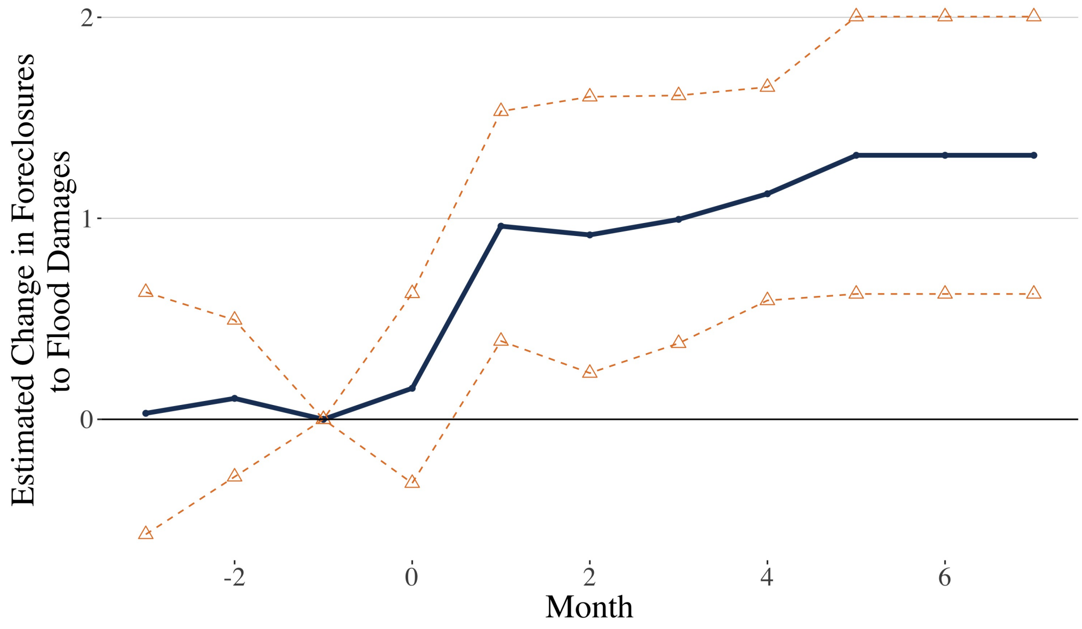


a) Non-performing Loans

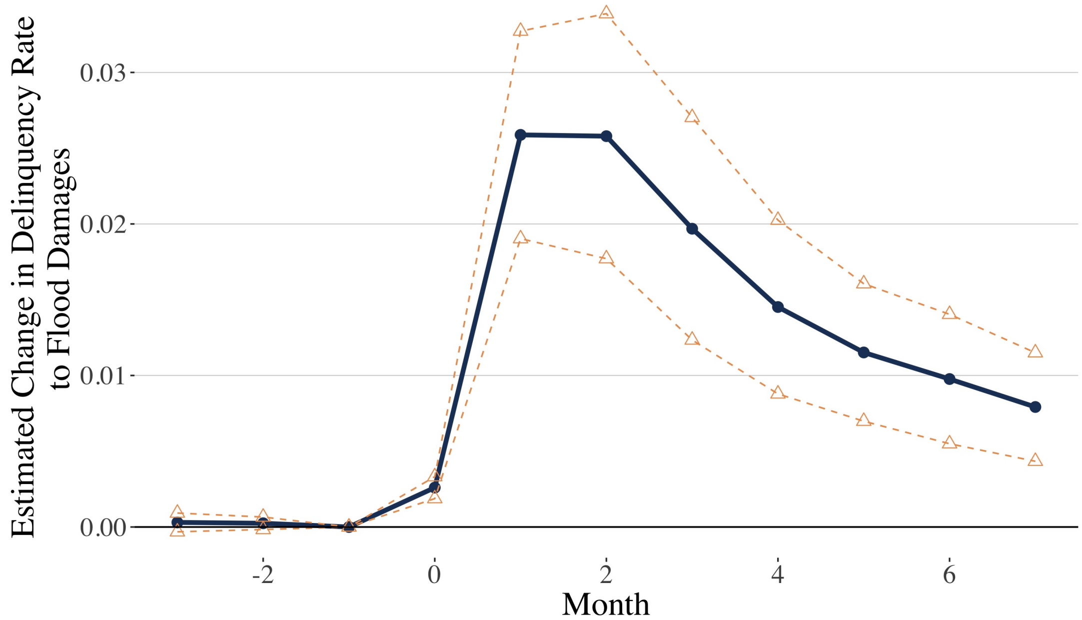


b) Loan Charge-Offs

Figure 6: 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 *Scaled Damages*. The short dashed lines present 95% confidence intervals on this estimate.



a) Mortgage Foreclosures



b) Mortgage Delinquencies

Figure 7: 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.

