# Is Flood Risk Priced in Bank Returns?

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**Abstract**

I quantify the costs of realized flood disasters for banks and create a novel measure of bank-level flood risk exposure using expected flood risk estimates and mortgage lending data. I document that banks with large shares of mortgages in affected areas experience lower profits and capital ratios following flood disasters. In the cross-section of stock returns, small banks with high exposure to flood risk underperform other banks, on average, by up to 9.6% per year; this implies that exposure to flood is not fully priced. Underperformance persists when controlling for the negative effects of disasters on realized returns and adjusting for investors' 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

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# 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 damage since 1980.[1] The widespread consensus is that the costs of such disasters will likely increase over the next decades (Intergovernmental Panel on Climate Change, 2015). Central banks have started to conduct climate-related stress tests of the banking sector, and regulators are considering new climate-related disclosures (SEC, 2022).[2] Yet there is limited empirical evidence of how physical risks from climate change affect individual financial institutions and overall financial stability. It is unclear whether physical risks would necessarily affect bank equity because banks actively manage their risk exposures through diversification, securitization, or by adjusting lending and loan terms.[3]

This paper studies how bank equity is exposed to climate change-induced natural disaster risk by quantifying the costs of *realized* flood disasters for U.S. banks and by developing a novel bank-level measure of *ex ante* flood risk exposure using expected flood risk estimates and geographic information on mortgages. I combine flood damage estimates with mortgage-level data to measure the costs of realized floods for banks. Banks exposed to realized floods exhibit lower profitability and a lower capital ratio. The estimates on realized flood costs are quantitatively similar for large and small banks, which suggests that even larger banks do not fully hedge the risks associated with flooding.

Next, I test whether investors price expected flood risk in bank stock returns using ex ante flood risk exposure, which combines expected flood risk estimates from the First Street Foundation (FSF) with a bank's portfolios of originated mortgages to create a

[1]See `https://www.ncei.noaa.gov/access/billions/` for more details. Accessed August 2022.

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

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

novel flood risk exposure measure for banks. Since climate and environmental risks are fundamentally downside risks for most firms (Seltzer, Starks, and Zhu, 2022), exposed banks should, if the risk is aggregate, command a higher expected return—and thus reflect the higher risk exposure. Alternatively, if the risk is purely idiosyncratic, we would expect an insignificant relation. The ex ante measure weighs the level of flood risk in a county by the share of mortgages originated in that county by a bank. I find that within the sample of small banks, those with high exposure to the risk of flooding underperform compared with banks with zero exposure. The effect is sizeable: A portfolio of small banks with high exposure to flood risk underperforms a portfolio of non-exposed small banks, on average, by 9.6% per year. Flood risk exposure is a robust return predictor and cannot be explained by other standard bank characteristics in cross-sectional regressions using pooled OLS. In comparison, flood risk seems to be better priced for larger banks: Flood risk exposure does not predict underperformance in the sample of large banks.[4] The negative coefficient on expected flood risk is not due to negative risk realizations (i.e., actual floods). Realized disasters do not subsume the result. The underperformance likely reflects a simultaneous combination of unanticipated shocks, such as unanticipated regulatory shocks, changes in investor preferences, and abnormally large realized disasters.

My novel exposure measure builds on the notion that banks are exposed to floods through their mortgage portfolios. As highlighted by the European Central Bank (ECB, 2019), natural disasters can lead to abrupt value losses in assets, especially in climate-risk-sensitive geographic areas. Homes in flood zones are particularly exposed to disasters, which ultimately affect collateral values for the banks that originated the mortgages. My measure of flood damage exposure is constructed in two steps. First, I depart from the literature and define bank-level regional weights as the share of the originated mortgage amount by a U.S. bank in a county relative to its total originated mortgage amount in a given year using mortgage-level location information instead of relying on branch location. Since the mortgage portfolio exposes banks to costs from floods, information

[4] Large banks are defined as above-median total assets, but the findings hold for top quartile or dollar thresholds, such as above $50bn in total assets.

on the location of banks' assets rather than branches allows me to assess the exposure more accurately;[5] Bank assets can be viewed as a proxy for business risk, while branches proxy for operational risks. Second, the share of the originated mortgages is matched to the flood measure. To quantify the cost of floods, the mortgage portfolio is matched to the estimated flood damage from Sheldus to calculate bank-level scaled flood damage. To measure ex ante flood risk exposure, the shares of the originated mortgages are matched to county-level flood probabilities.

Realized flood disasters significantly decrease bank profitability and increase leverage ratios for up to 1 year. For banks that specialize in mortgage lending, non-performing loans and mortgage charge-offs are significantly higher for several quarters after major flood disasters. Further, I illustrate the negative relation between natural disasters and bank equity using Hurricane Katrina. Banks exclusively lending to affected counties had abnormal returns of -15% compared with banks lending to other counties in the U.S. Gulf Coast region.

I examine the cross-sectional relation between ex ante flood risk exposure and U.S. bank excess stock returns by running bank-level pooled OLS regressions. Bank-level excess returns and flood risk exposure have a strong negative relation, which suggests a return discount for exposure to the risk of flooding. In pooled OLS, a one-standard-deviation increase in flood risk exposure is linked to a 2.4-percentage-points (pp) lower annualized excess return. This finding is in line with physical risks from climate change not being adequately priced, as previously documented for non-bank equities.[6] One explanation is that these risks have proven difficult to adequately assess and price—especially in equities, but also in insurance policies or real estate—because unlike other (non-climate) risks, which have remained relatively constant over the last decades, climate risks have changed significantly (Oh, Sen, and Tenekedjieva, 2022). Underperformance is limited to the sample of small banks. Within the sample of small banks, a one-standard-deviation

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

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

increase in flood risk exposure is associated with a 3.6 pp lower annualized excess return; the estimate for the sample of large banks is positive but insignificant. Importantly, although small banks have smaller balance sheets, they are not less profitable or less well capitalized. They are typically also active in many counties and across several states, which underlines the importance of capturing total exposure using banks' assets. Moreover, if anything, 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. In recent years, larger banks have been required to disclose more information than smaller institutions, and typically receive more scrutiny from regulators.[7] The additional regulations could enable a better assessment of the flood risk exposure of large banks, which partly explains the different results between the size-sorted samples.

I confirm the previous result, whereby the underperformance is restricted to the sample of small banks in bivariate portfolio sorts. Among small banks, a long-short portfolio of banks more exposed to flood risk underperforms, on average, by 77 bps per month, or over 9.6% annualized. In contrast, the alpha on the long-short portfolio of large banks is positive, albeit not significant. Over the period from 2004 to 2020, the long-short portfolio lost around 50% in the entire sample of banks, or 80% for small banks. The negative alpha for small banks cannot be explained by a selection of risk factors used in the banking literature, such as the four equity factors of Carhart (1997) and the two bond factors of Gandhi and Lustig (2015).

I proxy for expected return with a measure of realized return, but these two might diverge for several reasons. A negative relation between expected returns and realized returns in equity has been documented previously, and thus is not a new phenomenon.[8] In this setting, the sample of counties with high flood probability correlates with counties experiencing realized flood disasters. It could be the case that the U.S. experienced a series of bad shocks, which is picked up by the floor risk exposure. This implies that the

[7]For example, the Basel III disclosure requirements introduced by the Basel Committee on Banking Supervision.

[8]See Fama and French (2002) or Pastor, Stambaugh, and Taylor (2021) for a more recent example.

underperformance is merely an artifact of the sample and that the risk might be positively priced. However, changes in weather patterns due to climate change complicate precise forecasting of flood disasters. Thus, it is highly likely that the underperformance is due to a series of unanticipated shocks. I perform three tests to examine whether negative shock realizations explain the underperformance. First, the flood discount captured by flood risk exposure prevails in a sample without periods of significant floods and storms. Second, the underperformance of flood-risk-exposed banks persists even when explicitly controlling for past disasters using damage estimates. Third, underperformance prevails when using disaster-adjusted returns as dependent variables. This finding suggests that markets might not have fully adapted to the "new normal" ushered in by climate change.

Next, the sample period from 2004 to 2020 coincides with a fundamental change in assessing climate change-related risks from the perspective of investors. Recent studies have found that this transition period can explain differences in expected and realized returns for the stocks of climate-risk-exposed firms (e.g., Pastor, Stambaugh, and Taylor, 2021). As investors' preferences for assets less exposed to climate risk increase, returns on low-risk assets can outperform riskier ones. I test whether the observed increase in climate change concerns coincide with flood risk exposure. Whereas 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, concern proxies do not entirely subsume the negative coefficient on the flood risk exposure.

Previous literature has found that views on climate change play an important role in the pricing of climate-risk-exposed assets.[9] Using county-level election data, I find that that underperformance is stronger for banks that primarily lend to counties with a majority of Democratic voters. Further, it is strongest in the years when a Democratic president was in office (i.e., Barack Obama). Democratic officials are more likely to introduce new climate policies and regulate business in ways that affect local banks

[9]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.

negatively, and thus, the underperformance might be a reaction to unanticipated policy shocks.

Next, I perform a series of tests the examine whether the underperformance of flood risk exposure is driven by an omitted variable. When using banks' implied cost of capital (ICC) derived from analyst earnings forecasts and observed equity prices as measure of expected returns, the coefficient on the flood risk exposure is positive and insignificant. This alleviates any concern that the underperformance is driven by unobserved bank fundamentals and further strengthens the argument that it is likely due to unanticipated shocks. Overall, the results are robust to including HQ-state-times-month fixed effects and a wide range of controls, including flood insurance coverage, local differences in economic growth, or local real estate market performance.

This paper is most closely related to the literature that examines the pricing of climate risk, and generally in equities. Examples include Bolton and Kacperczyk (2021); Bolton and Kacperczyk (forthcoming); Duan, Li, and Wen (2021); and Hsu, Li, and Tsou (2021). Whereas these papers focus on the transition risk from climate change, I examine 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) who focus on heat-related climate risk in nonfinancial sectors. Painter (2020) and Goldsmith-Pinkham, Gustafson, Schwert, and Lewis (2021) analyze climate risk in municipal bonds. In contrast, this paper analyzes the risk of flooding in U.S. bank equities.

The paper's evidence is also related to Ardia, Bluteau, Boudt, and Inghelbrecht (2022); Engle, Giglio, Kelly, Lee, and Stroebel (2020); and Pastor, Stambaugh, and Taylor (2021), who discuss the importance of climate change concerns in asset pricing. Climate change concerns cannot explain the results in this paper.

The paper also contributes to the literature on natural disasters and bank performance. The existing literature is unclear about the effects on bank performance. Schüwer, Lambert, and Noth (2019) and Blickle, Hamerling, and Morgan (2022) find a negative or insignificant effect of disasters on performance, while Noth and Schüwer (2018) provide evidence of a positive effect. The common approach to measuring banks' exposure to natural disasters has been to use branch information.Instead, I develop a new exposure measure based on banks' balance sheet data. Specifically, I use banks' mortgage lending activity to map their balance sheets to flood disasters and expected flood risk. The benefit of this novel measure is that it more accurately maps banks' business risks. I show that using branch location to measure exposure to floods underestimates the effects compared with using balance sheet information. Further, I also analyze loan performance and equity measures.

Further, the paper contributes to the extensive literature on natural disasters and bank lending. The evidence 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 confined to certain types of banks.Ouazad and Kahn (2021) document that commercial banks react to climate risk when disasters realize, while Garbarino and Guin (2021) find that home loan lenders do not adjust their loan terms following severe flooding. The literature has only focused on realized disasters, while this paper also analyzes the effect of ex ante risks from climate change.

The paper also contributes to the literature studying the effect of weather hazards on real estate markets (Bernstein, Gustafson, and Lewis, 2019; Baldauf, Garlappi, and Yannelis, 2020; Gibson and Mullins, 2020; Keys and Mulder, 2020; Murfin and Spiegel, 2020; Giglio, Maggiori, Rao, Stroebel, and Weber, 2021), which suggests that not all risk from flooding is priced in the residential real estate market.

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

## 2 Data and Summary Statistics

This section describes the different data sources and introduces key explanatory variables. I focus on floods and hurricanes, which are the costliest disasters in the United States (Davenport et al., 2021). Weather disasters have caused over $1 trillion in property damage since 2010, of which almost $300 billion is attributed to floods and storms (Figure 1).[10] 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), and sea level rise will exacerbate the problem even further (Davenport et al., 2021). Some estimates predict that property damage 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 the frequency and severity of climate disasters, the risk of abrupt losses of asset value in climate risk-sensitive geographic areas also increases. Real estate is inextricably linked to its geographic location, and 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 billion and $250 billion in new mortgages in flood zones, which represents roughly 12.5% of total bank equity (Ouazad, 2020), and potentially large financial losses. At the same time, mortgage borrowers are required to have flood insurance when situated in flood plains, and banks manage their risk exposure through securitization or by selling riskier mortgages to Fannie Mae and Freddie Mac (Ouazad and Kahn, 2021). Yet there is mixed evidence that banks account for the risk from disasters in their lending decisions (e.g., Garbarino and Guin, 2021) Alternatively, a bank may lose business beyond mortgage lending if economic activity in the area in which the bank has a large portfolio share shrinks, either following a realized flood or anticipating a deteriorating

[10]Since 1980, costs from billion-dollar natural disasters have amounted to $2.3 trillion, with a significant increase in inflation-adjusted costs in the last 5 to 10 years. See `https://www.ncei.noaa.gov/access/billions/` for more details, accessed in August 2022.

environment. Further, 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, and mortgage-backed securities are also more likely to be write-offs. Thus, constructing an exposure measure based on mortgage lending patterns proxies for a bank's overall business exposure in an area.

To test the link between bank performance and flood disasters, I require estimates of property damage from floods. To test for the existence of a flood risk premium, I use regional probabilities of flooding, combined with a bank-level county share measure based on mortgage lending data, to create novel flood risk exposure. The final data contain information from 771 bank holding companies (BHC) and cover 2004 to 2020.[11]

[Place Figure 1 about here]

## 2.1 Bank-level Shares

To compute the geographic exposure measure at 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 mortgage loan applications and decisions at yearly frequency.[12] However, since the analysis focuses on publicly listed banks, which are typically large, there is no reason to expect that this threshold and feature of the data should bias the findings.

The HMDA data contain mortgage application-level data and includes detailed information on the mortgage. Importantly, the data contain information about the status of the application (e.g., accepted) and typically covers over 90 % of annual mortgage activity (Favara and Giannetti, 2017). This study focuses on conventional loans and one-

[11] The full sample includes 771 different banks and 426 banks on average per year.

[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.

to four-family home purchase loans that were originated. This is because bankruptcy and foreclosure laws, as well as government bailout programs, differ for large multi-family 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 the Spatial Hazard Event and Losses Database for the United States (SHELDUS) maintained by the University of Arizona.[13]The data provide information on the date, location, and intensity of all presidentially declared natural disasters in the U.S.. For this study, the data are restricted to major floodings and storms. While the National Oceanic and Atmospheric Administration (NOAA) also collects information on non-presidentially declared natural disasters, SHELDUS has the advantage of estimating dollar damages linked to individual disasters. Also, 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(a) plots the total estimated damage from floods in each U.S. county for the years 1980 to 2020. Unsurprisingly, coastal regions have higher estimated flood damage over the sample. Damage estimates are especially high in 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 damage in a given county and quarter scaled by total personal income in that county.

[13]Data are available for download from the Center for Emergency Management and Homeland Security (2018) at `https://cemhs.asu.edu/sheldus`.

## 2.3 Expected Flood Risk

To test the existence of a flood risk premium, I require a comprehensive map that defines the geographic distribution of flood probabilities in the contiguous United States. For this purpose, I use a map produced by the First Street Foundation (FSF). The data provide information on the share of housing with a 1% probability of experiencing a 100-year flood in the cross-section of U.S. counties. The estimates consider increased risk from sea-level rise and changes in weather patterns. I use this map over the more widely used flood maps produced by FEMA, because FEMA maps are shown to be outdated. Maps produced by the FSF cover more counties and use an up-to-date methodology compared with maps provided by FEMA. For instance, 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 provide a better measure of a county's underlying flood probability.

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

The key variable is shown in Figure 2(b). 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 in the Appalachians are also projected to be at high risk.

## 2.4 Bank Outcomes

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

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

## 2.5 Measuring Banks' Exposure to Floods and Flood Risk

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 county level. Therefore, county-level variables must be aggregated at bank level. An important aspect of this step is carefully considering the relevant exposure for a given bank. A common approach in the literature has been to use a bank's headquarters or a bank's branches as a measure of regional bank exposure (e.g., Cortés and Strahan, 2017; Blickle et al., 2022). The shortcoming of this approach is that banks typically lend outside of the counties in which they are physically located. Further, banks are assumed to be exposed to flood risk and disasters through their asset holdings. I introduce a novel share measure for each bank based on a bank's mortgage lending activity. Specifically, using HMDA, I compute 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:

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

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 Fannie Mae and Freddie Mac (Ouazad and Kahn, 2021). This reduces the bank's exposure to negative shocks to collateral value. The empirical analysis accounts for this possibility by focusing on non-securitized mortgages in alternative share measures. All main results hold if the share 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 in a county, and therefore the focus is on mortgages retained in banks' portfolios. The benefit of using originated amounts instead of retained amounts is that they more accurately reflect a bank's overall business in a region than by only focusing on retained mortgages (Giannetti and Saidi, 2019). Along the same line, as additional measures, I compute the rolling averages of retained and originated mortgages. Rolling averages alleviate concerns that outlier exposure in mortgage lending drives the results. Rolling averages arguably capture underlying lending patterns more closely than yearly flow measures and 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 county-level exposure with county-level property damage estimates from SHELDUS. Formally, I have:

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

Scaled damages can be viewed as a weighted average of the damage that occurred in quarter $q$. In the baseline, property damage is 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 exposure to the risk of flooding is priced in the cross-section of bank stock returns, I create a bank-level flood risk exposure measure by weighting the share of properties with a high flood probability with the bank's county share. Formally, I have equation 3:

$$\textit{Flood Risk Exposure}_{b,y} = \sum_{c} (\textit{Share}_{b,c,y} \times \textit{Flood Probability}_{c}), \tag{3}$$

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 summary statistics and differences between banks with high exposure to flood 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, and *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 in terms of 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 Call Reports are updated at 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. *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-day delinquent loans by total assets. From the table, it also becomes apparent that the two groups differ in some important variables. They are smaller on average and therefore are somewhat more focused on mortgage lending. On average, 19% of total assets are home mortgages for high-exposure banks and 18.6% for low-exposed banks. While the difference is statistically significant, it is not that meaningful economically. For both groups, roughly 20% of the balance sheet is dedicated to household mortgages. When including commercial properties, the share jumps to almost half of total assets. Exposed banks rely more on deposit funding. Notably, on average, they do not differ in profitability, the share of non-performing loans, or leverage ratio. In 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 disaster, 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 20 years. Estimates from the Bureau of Labor Statistics show that industrial production decreased by 12.6%, with approximately 230 thousand job losses. As the storm's intensity became clear, markets priced potential exposure to the damage.

The methodology involves plotting the cumulative abnormal returns (CARs) of banks active in counties affected by the hurricane (i.e., the treated) and comparing it with 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, $\Delta$VIX), 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 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 control. 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 as 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 3(a)). 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 Coast region or a neighboring state.[15] These counties are shown in dark blue in Figure 3(a). Counties that only received public assistance are excluded. Schüwer et al. (2019) point out, some counties received public assistance because they housed evacuees but were not otherwise affected. Consequently, 19 banks are cleanly identified as only active in affected counties, and 27 as located in unaffected counties.

Figure 3(b) plots the daily CAR 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 crossed the southern tip

[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.

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 with the control group. On August 28, the National Weather Service issued a statement that Hurricane Katrina was 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 \$4.5 bn loss in the 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 threat materializes and salience is high. While banks in the control group are also active in the extended coastal region, only the abnormal returns of ex post-affected banks decreased. This points to evidence that markets correctly identify banks' exposures when faced with a disaster.

[Figure 3 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 damage introduced in Section 2. Formally, I estimate the following equation:

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

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

[Table 2 about here]

Table 2 reports estimates of equation 5 for bank-level ROA. The baseline regression in column (1) estimates a negative and statistically significant relationship between exposure to flood damage and ROA. The variable *Scaled Damages* has a $t$-statistic of -3.8 and 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 ROA of 0.4 basis points. Given an average of 0.4%, this equals a 1% reduction in the average ROA. However, the distribution of flood disasters typically has a large right tail. Hurricane Katrina had a magnitude of almost 100 standard deviations, and wiped out the entire income of affected banks. This shows that large shocks are plausible (and likely). A 10-standard-deviation increase in flood shocks is associated with 10% lower ROA of affected banks, consistent with flood damage's 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.

The last two columns of Table 2 report estimates from regressions using bank deposits and headquarters locations to construct the ex ante flood risk exposure. In column (4), county-level flood damages are aggregated using deposits as weights instead of mortgage-weighted exposure. In contrast, column (5) weights by physical office location.[16] The coefficients of interest are insignificant in both cases. This additional test helps reconcile the findings in this study with the conclusions of 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 worry 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

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

as property damage estimates weighted by the amount of retained mortgages. In this context, the coefficient is similar to baseline results, which suggests that wealth differences are not driving the results. Further, an 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 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 accounting variables. 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 bank holding company level. Column (1) replicates the baseline results for ROA. The coefficient on *Scaled Damages* has the same sign and very similar magnitude as in Panel A of Table 2, which suggests that the effect is propagated at bank holding company level. 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 damage increases: A one-standard-deviation increase in flood damage reduces the ratios by approximately 2 bps. However, given average ratios between 8% and 14%, the effect is small even for larger episodes. Nevertheless, the coefficients are statistically significant, with $t$-statistics below -2.56. The net stable wholesale funding ratio also declines by 5 bps after a one-standard-deviation increase in flood damage, as reported in column (4). The estimates suggest that banks not only have lower profits but experience losses in their equity. However, the reduced ROA is not matched one-to-one with a reduction in equity, which implies that banks can offset most of the shock without losing equity.

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

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

where $\sigma(roa_{bt})$ is the standard deviation of ROA. 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 damage increasing the default likelihood of a bank.

The results in columns (6) to (7) are based on loan performance variables. The effects on NPLs, 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 lead to poorer loan performance and, therefore, higher loan losses. As a placebo test, Table A2.1 in the Online Appendix reports the results from a regression in which the scaled damage are weighted by denied mortgage share. Denied mortgages should not expose banks to floods, which is confirmed by the insignificant coefficients.

## 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 heterogeneous 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 fewer 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 that are more active in mortgage lending, with a higher fraction of mortgage loans on their balance sheets, 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 with banks with a lower share of mortgage lending (Low) and small banks compared with large banks. The partitioning is based on the median mortgage lending share and size. All regressions are robust to bank controls and bank and quarter fixed effects.

[Table 4 about here]

Panel A of Table 4 reports results for ROA 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 coefficients across size-sorted samples, the magnitude of the coefficient in the sample of large banks is larger, suggesting that the ROA 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 more geographically diversified. A possible explanation is that larger banks are more transparent and recognize losses more quickly than smaller banks.

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

Surprisingly, when we focus on small and large banks separately, the estimates show that a significant effect on NPL is unique to the sample of larger banks: The NPL ratio increases after flood damage only for large banks. Specifically, I find no evidence that the sample of small banks incurs an increase in their NPL—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 remarkable, because larger banks are more diversified and typically have more tools to weather natural disasters (Cortés and Strahan, 2017). However, the result could also show that larger banks accept higher NPLs 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 damage and loan charge-offs is insignificant for large and small banks. Thus, the quality of reporting and balance sheet transparency for large banks possibly explains the differences between size-sorted samples.