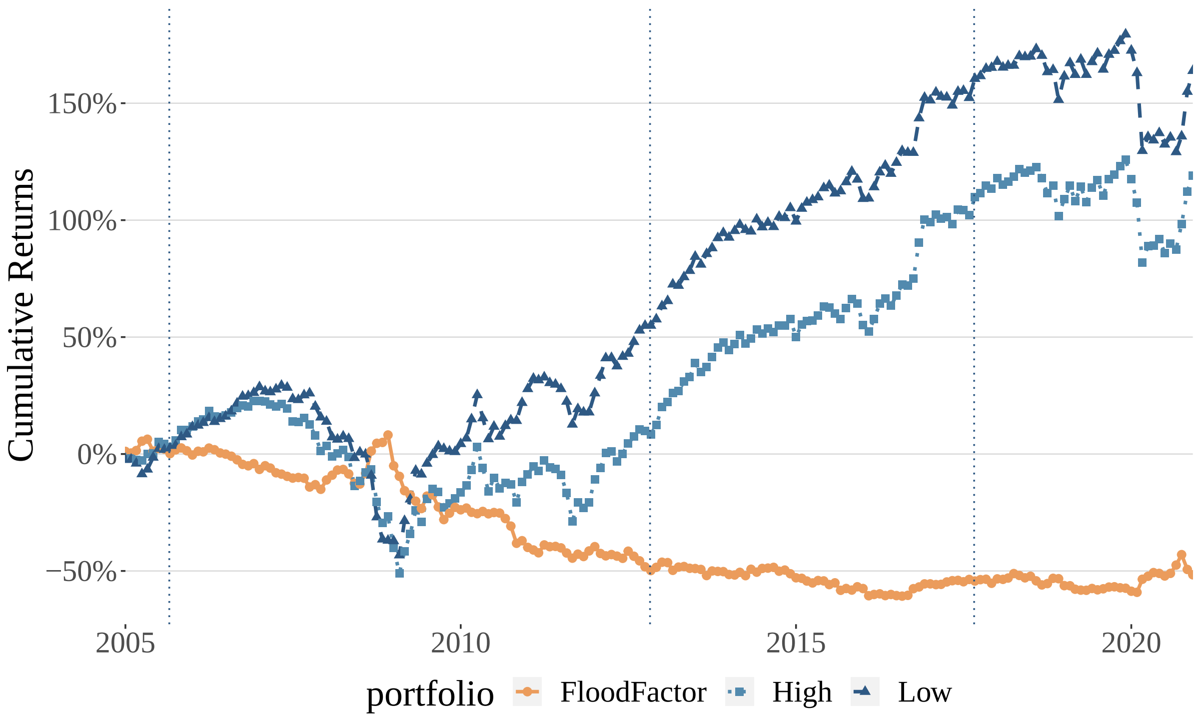


Figure 8: Cumulative Return of the Exposure-Weighted Flood Factor. The solid line plots the cumulative return of the flood factor constructed with banksf́lood risk exposure. The dotted-blue line (High) plots the cumulative return of the portfolio of banks with high flood exposure, while the dashed blue line (Low) reports the cumulative return of the portfolio of banks with low flood risk exposure.