## 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 sheets. For instance, 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 damage 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 $\beta_1^h$ on *Scaled Damages* for the two bank performance variables—ROA and the Tier 1 leverage ratio—in Figure 4. In both panels, the solid line (with circles) represents point estimates of $\beta_1^h$ from equation 6, and dashed lines (with triangles) represent 95% confidence intervals for this estimate. Standard errors are clustered at the bank level.

Figure 4(a) shows the long-run effect of flood damage on bank-level ROA. The quarter 1 coefficient is the same as the coefficient in column (1) of Table 2. The plot shows that the drop in ROA 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 impact on profitability occurs in the same quarter as the flood realizes. The finding is echoed in Figure 4(b), which plots the coefficient of Tier 1 leverage on flood damage. Again, most of the effect occurs between the first and the second quarter after the flood disaster. Because 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. The fact 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, which was also 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 Panels A and B of Figure 4 is consistent with banks' experiencing significant losses from floods that require them to offset losses with their equity.

[Figure 4 about here]

Figure 5 conducts a similar analysis using two loan portfolio variables as the outcomes of interest. As seen in Section 3.3, the effect on portfolio performance variables is only seen in the subsample of banks with a high share of mortgage loans on their balance sheet. As previously, the solid line (with circles) represents the point estimates of $\beta_1^h$ from equation 6, and dashed lines (with triangles) denote 95% confidence intervals for this estimate. Standard errors are clustered at bank level. The flood realizes at time 0. The coefficients are insignificant for periods before the shock. Figure 5(a) plots the coefficient from regressing the NPL ratio on flood damage for the sample of banks with a high share of mortgages. Following the shock, the coefficient is positive and implies an increase in NPLs 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 NPLs increases for 3 quarters before slowly reverting. Since NPLs are typically measured as loans with missed payments after 30 to 90 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 5(b), loan charge-offs increase in the quarter following the shock and remain elevated for the next 2 quarters. The increase in loan charge-offs is steeper than the increase in NPLs. While NPLs depend on borrowers' behavior, charge-offs are set by lenders. Thus the difference in slope suggests that lenders partly anticipate the increase in NPLs and the subsequent default of many borrowers.

[Figure 5 about here]

The evidence in Figures 4 and 5 is consistent with banks' balance sheets' deteriorating significantly after flood disasters and the fact 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 ROA. ROA and loan charge-offs revert to the pre-shock level faster than NPLs because of banks' anticipating behavior.

# 4 Exposure to Flood Risk

The previous section demonstrated that flood disasters are negatively linked to bank performance, measured by both ROA and stock returns. In this section, I examine whether the risk of future floods is priced in the cross-section of bank stock returns. Specifically, the conjecture is that investors may require higher expected returns from banks with high exposure to the risk of flooding.

## 4.1 Evidence in the Cross-section of Returns

First, I run cross-sectional regressions to test whether exposure matters at an individual bank. The benefit of cross-sectional regressions is that they enable controlling for multiple characteristics jointly. Therefore, the approach allows me to rule out other known characteristics that predict returns in the cross-section and ensures the novelty of the flood risk exposure. To do so, bank-level excess returns are regressed on lagged flood risk exposure and bank characteristics. Formally, the following cross-sectional regression model is estimated using pooled OLS:

$$
\begin{aligned}
r_{b,t} - r_{f,t} = \alpha &+ \beta_1 \mathit{Flood\ Risk\ Exposure}_{b,t-1} \\
&+ \beta_2 \mathit{log(Assets)}_{b,t-1} + \beta_3 \mathit{log(BE/ME)}_{b,t-1} \\
&+ \beta_4 \mathit{Leverage}_{b,t-1} + \beta_5 \mathit{Loan\ Ratio}_{b,t-1} \\
&+ \beta_6 \mathit{Mortgage\ Ratio}_{b,t-1} + beta_7 r_{b,t-1} + \epsilon_{b,t},
\end{aligned} \tag{7}
$$

where the dependent variable is the stock return of bank $b$ over the risk-free rate in month $t$. The main coefficient of interest is $\beta_1$ on *Flood Risk Exposure*, which captures a bank's balance sheet exposure to flood risk. A positive $\beta_1$ coefficient would imply that increased exposure earns a positive risk premium. Based on the focus of the analysis, standard errors are clustered at bank level. Month fixed effects absorb aggregate time-varying factors.

Column (1) of Table 5 reports the baseline result with the exposure measure based on the probability of a flood by 2050 and the share of originated 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 exposure leads to 17-bps lower monthly excess return or 2% per year. The estimate suggests that high flood risk exposure forecasts poor stock performance. Overall, the result implies that firms with high flood risk exhibit lower future excess returns net of well-known bank characteristics. This finding contradicts the initial conjecture that the additional risk should yield a positive return. It is, however, in line with other papers that test whether markets discount physical risk from climate change (e.g., Hong, Li, and Xu, 2019), and highlights the differences in studies that focus on transition risks from climate change, which typically find that investors require higher expected returns from firms with higher risk exposure (e.g., Bolton and Kacperczyk, 2021). Several potential explanations could, in theory, reconcile the finding; Some will be tested next.

[Table 5 about here]

The result does not hinge on the choice of flood risk exposure but is robust to a set of different approaches. Columns (2) to (7) of Table 5 report the results for six 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 that uses flood risk scores instead of the share of houses at risk. Column (4) weights underlying flood risk by the number of retained mortgages instead of the dollar amount. In column (5), only retained mortgages in a county are used to build the county weights. This approach reduces the risk that mortgage securitization and other risk-shifting operations drive the identified underperformance. Next, the primary measure of flood risk exposure is based on the yearly flow of new mortgages. This approach is prone to a potential problem: It tends to overweight outliers in lending patterns. For instance, a county might be highly relevant for a bank for all years except one or vice versa. Hence, columns (6) and (7) use 3-year rolling averages of mortgage lending as weights. Across all specifications, the result is negative and statistically significant, with a coefficient $\beta_1$ 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).

Notably, the different measures all capture very similar exposure. The last column of Table 5 reports a placebo test in which the exposure measure is intended to capture a different channel. Instead of dividing the number of mortgages retained in a county by the total amount of mortgages retained 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 county-level market concentration from the perspective of a single bank. The prediction is that the result from this regression should be insignificant and differ from other results. The coefficient on the exposure measure is positive and insignificant, which suggests that the balance sheet exposure of a bank to a county is the relevant measure.

All in all, the results suggest that bank stocks underreact to the risk of floods. The literature on climate risk has proposed several explanations, which I analyze next.

## 4.2 Size Differences

As seen in the summary statistics, flood-risk-exposed banks tend to be smaller. This subsection examines potential differences in the return predictability for different size-sorted samples.

Table 6 presents separate estimates of equation 7 for small and large banks. The partitioning is based on either the median or top quartile of size or banks with less than \$50 billion total assets. Only the point estimates on *Flood Risk Exposure* in the samples of small banks are negative and statistically significant (with $t$-statistics between -2.7 and -3.2). Point estimates range from -22 to -15 bps, which translates into up to 2.6% annualized. The coefficient decreases as the sample of small banks becomes broader. In column (1), only banks below the median are included, while in column (2) up to the top quartile and even banks with less than \$50 billion total assets are defined as small. The coefficient for the sample of larger banks is even positive in one case, albeit insignificant. This suggests that the result is not simply due to a lack of statistical power, since the coefficients are not only statistically insignificant but also of a different sign. Several hypotheses might explain the discrepancy between small and large banks. First, large firms are typically more transparent. They attract more scrutiny from investors and analysts and are often required to disclose more information. This is especially true in the banking industry, in which large banks have always been treated differently, but even more so since the Great Recession. Given that realized floods affect the accounting performance of large banks, investors could be learning about the exposure to exante flood risk for large banks. Thus, the positive (insignificant) coefficient for the sample of large banks is evidence that investors can better price risk exposure to flooding. The opacity and lack of disclosure of smaller banks render pricing risk more difficult.

[Table 6 about here]

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.

### 4.3 Realized Flood Disasters

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

Exposed assets have lower realized returns when the underlying risk materializes—i.e., the economy is shocked by a flood disaster. I test this explanation by explicitly controlling for realized flood disasters.

Bank-level flood risk exposure captures underlying differences in the flood probabilities of different regions in the United States. Therefore, it is likely correlated with past and future flood disasters. An area prone to floods in the future has likely experienced floods in the past. This implies that the flood risk exposure measure might pick 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 the possibility 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 of the negative coefficient on flood risk exposure. Table 7 reports results for four subsamples of the data. First, major disasters are removed from the sample. In column (1) of Table 7, the months around Hurricane Katrina are omitted; specifically, the months from August to October 2005 are deleted. Column (2) removes other major storms (e.g., Hurricanes Sandy and Harvey). Second, the sample is restricted to banks unaffected by any disasters. Column (3) limits 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 damage from floods. Panel A reports results for the entire sample of banks, Panel B is restricted to small banks, and Panel C includes large banks.

[Table 7 about here]

As previously, the negative coefficient on flood risk exposure remains significant and negative for the entire sample and the sample of small banks. Further, magnitudes are almost unchanged. The only insignificant coefficient is in column (4), which is the most restricted sample. Still, the point estimates are identical, which suggests 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 major disasters.

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

$$\begin{aligned} r_{bt} - r_{ft} = \alpha &+ \beta_1 \mathit{Flood\ Risk\ Exposure}_{bt} + \beta_2 \mathit{Scaled\ Damagess}_{bt} \\ &+ \beta_3 \mathit{Flood\ Risk\ Exposure}_{bt} \times \mathit{Scaled\ Damagess}_{bt} \\ &+ \beta_4 \mathit{log(Assets)}_{bt} + \beta_5 \mathit{log(ME)}_{bt} \\ &+ \beta_6 \mathit{Leverage}_{bt} + \beta_7 r_{bt-1} + \epsilon_{bt}. \end{aligned} \tag{8}$$

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

[Table 8 about here]

Table 8 reports estimates from equation 8 for three measures of exposure to flood damage. The damage measure used in columns (1) and (2) is based on the level of property damage 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 interpretation.

Column (3) reports the result using the indicator variable *High Damage*, which takes a value of 1 if 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 8 reports estimates for the total sample of banks. The coefficient on flood risk exposure remains negative and significant. Also, the magnitude is almost unchanged. Therefore, exposed banks still underperform. If the underperformance was due to disaster shocks, the sign on flood risk exposure should have flipped. The fact that the sign remains negative implies that disaster exposure cannot explain poor performance. Nevertheless, the coefficient on the measure of the scaled damages 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 measured by the interacted term, which would align with the explanation that past disasters drive performance. However, the effect is isolated to one regression. All in all, these results suggest that the current disaster is not the only or main driver of the results for the entire sample of banks.

This finding is echoed when I focus on the subsample of small banks. The estimates are reported in Panel B of Table 8. 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 8 reports estimates for the sample of large banks. Interestingly, coefficients on flood risk exposure are positive, albeit not significant. This suggests that larger banks are priced differently than smaller banks with respect to flood risk. The coefficient on scaled damages is negative and significant; therefore, exposure to disaster is associated with lower realized returns. Since negative shocks are expected to happen with some probability (smaller than one), negative realizations should produce negative returns for exposed banks. This is precisely what is captured by the coefficient on scaled damages. Thus, investors apparently price the risk of flooding for larger banks.

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 significant coefficients show that exposure to disasters has explanatory power. Large banks experience no underperformance with respect to flood risk exposure, while exposure to disasters also commands poor performance. The divergence between the size-sorted samples suggests that investors can 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, which could help to explain this finding.