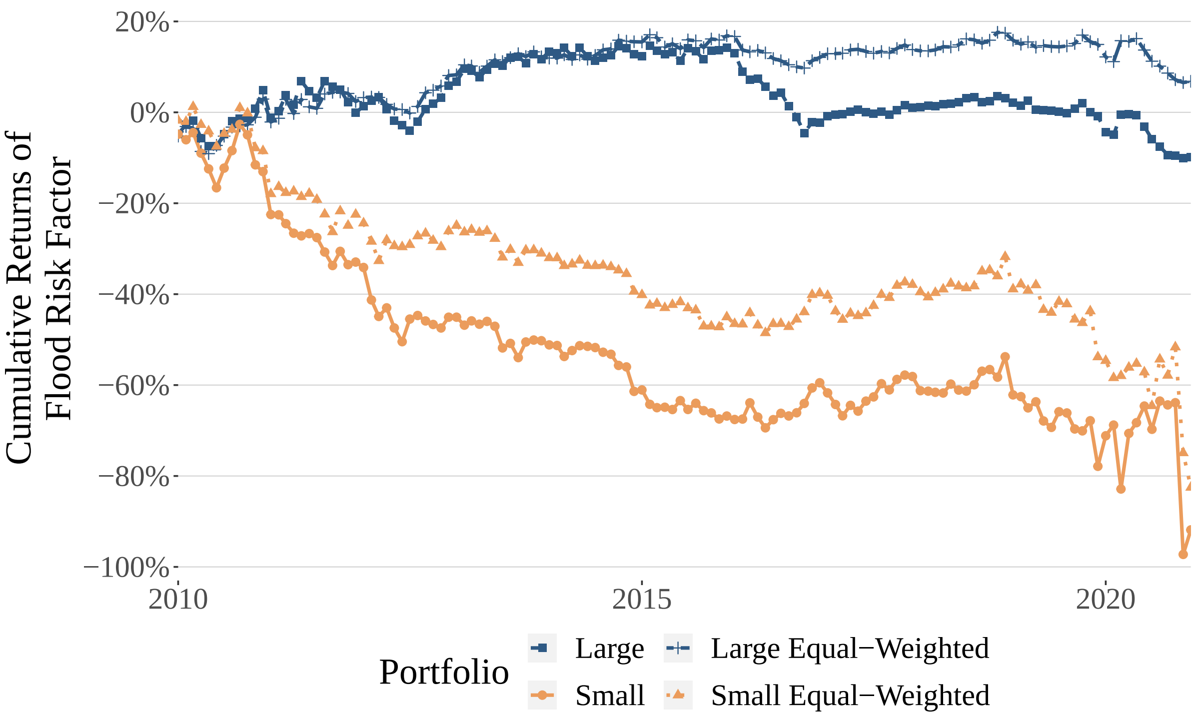


Figure 9: Cumulative Return of the Exposure-Weighted Flood Factor for Size-sorted Samples. The orange solid and dotted lines plot the cumulative returns of the flood factor from the sample restricted to small banks. The solid line is the exposure-weighted cumulative return and the dotted line is the equally-weighted returns. The two blue lines plot large banks' exposure-weighted cumulative return (two-dash) and equal-weighted cumulative return (dashed).

Table 1:
Summary Statistics

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

	High Exposure		Low Exposure				
	Mean	Obs	Mean	Obs.	Diff.	t-Stat	Signif.
Mortgage-based Variables							
Application (Mn $)	129.7	1,721	176.0	5,157	−46.3	−1.3	
Retained Amount (Mn $)	56.4	1,721	83.0	5,157	−26.7	−1.4	
Active Counties	101.2	1,721	115.7	5,157	−14.5	−1.9	*
Active States	7.9	1,721	8.9	5,157	−1.0	−3.2	***
Average Origination (Thsd $)	519.7	1,721	516.4	5,157	3.3	0.1	
Average Retained (Thsd $)	0.1	1,721	0.1	5,157	−0.03	−1.4	
Flood Risk Exposure (2050)	20.7	1,721	7.9	5,157	12.8	49.9	***
Flood Risk Exposure (2035)	19.0	1,721	7.6	5,157	11.5	55.3	***
Flood Risk (Score-based)	2.4	1,721	1.4	5,157	1.0	53.6	***
Insurance Policies	11,293.2	1,721	3,563.7	5,157	7,729.6	11.5	***
Insurance Sum (Mn$)	2,322.5	1,721	725.8	5,157	1,596.7	11.6	***
Stock Variables							
Return	0.3	8,248	0.4	71,911	−0.1	−1.1	
Excess Return	0.1	8,248	0.3	71,911	−0.1	−1.0	

Continued on next page

Table 1 – *Continued from previous page*

	Low Exposure		High Exposure				
	Mean	Obs	Mean	Obs.	Diff.	t-Stat.	Signif.
Balance Sheet Variables							
Total Assets (Bn)	20.5	5,909	50.7	16,511	−30.2	−12.4	***
Loan Ratio	68.0	5,909	68.1	16,511	−0.1	−0.4	
Tier 1 Leverage	10.6	5,909	10.0	16,511	58.1	1.1	
Deposit Ratio	77.3	5,909	75.4	16,511	1.9	11.6	***
Real Estate Loans Ratio	45.3	5,909	44.8	16,511	0.4	1.9	*
Mortgage Ratio	19.0	5,909	18.6	16,511	0.3	2.1	**
ROA	0.4	5,909	0.4	16,511	0.003	0.2	
NPL Ratio	1.2	5,909	1.2	16,511	0.02	0.8	
Z-score	21.9	5,909	29.6	16,511	−7.7	−4.8	***

Table 2:

Return on Assets and Flood Disasters

This table reports the results from pooled-OLS regressions with fixed effects. The main explanatory variable is *Scaled Damages*, 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 different county-weights. In columns (1) and (2) damages are waited by originated and retained mortgages respectively. Colum (3) first multiplies county-level damage amounts in dollars by the bank's market share before dividing by total assets. Column (4) uses deposit shares. In column (5) damages are waited by headquarters counties. Further, in all columns, scaled damages have been standardized to allow for comparison across regressions. The dependent variable is one-quarter ahead return on assets. 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}				
County Weight	Originated	Retained	Market-Share	Deposits	Headquarter
	(1)	(2)	(3)	(4)	(5)
Scaled Damages	-0.005***	-0.005***	-0.005**	-0.001	-0.001
	(-3.76)	(-4.24)	(-2.42)	(-0.600)	(-0.617)
ROA	0.255***	0.255***	0.255***	0.255***	0.255***
	(5.11)	(5.11)	(5.11)	(5.11)	(5.11)
Leverage	0.002***	0.002***	0.002***	0.002***	0.002***
	(3.44)	(3.44)	(3.43)	(3.44)	(3.44)
log(Assets)	-0.169***	-0.169***	-0.170***	-0.169***	-0.169***
	(-4.27)	(-4.27)	(-4.27)	(-4.26)	(-4.26)
Loan Ratio	-0.025	-0.025	-0.025	-0.025	-0.025
	(-0.147)	(-0.148)	(-0.149)	(-0.148)	(-0.148)
Mortgage Ratio	0.078	0.078	0.080	0.078	0.077
	(0.335)	(0.335)	(0.343)	(0.332)	(0.332)
Bank	YES	YES	YES	YES	YES
Quarter	YES	YES	YES	YES	YES
Obs.	19,126	19,126	19,125	19,126	19,126
R^2	0.498	0.498	0.498	0.498	0.498
Within R^2	0.058	0.057	0.057	0.057	0.057

Table 3:
Bank performance and Flood Disasters

This table reports the results from pooled-OLS regressions with fixed effects. The main explanatory variable is the *Scaled Damages*, 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)
Scaled Damages	-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***	
							(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)

Continued on next page

Table 3 – *Continued from previous page*

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

Table 4:

Heterogeneity in Bank Returns on Assets

This table partitions the results from Table 3 on mortgage loan share (High and Low) and bank size (Small and Large). The main explanatory variable is the *Scaled Damages*, 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)
Scaled Damages	-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)
Scaled Damages	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)
Scaled Damages	0.002**	-4×10^{-5}	0.0001	0.0003
	(2.31)	(-0.268)	(0.660)	(1.22)
Bank Controls	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES
Obs.	8,403	6,034	6,106	8,331
R^2	0.514	0.541	0.478	0.525

Table 5:
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

Table 6:
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 (1)	2035 Flood Risk (2)	Flood Risk Score (3)	Number-weighted (4)	Origination-weighted (5)	Rolling Retained (6)	Rolling Origination (7)	Competition-weighted (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**
	(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)

Continued on next page

Table 6 – *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)
Mortgage Exposure	-1.48***	-1.50***	-1.52***	-1.48***	-1.48***	-1.56***	-1.60***	-1.34***
	(-3.54)	(-3.57)	(-3.58)	(-3.54)	(-3.51)	(-3.66)	(-3.70)	(-3.23)
Month FE	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	43,227	43,227	43,227	43,227	43,227	43,227	43,227	43,227
R^2	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28

Table 7:
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
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)

Continued on next page

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

Table 10: Flood Risk Exposure without Disaster Periods

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

Panel A: All Banks

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

Panel B: Small Banks

	Excess Returns			
	Without Hurricane Katrina	Without Major Storms	Zero Damage	Zero Damage & High-Risk

Continued on next page

Table 10 – *Continued from previous page*

	(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

Panel C: Large Banks

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

Table 8:
Risk-adjusted Returns on Flood Risk sorted Portfolios

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

Panel A: Full Sample

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

Panel B: Small Banks

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

Panel C: Large Banks

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

Table 9:
Performance of the Exposure-Weighted Flood Factor

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

Panel A: Full Sample

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

Panel B: Small Banks

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

Panel C: Large Banks

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

Table 11:
Bank Stock Returns and Disaster Realizations

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

Panel A: All Banks

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

Panel B: Small Banks

	Excess Returns				Return Residuals
Flood Damages	Weighted Damages		High Damage	Total Damages	Weighted Damages
	(1)	(2)	(3)	(4)	(5)
Flood Risk Exposure	-0.200***	-0.200***	-0.223***	-0.202***	-0.180**
	(-2.59)	(-2.59)	(-2.68)	(-2.60)	(-2.53)
Flood Damages	-0.002	0.004	-0.550**	-0.141***	
	(-0.067)	(0.080)	(-2.41)	(-4.20)	
Flood Risk Exposure		-0.004	0.347*	0.002	
× Flood Damages		(-0.254)	(1.87)	(0.077)	
Obs.	24,677	24,677	24,677	24,677	24,677
R^2	0.059	0.059	0.059	0.059	0.038