## 4.4 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 sorted in quartiles according to their flood risk exposure, then the value-weighted returns of the four portfolios are computed. I estimate the following time-series regressions:

$$r_{i,t} - r_t^f = \alpha_i + \boldsymbol{\beta_i}'\mathbf{F}_t + \epsilon_{i,t}, \tag{9}$$

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 the two bond factors from Gandhi and Lustig (2015)—$ltg$, which is the excess return on an index of long-term U.S. Treasury bonds, and $crd$, which is the excess return on an index of investment-grade, high-quality corporate bonds.

[Table 9 about here]

Table 9 reports estimates from equation 9 for the four quartile portfolio and a portfolio that goes short portfolio 1 and long portfolio 5—i.e., it shorts the portfolio with the lowest exposure and goes long in the portfolio with the highest exposure. Panel A presents results for the full sample from 2005 to 2020. In columns (1) to (4), the intercept decreases from 0.38% to 0.05% as we move from portfolio 1 to portfolio 4, albeit not monotonically. 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 9 reports the intercepts of the four flood risk exposure-sorted portfolios for the sample of small banks. 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 loses 9.6% per month in annualized terms. Finally, Panel C of Table 9 reports intercepts for the sample of large banks. No discernible pattern in alphas is observed in this last panel. In line with previous findings, this suggests that the potential role of flood risk exposure is restricted to smaller banks.

[Figure 6 about here]

Figure 6 plots the cumulative returns of the bottom and top exposure-weighted portfolios and the cumulative returns of the High-Low portfolio for the full sample of banks. The cumulative returns of both portfolios increase over the sample running from 2005 to 2020. However, the return on the low-exposure portfolio grows much faster. This is seen in the negative cumulative return of the High-Low portfolio. Except for the period around the financial crisis in 2007-2009, the High-Low portfolio loses systematically and ends at -50% in 2020.

The findings are also robust to other factors prominent in the asset pricing literature. The monthly return difference, denoted by *High-Low*, averages -24 bps per month, as reported in the first column of Panel A of Table 10. 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 10 about here]

Nevertheless, as size heterogeneity played an important role in the previous analysis, Panel B of Table 10 constructs the High-Low portfolio 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, and column (4) reports results for 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 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. The alpha implies that the High-Low portfolio loses, on average, 6.9% per year.

For completeness, Panel C of Table 10 constructs the High-Low portfolio, using only 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 additional factors does not change the magnitude or significance by much. This finding validates 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 other findings based on bank heterogeneity.

Along the same lines, Figure 7 plots the cumulative return of the High-Low portfolio for the two size-sorted subsamples using exposure-weighted and equal-weighted cumulative returns. Using only small banks, the portfolio loses more than 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 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 the steady underperformance of high-exposure banks that is not solely driven by an outlier. The flatter curve around 2016 could be due to changes in the regulatory environment. As Republicans gained control of both houses and the presidency, fewer new climate bills were passed—and some were even scrapped—which reduced regulatory shocks and rendered the introduction of new legislation less likely. The cumulative return of the High-Low portfolio based on the 25% largest banks is flat over the sample. Equal-weighted and exposure-weighted cumulative returns increase until 2016, when they reach around 15%. The equal-weighted cumulative return remains at this level, while the exposure-weighted cumulative return decreases back to 0%.

[Figure 7 about here]

## 4.5 Time-series Variation of the Flood Risk Factor

To complement Table 8, I estimate how much of the return variation of the flood factor can be attributed to flood damage:

$$r_t^{FF} = \alpha + \beta \mathit{Flood\ Damages}_t + \epsilon_t, \tag{10}$$

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

[Table 11 about here]

Estimates for the full sample of banks are reported in Panel A of Table 11. Again, three measures of damage exposure are used. Column (1) uses flood-related damage, column (2) is again an indicator variable equal to 1 if the damage is 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). $R$-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 previous findings, but it is no longer statistically significant, which might be, albeit weak, evidence that flood risk exposure measures disaster realizations to some extent. However, if we only focus on the sample of smaller banks, this finding again vanishes, which suggests that underperformance for the sample of small banks is likely driven by other unanticipated shocks or investor mispricing.

Panel B of Table 11 presents results for small banks. While the sign on flood realization is still negative in all specifications, it is never significant. The estimated intercept remains negative and significant, as in results from the previous sections, which highlights the conclusion that the underperformance has other sources.

### 4.6 Climate Change Concerns

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 the 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. 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 the stocks of high flood risk banks perform significantly worse than unexposed stocks in periods of increased attention to 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 interpretation with the same implications is that climate change concern is a relatively new phenomenon, as Pastor et al. (2021) point out. Therefore, it is likely affecting returns. The last decade has been 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 with a bank without exposure, the changing nature of climate concerns leads to 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 because of the shift in asset demand.

Both conjectures are tested using a selection of measures that capture attention to climate change. First, I download frequency data from the Google Search Volume Index (SVI) for the topic of "Climate Change" and the topic "Flood" more specifically. In the literature, SVI has been shown to be a reliable proxy for investor attention to different risks (e.g., Da et al., 2011). The data are used as a proxy for widespread awareness of climate change and its potential effects. It is available at the national level at monthly frequency for the entire sample from 2004 to 2020.

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).[17] The index is available from January 2003 to June 2018 and is constructed from 10 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. Following Ardia et al. (2022), I use a measure of unexpected media climate change concerns (UMC), defined as the prediction errors from an AR(1) regression model calibrated on the MCCC index. A benefit of their data is that an index is available for various components that capture differences between transition and physical risks.[18] 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. So, using the different proxies for climate change concerns, the following regression is estimated:

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

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

[18] An additional advantage of the MCCC index is that it captures negative sentiment in news articles, as opposed to a measure introduced by Engle et al. (2020).

where $\Delta CC$ is the change in climate change concerns. If climate change concerns drive the underperformance of flood-risk-exposed banks, then the estimate on the interaction ($\beta_3$) is negative, and $\beta_1$ should become insignificant or even positive.

[Table 12 about here]

Estimates from these regressions are reported in Table 12. In columns (1) and (2), $\Delta CC$ is based on the SVI topics "Climate Change" and "Floods", while in columns (3) to (5), it is based on the MCCC index data. The measures have been standardized to ease comparison across regressions. Panel A of Table 12 reports results for the entire sample of banks. Estimates on the interaction term do not present a clear pattern. Only when using the measure based on the "Flood" topic from Google is the interaction significantly negative. Also, in all specifications, flood risk exposure estimates remain statistically significant and negative, which is evidence that climate change attention does not subsume flood risk exposure. Furthermore, 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. The estimate provides evidence that the effect of climate change concern holds for all banks (exposed and non-exposed), which suggests that investors might view banks as a bad hedge against climate change-related risks in general. Findings from the total sample of banks are echoed in the sample of small banks, as reported in Panel B of Table 12. Coefficients on *Flood Risk Exposure* are always negative and significant, with $t$-statistics below -3.2. Magnitudes of $\Delta CC$ for the entire sample and the sample of small banks are also very similar for the different measures.

The evidence shows that climate change concerns matter for the performance of bank stocks, but fail to explain the negative return predictability of flood risk exposure.

## 4.7 Regulatory Risks

Flood-risk-exposed banks are more likely to be exposed to changes in climate regulations. For instance, Democratic administrations are more likely to introduce new climate legislation. I test this by examining banks that are mostly lending in Democratic-leaning counties and states compared with those lending in mostly Republican-leaning counties and states.

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). This could affect banks in several ways. First, Democrats are more likely to introduce new climate legislation and regulate business activities, which negatively affects banks in majority Democratic counties or states. Therefore, the pricing of flood risk exposure might differ depending on which party controls the political agenda and the locations of banks. Alternatively, investors who believe less in climate change are worse at pricing the flood risk exposure of banks. I test the two hypotheses using election data to estimate the following regression:

$$\begin{aligned} r_{b,t} - r_{f,t} = \alpha &+ \beta_1 \mathit{Flood\ Risk\ Exposure}_{b,t} + \beta_2 \mathit{Political\ Indicator}_{b,t} \\ &+ \beta_3 \mathit{Flood\ Risk\ Exposure}_{b,t} \times \mathit{Political\ Indicator}_{b,t} \\ &+ \beta_4 \mathit{log(Assets)}_{b,t} + \beta_5 \mathit{log(ME)}_{b,t} \\ &+ \beta_6 \mathit{Leverage}_{b,t} + \beta_7 r_{b,t-1} + \epsilon_{b,t}, \end{aligned} \tag{12}$$

where *Political Indicator* is either based on county-level presidential election results or captures the party affiliation of the current president. The estimate on the interaction term is positive if unanticipated regulatory shocks that are more likely in majority Democratic counties drive the underperformance. In the case of pricing differences because of climate change beliefs, the underperformance should be stronger in majority Republican counties—i.e., the interaction term is negative. When using county-level data, vote shares are aggregated at bank level using the mortgage share.[19] If the majority of counties voted Republican, the indicator variable equals 1. For the party affiliation of the current president, the indicator variable is equal to 1 if the sitting president is a Republican (i.e., during the terms of President Bush and President Trump in the sample).

[Table 13 about here]

[19]Results are similar using simple means.

Results from the regression are tabulated in Table 13. Columns (1) to (3) use county-level election outcomes as the indicator variable for (i) all banks, (ii) small banks, and (iii) large banks. In all three specifications, flood risk exposure has a negative coefficient, which suggests that banks active in mostly Democratic counties underperform, no matter the size. 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, which suggests that banks in Republican counties underperform to a lesser extent and even outperform other banks in the case of large banks. This finding can be explained by the fact that Democratic-majority counties and states were more likely to introduce regulations that negatively affected exposed banks' stock prices.

In columns (4) to (6), the indicator variable reflects views at the federal level. Again, the coefficients suggest that the underperformance is strongest in years when a Democratic president was in office. During those years, public attention to climate risks and the probability of climate-related policies was higher than during President Bush's and President Trump's terms. Along the same line, Panel A in Table 14 separately investigates control of the House of Representatives, the Senate, and the presidency. As previously, the underperformance is insignificant if Republicans control Congress or the presidency. As the measures correlate, Panel B in Table 14 estimates the regression using three orthogonal indicator variables: Republican control of Congress, only the Senate, or only the House of Representatives. The effect is strongest if Republicans control neither house or only the Senate. The control of Congress nullifies the coefficient on flood risk exposure. This finding is explained by the fact that new climate legislation at the federal level can only be initiated by the House of Representatives and the president.

Overall, the evidence in this section supports the view that regulatory shocks, which are typically introduced by Democrats, lead to the underperformance of assets that are more exposed to climate risks.

# 5 Robustness

This section examines whether other potentially confounding factors drive the poor return performance of flood-risk-exposed banks.

## 5.1 Implied Cost of Capital

So far, realized returns have proxied for expected returns. As discussed, realized returns may diverge from expected returns for several reasons. An additional concern is that unobserved bank characteristics might drive the measured underperformance of banks exposed to flood risk. In this section, I use the implied cost of capital (ICC) as a measure of expected return. The ICC is based on ex ante data—in contrast to realized returns, which are based on ex post information—and is defined as the discount rate that sets today's stock price equal to expected future cash flows. I follow Dick-Nielsen et al. (forthcoming), who use the estimation approach of Gebhardt et al. (2001) in which expected cash flows are based on analysts' earnings forecasts.

Figure A1.3 in the Appendix plots the time series of the ICC. Panel A plots the series of the portfolio of high flood-exposed banks and the series of low flood-exposed banks. Both series are very similar, suggesting little difference in expected returns between both samples. This is tested more rigorously in Table A2.3. When running baseline regression 1, using the ICC as the dependent variable, the estimated coefficient on flood risk exposure is positive but statistically insignificant. This finding alleviates concern that the underperformance is driven by unobserved fundamental differences between exposed and non-exposed banks. Further, it is suggestive evidence that unanticipated shocks cause the underperformance of exposed banks.

## 5.2 Heterogeneity of Effects

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

To examine the importance of heterogeneity for the return predictability, Table A2.4

presents separate estimates of equation 7 for banks with a high share of mortgage lending (High) compared with banks with a lower share of mortgage lending (Low), and small banks compared with large banks. The partitioning is based on the median mortgage lending share and size.

Panel A of Table A2.4 reports estimates from regressing excess return on the *Flood Risk Exposure* for mortgage share-sorted banks. Columns (1) and (2) report the coefficients for the subsamples, and the result in column (3) includes an interaction term between *Flood Risk Exposure* and an indicator variable for whether the bank has a large share of mortgages. Coefficients on *Flood Risk Exposure* are negative for the two subsamples, but only significantly for the subsample of banks that specialize 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 that specialize in mortgage lending, a one-standard-deviation increase in exposure reduces the excess return by -25 bps, or -3% annualized. However, the interaction in column (3) is not statistically significant. This suggests that flood risk exposure also captures the exposure to floods through other bank activities, such as other retail or commercial loans. Hence, the measure is a good proxy for total bank-level flood risk exposure beyond mortgage lending.

Panel B of Table A2.4 reports results for the flood risk exposure-sorted samples. This exercise is a confidence check that the previous findings are really driven by banks with high exposure to exante flood risk. The estimate in column (1) is for the sample of banks with above-median flood risk exposure. The coefficient on *Flood Risk Exposure* is negative, with a value of $-0.18$, and is statistically significant at the 1% level. The relation between excess return and flood risk exposure is not significant for banks with low exposure; if anything, it would be slightly positive. This is evidence that the negative relation is driven by high-exposure banks and does not capture the bank characteristics of low-exposure banks.

The results suggest that the effect is not driven by sample differences but is stronger for specific subsamples. The negative predictability of flood risk exposure is concentrated in banks with a higher share of mortgage lending and banks with high-risk exposure.

## 5.3 Flood Insurance

Flood insurance could be another cause for the stock 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. Section 3 shows that this is most likely not the case, since bank performance measured by diverse variables deteriorates after a flood disaster. Nevertheless, in this section I discusses the U.S. flood insurance market and test for potential bias in the results by explicitly controlling for different insurance proxies.

In the United States, the standard home insurance contract covers some natural disasters, such as a fire, but explicitly excludes floods (Oh et al., 2022).[20] Flood insurance is taken out separately and is provided federally by the National Flood Insurance Program (NFIP), administered by FEMA. 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 to drop out. Also, flood insurance is only mandatory in officially designated flood zones, which leaves many properties at risk. The NFIP has, on average, 4 million active contracts compared with 15 to 36 million homes that are estimated to be exposed to disaster risk.[21] An additional reason for the diverging numbers between insured and at-risk homes is that climate change has led to significant changes in the underlying risk and increased risk-sensitive regions. Therefore, keeping up with these changing patterns is important if insurance coverage is to match actual risks. Although FEMA is mandated to update its maps at a 5-year intervals, most are older. This results in a mismatch of

[20]The most widespread home insurance contract, called HO3, accounts for 95% of all sold contracts and does not cover flood damage.

[21]Flavelle et al. (2020) estimate that 15 million properties are at risk from a 100-year flood, and RealtyTrac (2016) estimate 36 million homes at risk from natural disasters.

insured and exposed homes.

To formally test the effect of flood insurance, I use the publicly available NFIP-flood insurance policy published by FEMA. The data are available in two separate files. The first file includes information on the universe of active policies and is available from 2009 to 2022. It provides information such as the coverage and premium of individual policies. On average, the data contain around 4 million active policies, compared with the estimated 15 million homes at high risk of flooding. The total insured amount is $1 trillion, with building coverage of roughly $750 billion; around $250 billion in contents is covered, compared with a total estimate of $5-10 trillion actually at risk from flooding (RealtyTrac, 2016). The number of active policies has slightly decreased in recent years. As expected, Gulf Coast regions have the highest number of active policies. The second NFIP file contains information on policy claims after flood disasters; as before, claims are concentrated around the Gulf Coast. The assumption to be tested is that banks exposed to counties with more extensive insurance coverage should be less affected by floods. Therefore, the unanticipated shocks captured by flood risk exposure should be attenuated—i.e., the coefficient on the interaction should be positive when analyzing flood insurance policies.

Columns (1) and (2) of Table A2.5 report estimates of the cross-sectional regressions that include 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 potential fallout from future floods for exposed banks. The control in column (2) is based on policy payouts for insured buildings and captures flood realization. For the three samples of banks, controlling for flood insurance does not alter the magnitude or significance of the estimate of 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 evidence suggests that banks remain exposed to floods, even if they partly manage flood risk when originating mortgages and some borrowers are insured against floods. The finding also highlights the likelihood that mortgage-based flood risk exposure proxies for general exposure to flood-prone regions, and captures the risk of general economic downturns' affecting exposed banks.

## 5.4 Mortgage Delinquencies

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

Columns (3) and (4) of Table A2.5 test this conjecture by controlling for banks' exposure to foreclosures or defaults. Again, the baseline results persist through the different samples: 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, which suggests that, as hypothesized, poor real estate performance is associated with lower future returns.

## 5.5 Regional Shocks

To rule out the possibility of other shocks, I control for additional regional measures and report the estimates in Table A2.6. Column (1) includes state-level macroeconomic variables, such as $log(GDP)$, inflation, income per capita, and unemployment rate. State-level variables are aggregated at 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 state. Column (2) includes 50 state indicator variables. For a given bank, a state indicator takes on 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 state dummies with year dummies. Finally, column (4) includes Headquarters-state fixed effects.

Across the four specifications, the coefficient on *Flood Risk Exposure* is negative, ranging from -0.24 to -0.12, which suggests that unobserved regional characteristics do not drive the finding. Results from Table A2.6 show that the baseline finding is not driven by unobserved regional characteristics captured by *Flood Risk Exposure*.

# 6 Conclusion

Climate change-related disasters are projected to 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.

I focus on flood disasters in this paper, and 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 different types of shocks, but this paper shows that balance sheet composition matters. I document that banks' return on assets is significantly lower following a flood disaster. Not only is the initial shock significant, but the effects are also long-lasting, with lower returns on assets up to 1 year after a flood. Floods affect bank performance in part through banks' mortgage portfolios; 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 assessing whether these risks are priced in bank stock returns. I address this question by undertaking a cross-sectional stock returns analysis, with bank-level flood risk exposure as the key bank characteristic. I reveal a puzzling finding: flood risk exposure predicts 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 by 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 high flood exposure and short a portfolio of banks with low exposure loses around 20 bps per month in the full sample, or 77 bps when only considering small banks. This return on the portfolio cannot be explained by a selection of 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 flood risk exposure negatively relates to 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 to flood risk exposure decreases but persists. Second, the effect is not driven by investor attention or knowledge of 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 in banks active in Democratic-leaning counties, and specifically during President Obama's administration.

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. This highlights concerns that markets might not have fully adapted to the "new normal" ushered in by climate change. Further, investors are more worried about climate policy risks rather than physical risks, in line with findings by Ardia et al. (2022). This could also explain the lower predictability from 2016 to 2019, since regulatory changes were reduced during the Trump presidency. The negative return predictability of flood risk exposure for smaller banks suggests that investors withdraw from this segment of the market. In contrast, both types of banks are affected by disaster realizations. Therefore, the results may warrant the view of by a number of policymakers, whereby exposure to physical risks from climate change should be monitored.

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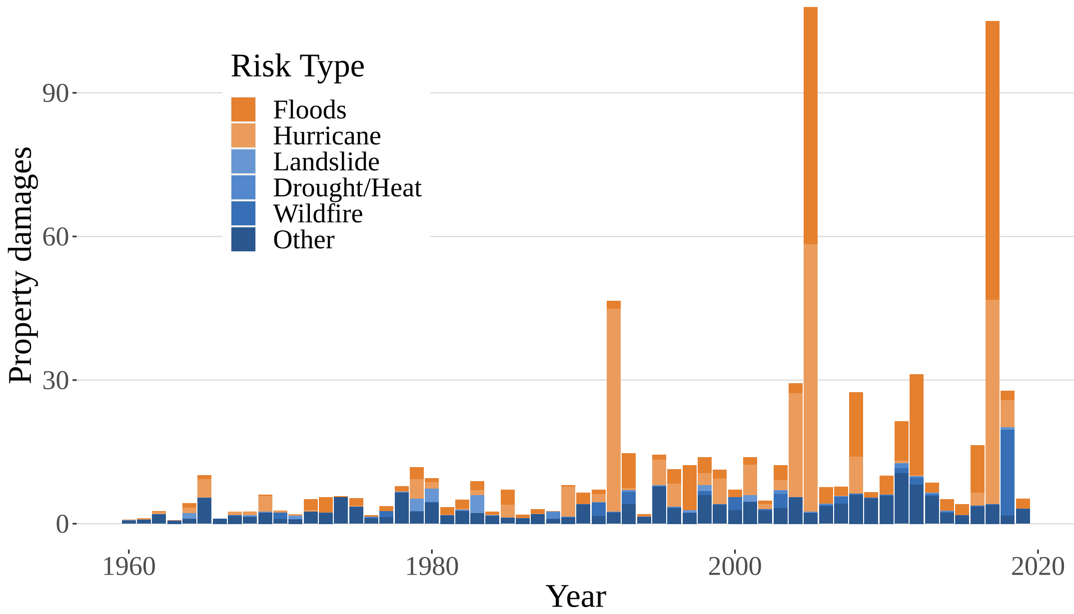
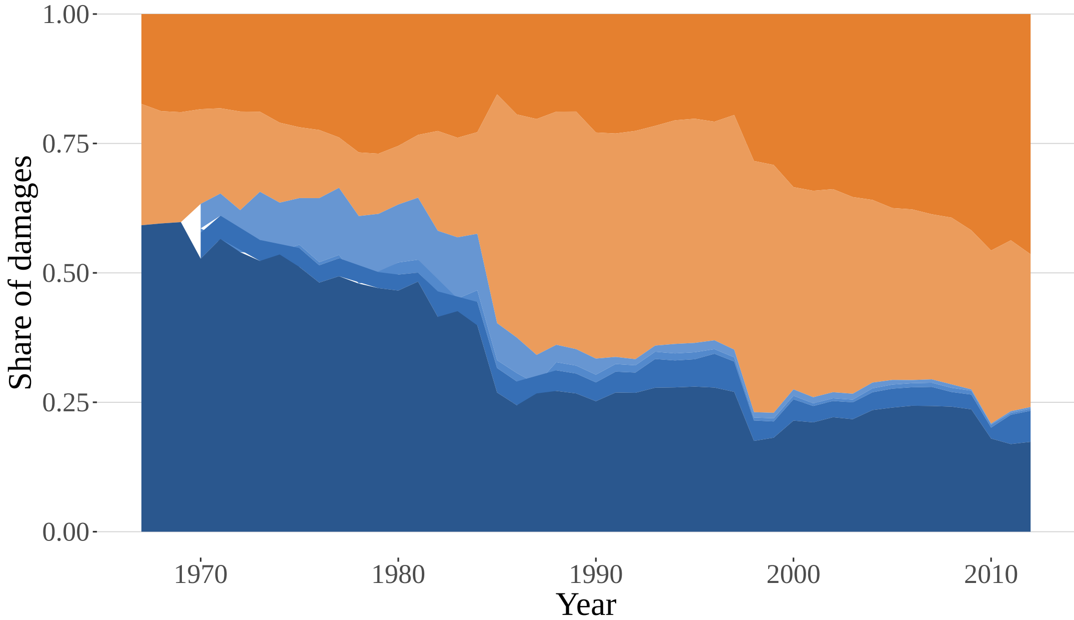
# 7 Figures