Panel B: Large Banks

Continued on next page

Table 11 – *Continued from previous page*

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

Table 12:
Flood Disasters as Sources of Flood Factor Performance

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

Panel A: Full Sample

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

Panel B: Small Banks

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

Table 13:
Bank Stock Returns and Climate Change Concerns

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

Panel A: Full Sample

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

Panel B: Small Banks

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

Table 14:
Political Landscape

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 expected flood risk. The dependent variable is excess return. All regressions include bank-level controls, such as log(market value), Tier 1 leverage, mortgage ratio, loan ratio, log(assets), past-month return, and mortgage exposure. The political indicator is either an indicator that equals one if the majority of the counties in which a given bank originated mortgages has voted Republican during the most recent federal election or equals one if the president is a Republican. Standard errors are clustered at the bank level. t-statistics are in parenthesis. Statistical significance is given by $*$: $p < 0.10$; $**$:$p < 0.05$; $***$:$p < 0.01$

	Excess Returns					
Political Indicator	Majority Republican Counties			Republican President		
	Full	Small	Large	Full	Small	Large
	(1)	(2)	(3)	(4)	(5)	(6)
Flood Risk Exposure	-0.288***	-0.302**	-0.235*	-0.307***	-0.345***	-0.093
	(-2.79)	(-2.56)	(-1.66)	(-3.65)	(-3.63)	(-0.659)
Flood Risk Exposure × Political Indicator	0.192*	0.126	0.438**	0.295***	0.259**	0.293
	(1.68)	(0.967)	(2.12)	(2.93)	(2.35)	(1.43)
Political Indicator	-0.088	-0.091	-0.109			
	(-0.824)	(-0.692)	(-0.700)			
Bank Controls	YES	YES	YES	YES	YES	YES
Month	YES	YES	YES	YES	YES	YES
Obs.	57,126	42,668	14,458	57,126	42,668	14,458
R^2	0.289	0.255	0.498	0.289	0.255	0.498
Within R^2	0.029	0.034	0.023	0.029	0.034	0.022

Table 15:
Flood Risk Exposure and Federal Control

This table reports the results from pooled-OLS regressions with bank and month fixed effects. *Flood Risk Exposure* captures banks' exposure to expected flood risk. The variables *Repub. House*; *Repub. Senate*; or *Repub. President* is equal to one if the House of Representatives, Senate, or the presidency is controlled by Republicans. The variables *Congress*; *Senate*; or *House* is equal to one if Republicans control the Congress, only Senate, or only the House. All regressions control for 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: Federal Control

	Excess Return		
	Full	Small	Large
	(1)	(2)	(3)
Flood Risk Exposure	-0.451***	-0.525***	-0.045
	(-2.90)	(-2.95)	(-0.162)
Flood Risk Exposure × Repub. House	0.454***	0.550***	0.147
	(4.01)	(4.41)	(0.735)
Flood Risk Exposure × Repub. Senate	-0.272	-0.351*	0.022
	(-1.34)	(-1.70)	(0.065)
Flood Risk Exposure × Repub. President	0.590***	0.606***	0.377
	(2.75)	(2.64)	(0.907)
Bank Controls	YES	YES	YES
Bank	YES	YES	YES
Month	YES	YES	YES
Observations	57,126	42,668	14,458
R^2	0.306	0.273	0.510

Panel B: Orthogonal Indicators

	Excess Return		
	Full	Small	Large
	(1)	(2)	(3)
Flood Risk Exposure	-0.225*	-0.321**	0.198
	(-1.76)	(-2.24)	(0.925)
Flood Risk Exposure × Congress	0.466***	0.507***	0.311
	(3.91)	(3.77)	(1.34)
Flood Risk Exposure × Senate	-0.108	-0.143	-0.082
	(-0.470)	(-0.548)	(-0.191)
Flood Risk Exposure × House	0.280**	0.393**	-0.091
	(1.97)	(2.52)	(-0.412)
Bank Controls	YES	YES	YES
Bank	YES	YES	YES
Month	YES	YES	YES
Obs.	57,126	42,668	14,458
R^2	0.306	0.273	0.510

Table 16:
Institutional Investors

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 expected flood risk. All regressions control for Tier 1 leverage, mortgage ratio, loan ratio, log(assets), past-month return, and mortgage exposure. Investor indicator is equal to one if the change in the share held by institutional investors is negative (columns (1)-(4)) or the level of shares held by institutional investors. The political indicator is an indicator that equals one if the president is a Republican. Standard errors are clustered at the bank level. t-statistics are in parenthesis. Statistical significance is given by $*$: $p < 0.10$; $**$:$p < 0.05$; $***$:$p < 0.01$