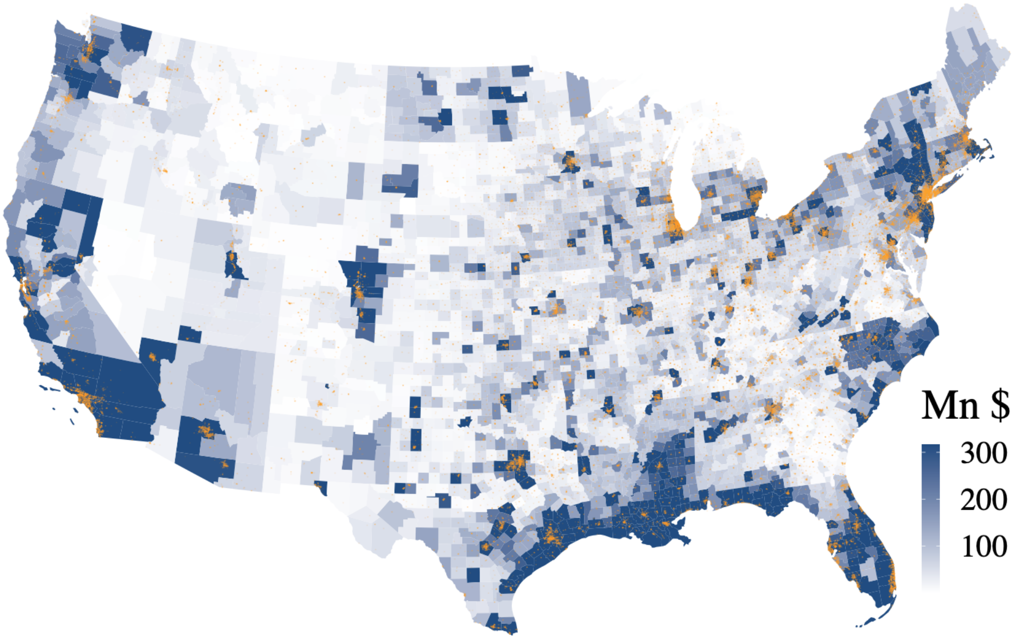



**(a)** Property Damage Estimates

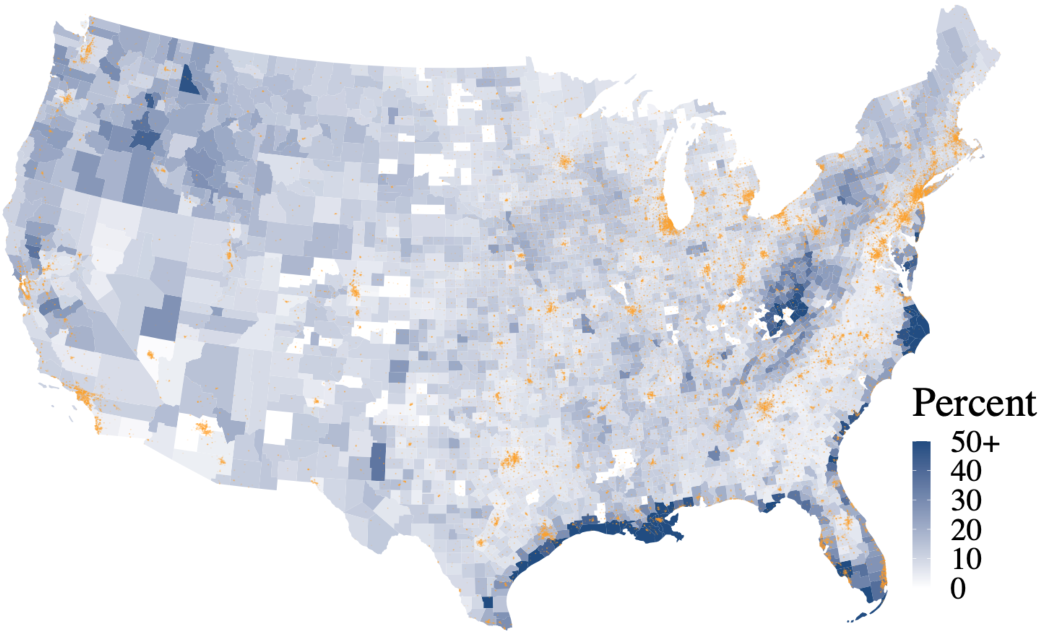



**(b)** Share of Damage Estimates

**Figure 1: Property Damage Estimates from Natural Disasters**. This figure reports estimates of property damage 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 total damage in a year. Shares are computed with a 10-year rolling window.

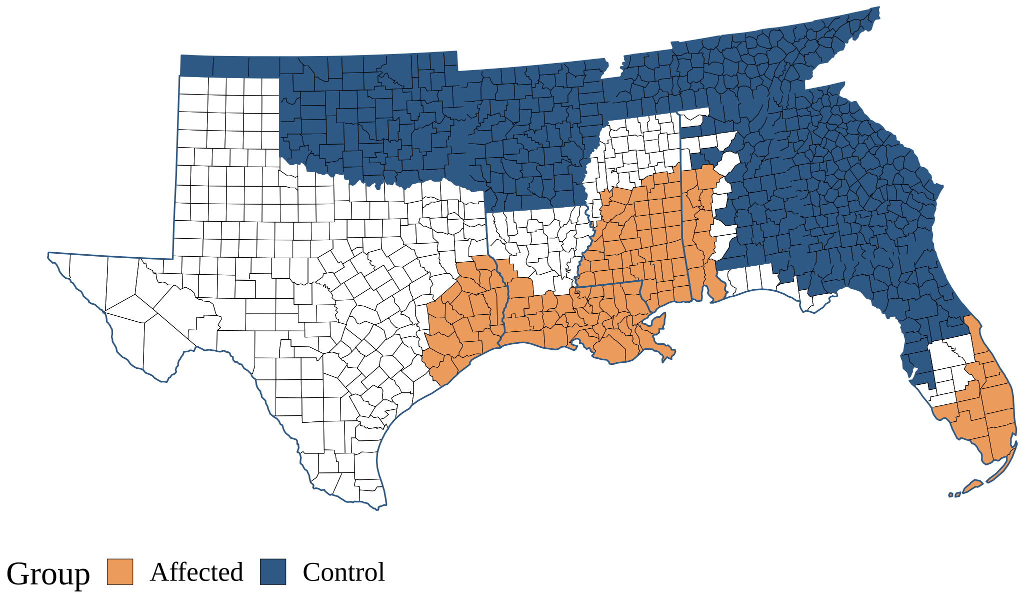



**(a)** Flood Damage Map

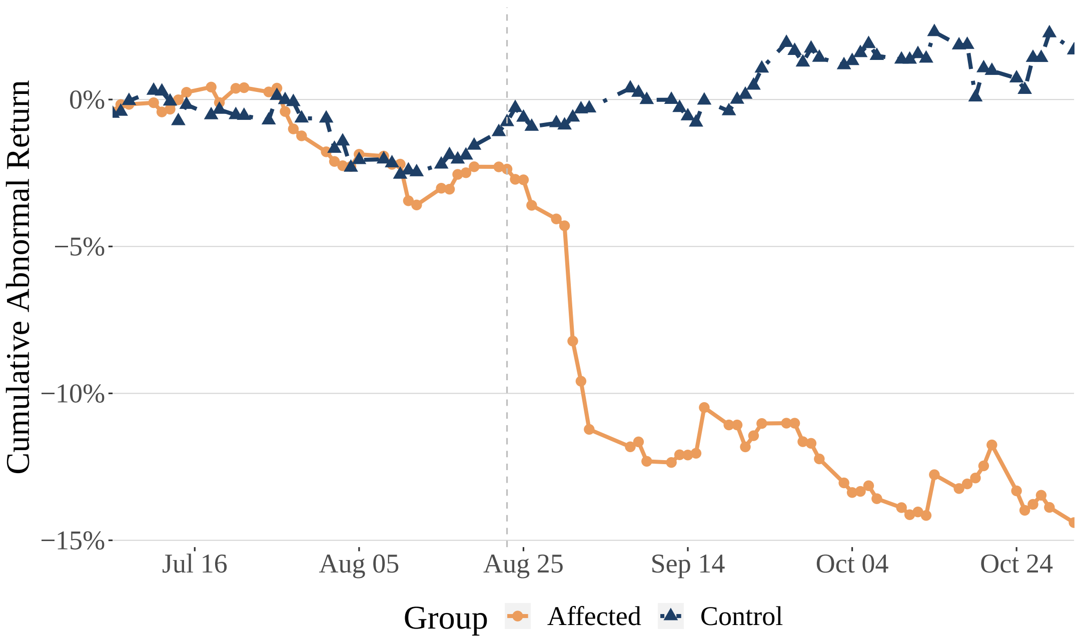



**(b)** Flood Risk Map

**Figure 2: Flood Maps**. Figure (a) plots county-level SHELDUS property damage from floods for the years 1980 to 2020 in shaded blue. Figure (b) plots county-level flood risk from the First Street Foundation and shows the number of properties with a 1% probability of flooding by 2050. Orange dots represent bank branches and are obtained from FDIC Summary of Deposits for the year 2020.

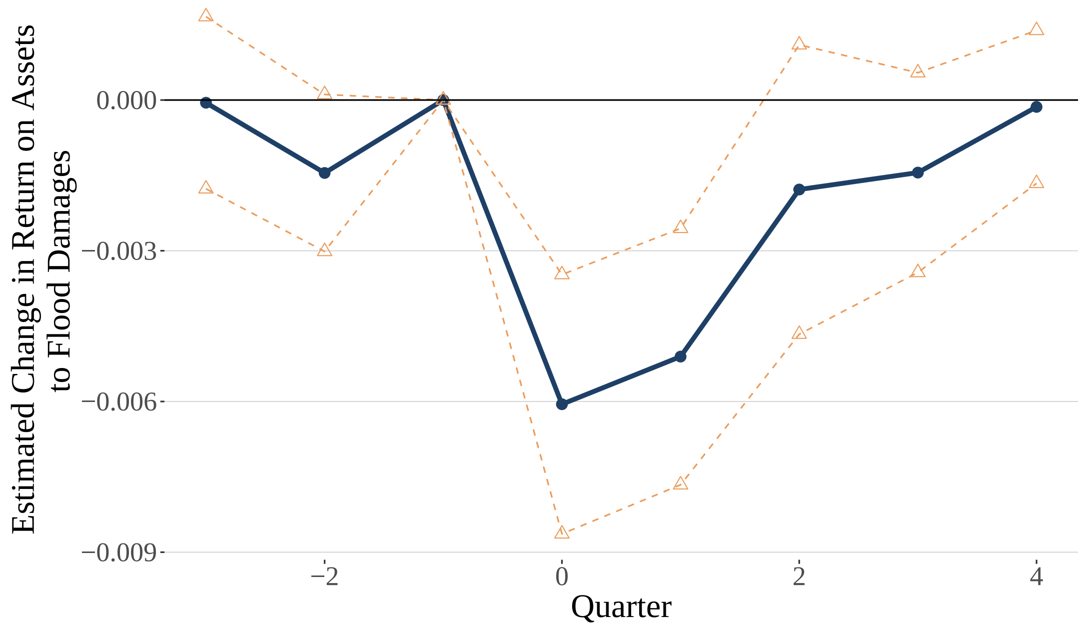



**(a)** Affected Areas

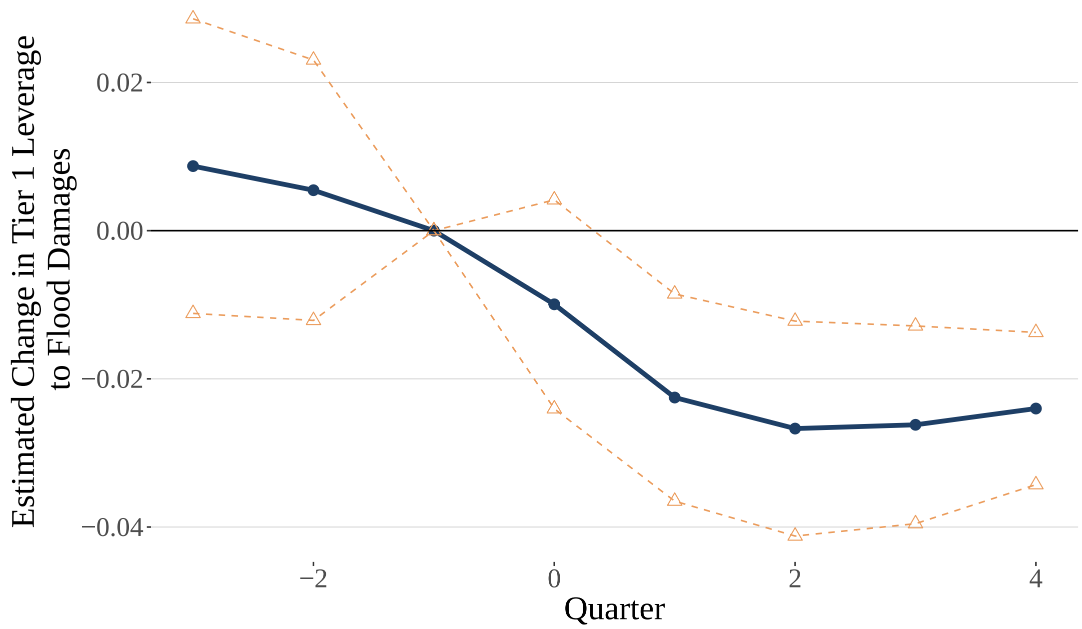



**(b)** Cumulative Abnormal Return

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

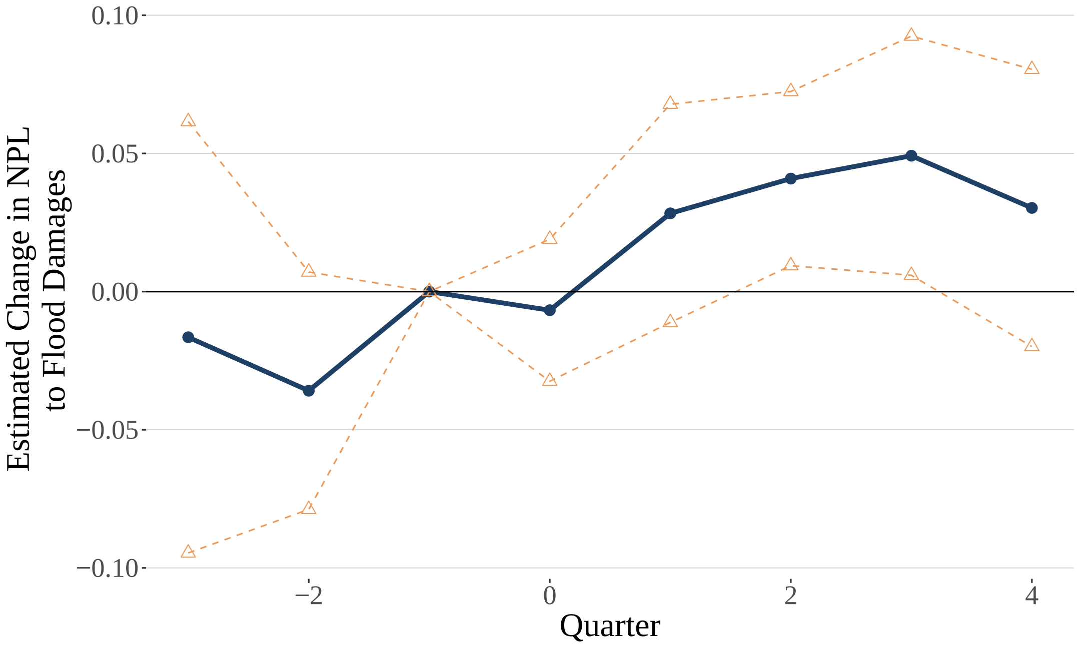



**(a)** Return on Assets

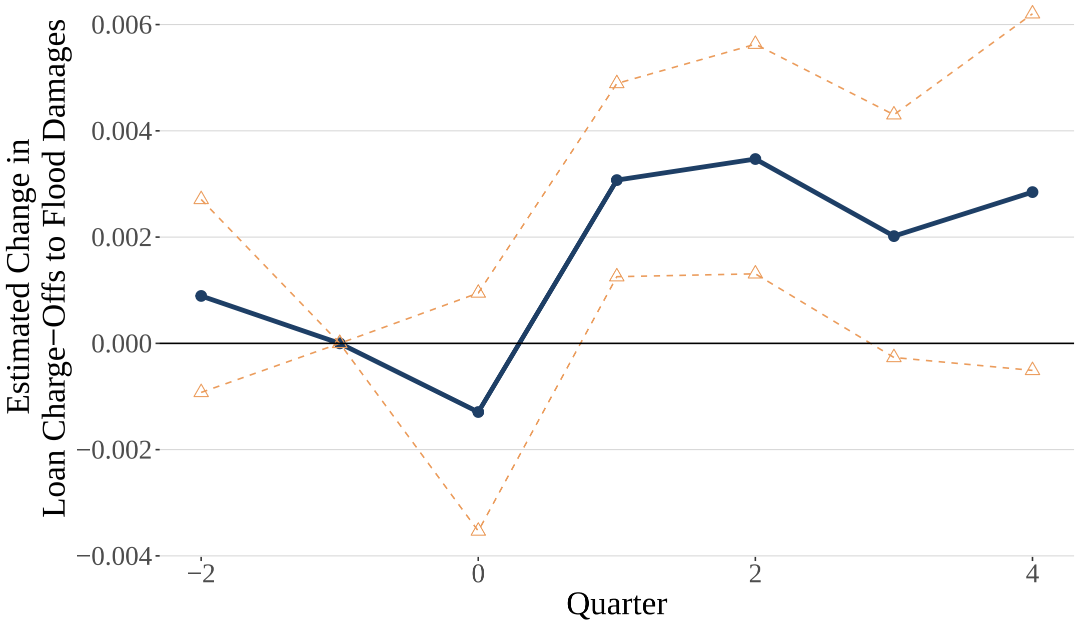



**(b)** Tier 1 Leverage Ratio

**Figure 4: Effect of flood disasters on bank performance**. This figure depicts the relation between bank-level exposure to current flood damage and returns on assets (Panel A) and Tier 1 leverage ratio (Panel B). The figure is estimated by regressing the bank variable in $t + h$ on the exposure to current $(t)$ flood damage, 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 bank level. The solid line plots point estimates for *Scaled Damages*. Short dashed lines denote 97.5% confidence intervals for this estimate.




**(a)** Non-performing Loans




**(b)** Loan Charge-offs

**Figure 5: Effect of flood disasters on loan performance**. This figure presents the relation between bank-level exposure to current flood damage and non-performing loans (Panel A) and loan charge-offs (Panel B) for banks with a high share of mortgage lending. The figure is estimated by regressing the bank variable in $t+h$ on the interaction between exposure to current ($t$) flood damage 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 bank level. The solid line plots the point estimates for *Scaled Damages*. Short dashed lines denote 95% confidence intervals for this estimate.

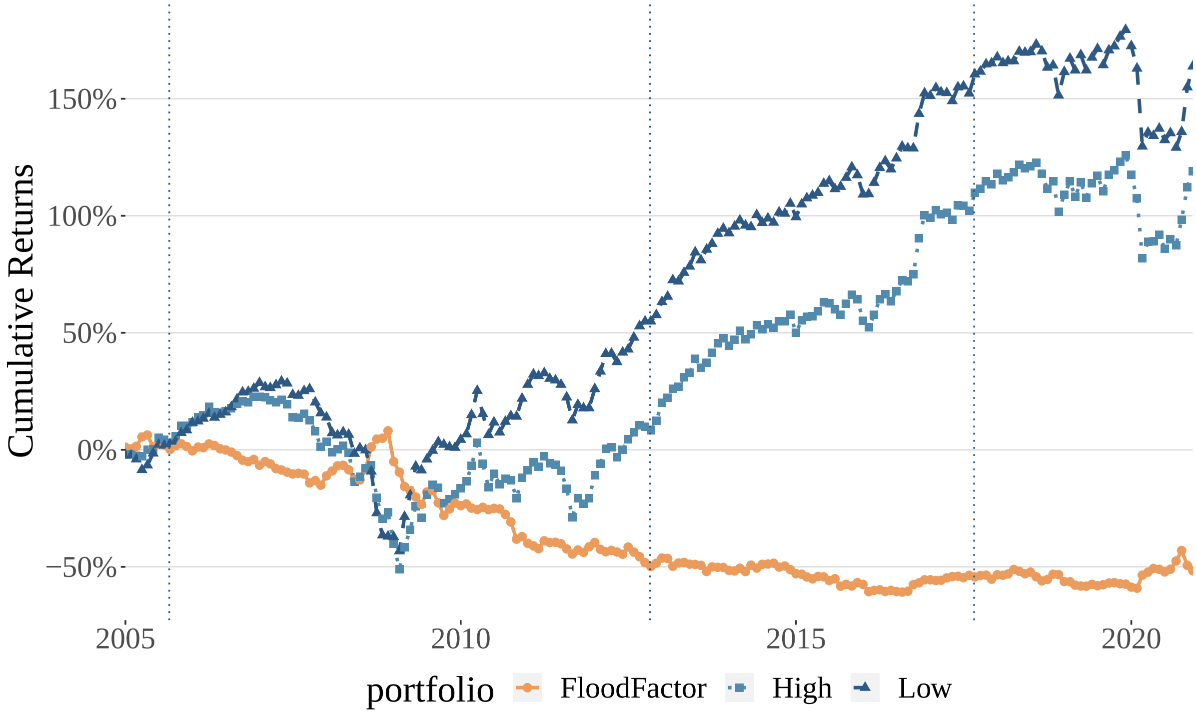



**Figure 6: Cumulative Return of the Exposure-weighted Flood Factor**. The solid line plots the cumulative return of the flood factor constructed with banksflood risk exposure. The dotted blue line (High) plots the cumulative return of the portfolio of banks with high flood exposure, while the dashed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