	Excess Returns					
Investor Indicator	Negative Δ Institutional Investors				High Instit. Share	
	Full		Small	Large	Full	
	(1)	(2)	(3)	(4)	(5)	(6)
Flood Risk Exposure	-0.145**	-0.211**	-0.219**	-0.134	-0.160***	-0.272***
	(-2.56)	(-2.38)	(-2.11)	(-0.892)	(-2.82)	(-2.88)
Flood Risk Exposure × Inv. Indicator	0.033	-0.120	-0.148	-0.042	0.116*	0.095
	(0.302)	(-0.746)	(-0.937)	(-0.088)	(1.73)	(0.873)
Flood Risk Exposure × Pol. Indicator		0.148	0.083	0.238		0.258**
		(1.38)	(0.672)	(1.44)		(2.21)
Flood Risk Exposure × Pol. Indicator × Inv. Indicator		0.414*	0.402*	0.436		-0.009
		(1.93)	(1.88)	(0.708)		(-0.060)
Investor Indicator	-0.291**	-0.417**	-0.262	-0.884***	-0.384***	-0.611***
	(-2.32)	(-2.16)	(-1.11)	(-2.72)	(-4.32)	(-4.27)
Political Indicator × Investor Indicator		0.310	-0.057	0.683*		0.466***
		(1.22)	(-0.186)	(1.67)		(2.73)
Bank Controls	YES	YES	YES	YES	YES	YES
Month	YES	YES	YES	YES	YES	YES
Obs.	48,469	48,469	34,586	13,883	50,788	50,788
R^2	0.326	0.327	0.289	0.507	0.316	0.316

Table 17:
Bank Stock Returns and Local Real Estate Markets

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

Panel A: Full Sample

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

Panel B: Small Banks

	Excess Returns			
	(1)	(2)	(3)	(4)
Flood Risk Exposure	-0.290***	-0.285***	-0.311***	-0.304***
	(-3.68)	(-3.68)	(-3.20)	(-3.29)
Flood Policies	-0.014			
	(-0.076)			
Flood Claim Amount		-0.192**		
		(-2.06)		
Foreclosures			0.137***	
			(2.60)	
Defaults				-0.010
				(-0.389)
Bank Controls	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Obs.	23,648	23,648	19,126	19,126
R^2	0.20	0.20	0.20	0.20

Continued on next page

Table 17 – *Continued from previous page*

Panel C: Large Banks

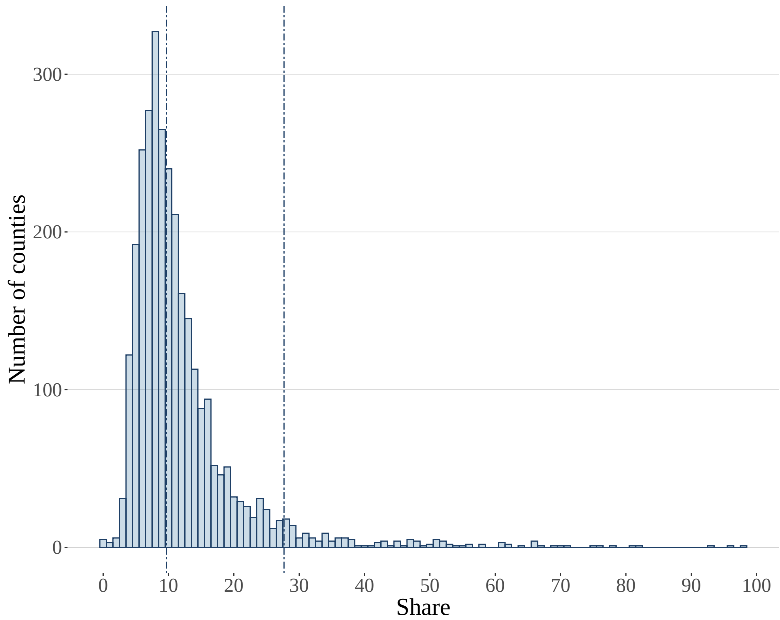
Dependent Variable:	Excess Returns			
	(1)	(2)	(3)	(4)
Flood Risk Exposure	0.038	0.016	0.028	0.039
	(0.482)	(0.193)	(0.241)	(0.342)
Flood Policies	-0.058*			
	(-1.66)			
Flood Claim Amount		-0.038		
		(-0.765)		
Foreclosures			-0.081	
			(-1.47)	
Defaults				-0.040*
				(-1.77)
Bank Controls	YES	YES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

Table 18:
Regional Factors and Bank Stock Returns

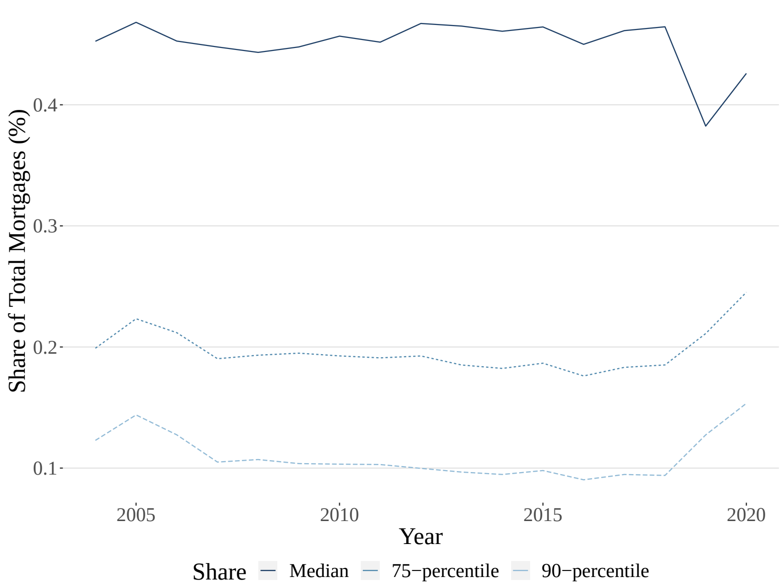
This Table reports results from regressing bank equity returns on the main flood risk exposure and controlling for general regional exposure. Column (1) includes state-level controls (GDP growth, inflation, unemployment rate, and the change in the house price index) weighted by the bank's exposure measure.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

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

A1. Additional Figures



a) Number of Counties by Risk Group



b) Share of Mortgage Amounts by Risk Percentiles

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

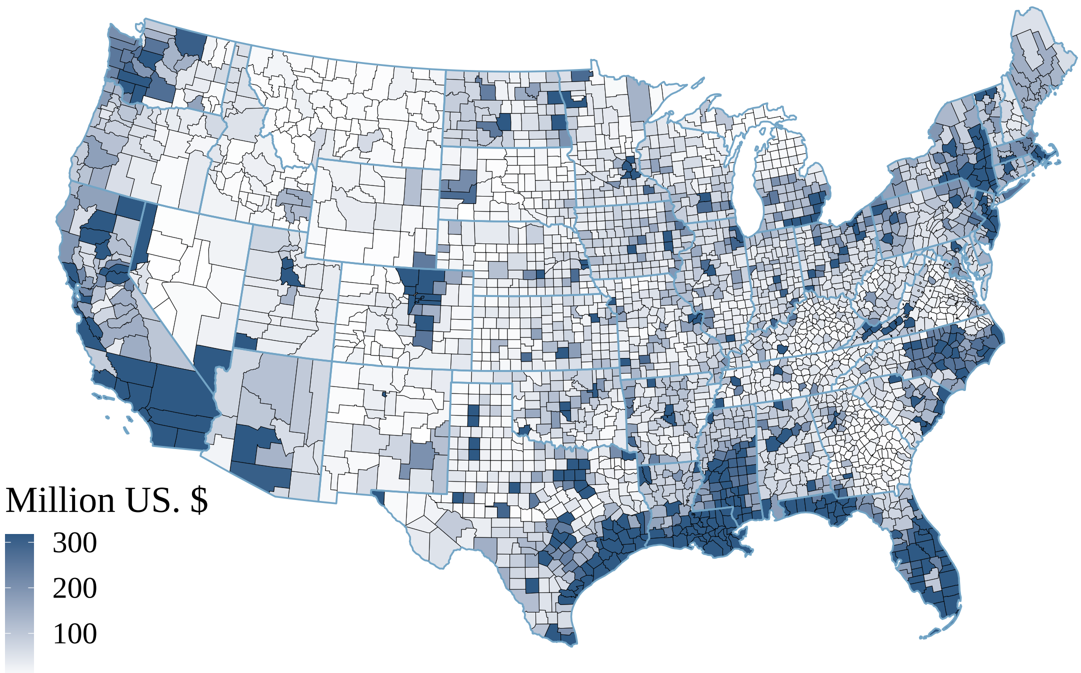


Figure A1.2: Property Damages from Floods. This figure plots the estimated property damages from floods since 1960 in the United States. The estimates come from SHELDUS and are available at the county level.

A2. Systematic Risk Decomposition

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

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

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:

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

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

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

where $F_{T\times K}$ are the original factors and $S_{K\times K}$ is a symmetric matrix that represents the inverse of the correlation matrix between the original and orthogonalized factors. In short, it is a linear combination of the eigenvector matrix and eigenvalues of the original factors.[21]. I estimate $F^{\perp}_{T\times K}$ for every subsample separately and use a fixed rolling window of 48 months to conduct time-varying democratic variance decompositions for analyzing the relative factor contributions over time.

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

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

a very similar pattern in both samples. It's almost irrelevant in the first half. In either sample, the flood risk factor contributes very little to the return variation.

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

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

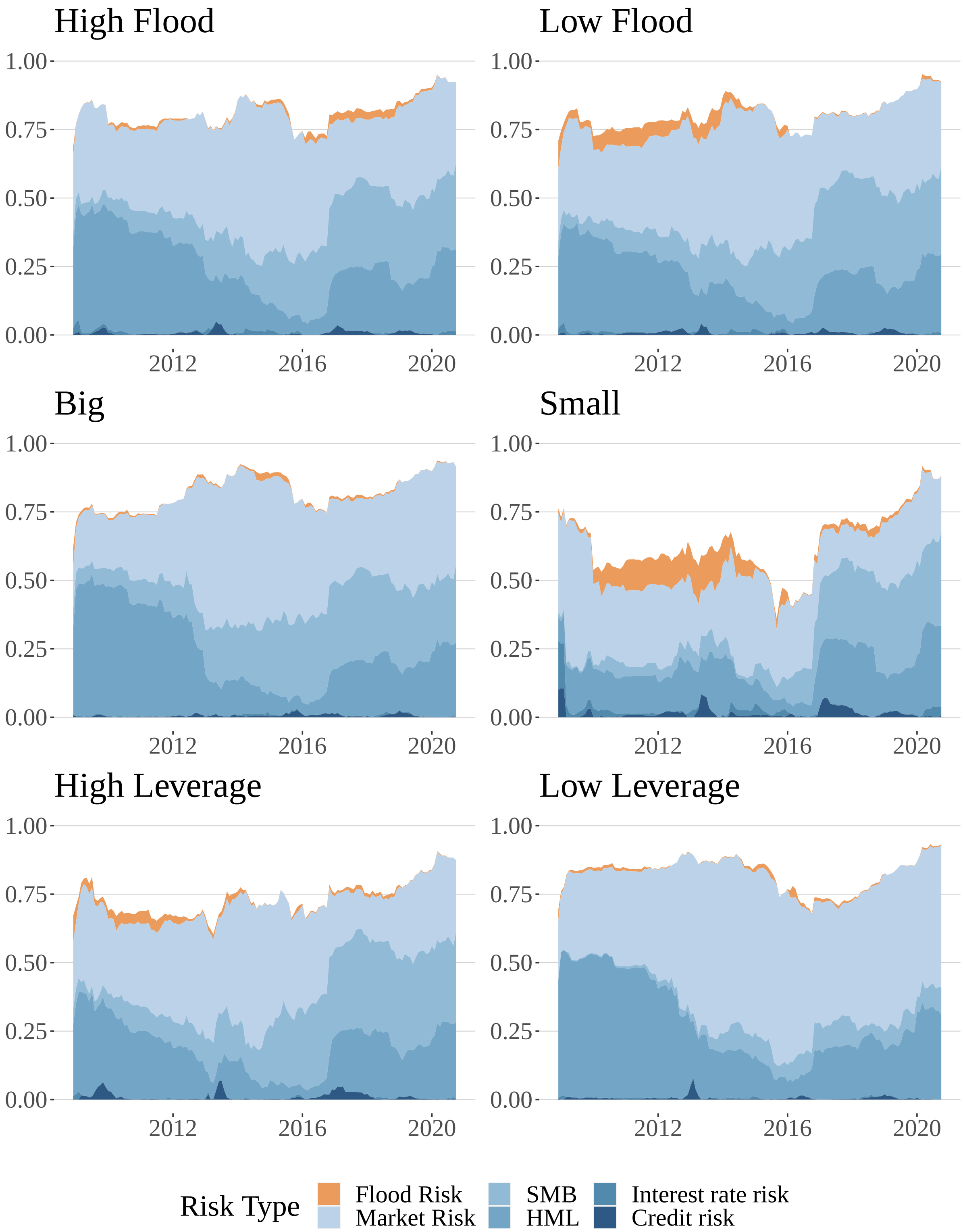


Figure A2.1: Variance Decomposition. Rolling variance decompositions for US bank portfolios. This figure shows variance decompositions for portfolios of US banks depending on bank characteristics. In the first row, the graphs plot the variance for the portfolio divided along their flood risk (above and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