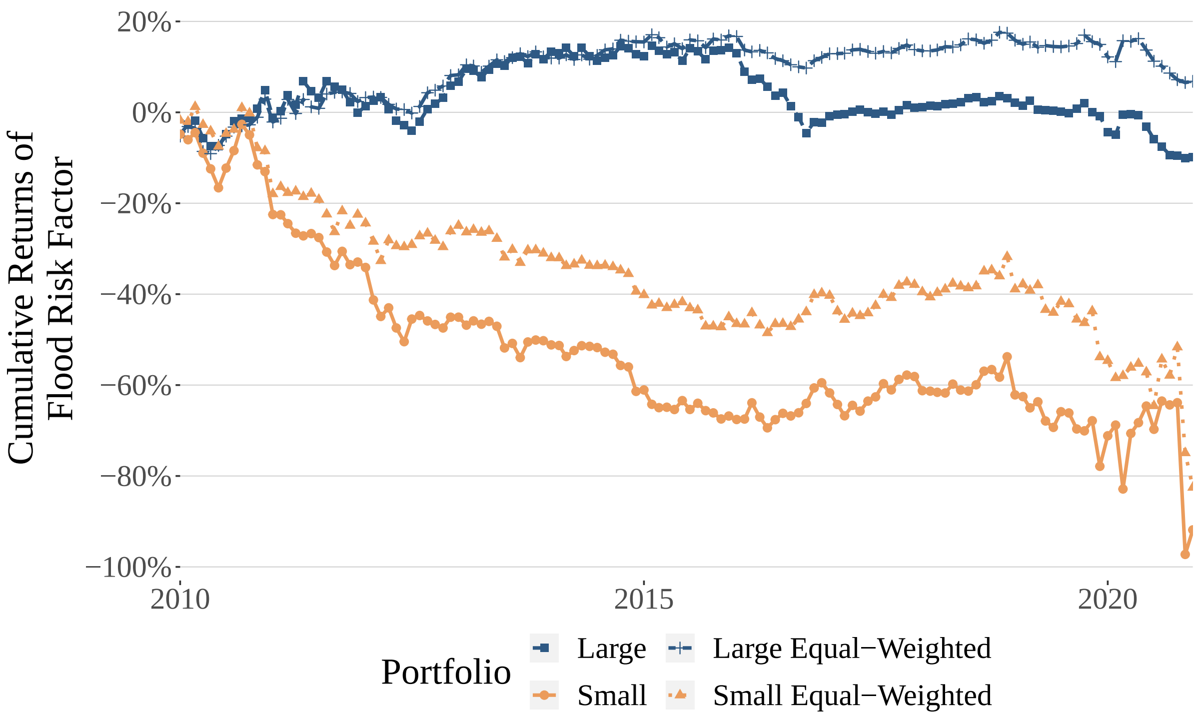



**Figure 7: Cumulative Return of the Exposure-weighted Flood Factor for Size-sorted Samples**. Orange solid and dotted lines plot the cumulative returns of the flood factor from the sample restricted to small banks. The solid line is the exposure-weighted cumulative return and the dotted line is the equal-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 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 quarterly level and stock returns are monthly. Means and differences are computed at the respective frequencies to avoid repetitions. *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, and 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 | *** |

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Table 1 – *Continued from previous page*

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

**Table 2:**

## Return on Assets and Flood Disasters

This table reports 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 county-month level and aggregated at the bank level using different county weights. In columns (1) and (2) damages are weighted by originated and retained mortgages, respectively. Column (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 weighted by headquarters counties. Further, in all columns, scaled damages have been standardized to allow for comparison across regressions. The dependent variable is the one-quarter-ahead return on assets. Standard errors are clustered at bank level. $t$-statistics are in parentheses. Statistical significance is given by $*$: $p < 0.10$; $**$:$p < 0.05$; $***$:$p < 0.01$

| | $ROA_{t+1}$ | | | | |
|---|---|---|---|---|---|
| County Weight | Originated | Retained | Market-Share | Deposits | Headquarters |
| | (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 FE | YES | YES | YES | YES | YES |
| Quarter FE | 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 |

**Table 3:**

## Bank Performance and Flood Disasters

This table reports 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 county-month level and aggregated at the bank level using a bank's mortgage lending activity. 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 bank level. $t$-statistics are in parentheses. Statistical significance is given by $*$: $p < 0.10$; $**$:$p < 0.05$; $***$:$p < 0.01$

| | $\text{ROA}_{t+1}$ | $\text{Leverage}_{t+1}$ | Capital $\text{Ratio}_{t+1}$ | $\text{SWFR}_{t+1}$ | $\text{Z-Score}_{t+1}$ | $\text{NPL}_{t+1}$ | Charge-$\text{Offs}_{t+1}$ | Loan $\text{Loss}_{t+1}$ |
|---|---|---|---|---|---|---|---|---|
| | (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) |

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Table 3 – *Continued from previous page*

| | $ROA_{t+1}$ | $Leverage_{t+1}$ | Capital $Ratio_{t+1}$ | $SWFR_{t+1}$ | $Z$-$Score_{t+1}$ | $NPL_{t+1}$ | Charge-$Offs_{t+1}$ | Loan $Loss_{t+1}$ |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Leverage | 0.002 | 0.023 | -1.19*** | -0.003 | -0.009 | -0.0002 | -0.0002 | -0.001 |
| | (0.975) | (0.470) | (-13.0) | (-0.887) | (-0.973) | (-0.120) | (-0.942) | (-0.869) |
| log(Assets) | -0.227*** | -1.62*** | -1.31*** | 1.36*** | -0.007 | 0.430*** | 0.0004 | 0.251*** |
| | (-4.25) | (-4.68) | (-3.88) | (6.56) | (-0.093) | (6.34) | (0.068) | (5.95) |
| Loan Ratio | 0.060 | 2.28 | 6.87*** | -3.09*** | -0.550 | 1.11*** | -0.004 | 0.706*** |
| | (0.283) | (1.53) | (3.22) | (-3.15) | (-1.13) | (3.60) | (-0.152) | (4.06) |
| Mortgage Ratio | -0.033 | -6.78* | -10.1** | -0.530 | 0.051 | -0.661 | 0.086** | -0.622*** |
| | (-0.106) | (-1.66) | (-2.22) | (-0.349) | (0.105) | (-1.62) | (2.27) | (-2.93) |
| Bank FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Quarter FE | 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 |

## Table 4:
## Heterogeneity in Bank Returns on Assets

This table partitions results from Table 3 on mortgage loan share (High and Low) and bank size (Small and Large). 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 county-month level and aggregated at bank level using a bank's mortgage lending activity. Dependent variables are one-quarter-ahead measures. Bank controls include lagged dependent variables, leverage, log(assets), loan ratio, and mortgage loan share. Standard errors are clustered at bank level. $t$-statistics are in parentheses. 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** | $-4 \times 10^{-5}$ | 0.0001 | 0.0003 |
| | (2.31) | (-0.268) | (0.660) | (1.22) |
| Bank Controls | YES | YES | YES | YES |
| Bank FE | YES | YES | YES | YES |
| Quarter FE | YES | YES | YES | YES |
| Obs. | 8,403 | 6,034 | 6,106 | 8,331 |
| $R^2$ | 0.514 | 0.541 | 0.478 | 0.525 |

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

This table reports results from regressing bank-level excess returns on the flood risk exposure. Baseline exposure is based on flood risk by 2050. Column (2) uses flood risk by 2035 using a second variable provided by the First Street Foundation. 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. Rolling measures are computed as 3-year rolling averages. Flood risk exposure in the final column is constructed using local mortgage concentration and therefore captures a different channel. The dependent variable is the difference between the bank's stock return and the risk-free rate. Bank balance sheet data are from Call Reports. Equity data are from CRSP. The Flood Risk Exposure is based on county-level flood risk from the First Street Foundation and aggregated at bank level using local mortgage activity of a bank from Home Mortgage Disclosure Act (HMDA) data. Standard errors are clustered at 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) |

*Continued on next page*

Table 5 – *Continued from previous page*

| | Excess Returns | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 2050 Risk | 2035 Risk | Risk Score | Number-weighted | Origination-weighted | Rolling Retained | Rolling Origination | Competition-weighted |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| log(BE/ME) | 2.86*** | 2.87*** | 2.86*** | 2.87*** | 2.86*** | 2.86*** | 2.87*** | 2.84*** |
| | (15.8) | (15.8) | (15.7) | (15.7) | (15.9) | (15.7) | (15.7) | (15.9) |
| Return | -0.089*** | -0.089*** | -0.089*** | -0.089*** | -0.089*** | -0.089*** | -0.089*** | -0.089*** |
| | (-10.1) | (-10.1) | (-10.1) | (-10.1) | (-10.1) | (-10.1) | (-10.1) | (-10.1) |
| Mortgage Exposure | -1.48*** | -1.50*** | -1.52*** | -1.48*** | -1.48*** | -1.56*** | -1.60*** | -1.34*** |
| | (-3.54) | (-3.57) | (-3.58) | (-3.54) | (-3.51) | (-3.66) | (-3.70) | (-3.23) |
| Month FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Obs. | 43,227 | 43,227 | 43,227 | 43,227 | 43,227 | 43,227 | 43,227 | 43,227 |
| $R^2$ | 0.28 | 0.28 | 0.28 | 0.28 | 0.28 | 0.28 | 0.28 | 0.28 |

## Table 6:
## Flood Risk Exposure in Size-sorted Samples

This table reports results from pooled-OLS regressions with fixed effects for different size-sorted samples. The main explanatory variable is the *Flood Risk Exposure*, which captures banks' exposure to ex ante flood risk. The measure is based on expected flood risk estimates from the FSF available at county level and aggregated at bank level using a bank's mortgage lending activity. Columns (1) to (3) are estimates for the sample of small banks defined as either below median size, below top quartile size, or less than $50 billion in total assets. Columns (4) to (6) are estimates for samples of large banks. The dependent variable is 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 bank level. $t$-statistics are in parentheses. Statistical significance is given by $*$: $p < 0.10$; $**$:$p < 0.05$; $***$:$p < 0.01$

| | Excess Returns | | | | | |
|---|---|---|---|---|---|---|
| | Small Banks | | | Large Banks | | |
| | <Median | <Top Quartile | <$50 bn | >Median | >Top Quartile | >$50 bn |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Flood Risk Exposure | -0.218*** | -0.195*** | -0.149*** | -0.058 | 0.017 | -0.188 |
| | (-3.24) | (-3.23) | (-2.66) | (-0.648) | (0.191) | (-0.926) |
| Leverage | -0.022* | -0.002 | -0.003 | -0.0004 | -0.004 | 0.002*** |
| | (-1.91) | (-0.538) | (-0.757) | (-0.231) | (-0.688) | (3.20) |
| log(Assets) | -3.60*** | -3.55*** | -3.25*** | -2.45*** | -2.05*** | -2.73*** |
| | (-11.7) | (-16.2) | (-17.1) | (-8.72) | (-6.00) | (-3.89) |
| Loan Ratio | -1.43* | -1.09 | -0.322 | 0.020 | 0.427 | -1.60 |
| | (-1.83) | (-1.46) | (-0.453) | (0.026) | (0.545) | (-1.31) |
| Mortgage Ratio | 1.44* | 1.15** | 1.12** | 0.470 | 0.225 | 0.044 |
| | (1.76) | (2.02) | (2.27) | (0.956) | (0.341) | (0.022) |
| log(BE/ME) | 3.15*** | 3.02*** | 2.86*** | 2.54*** | 2.29*** | 2.72*** |
| | (14.8) | (17.3) | (16.8) | (8.98) | (6.59) | (3.90) |
| lag Return | -0.110*** | -0.105*** | -0.094*** | -0.043*** | -0.002 | 0.021 |
| | (-9.61) | (-11.3) | (-11.2) | (-3.58) | (-0.153) | (0.669) |
| Mortgage Exposure | -2.11*** | -1.75*** | -1.61*** | -0.331 | -0.799 | -19.2 |
| | (-4.20) | (-4.10) | (-4.04) | (-0.521) | (-0.382) | (-1.28) |
| Month FE | YES | YES | YES | YES | YES | YES |
| Obs. | 27,747 | 42,371 | 52,555 | 28,967 | 14,343 | 4,159 |
| $R^2$ | 0.207 | 0.260 | 0.296 | 0.483 | 0.544 | 0.613 |

**Table 7:**
## 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 months 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 high flood risk exposure but experiencing no damages from floods in a given month. Disasters data come from SHELDUS. All regressions include 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's stock return and the risk-free rate. Bank balance sheet data come from Call Reports. Equity data are from CRSP. The sample runs from 2004 to 2020. Standard errors are clustered at bank level. Statistical significance is given by $*$: $p < 0.10$; $**$:$p < 0.05$; $***$:$p < 0.01$

Panel A: All Banks

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

Panel B: Small Banks

| | Excess Returns | | | |
|---|---|---|---|---|
| | Without Hurricane Katrina | Without Major Storms | Zero Damage | Zero Damage & High-Risk |
| | (1) | (2) | (3) | (4) |
| Flood Risk Exposure | -0.179*** | -0.185*** | -0.267** | -0.236 |
| | (-2.68) | (-2.78) | (-2.58) | (-1.29) |
| Bank Controls | YES | YES | YES | YES |
| Month FE | YES | YES | YES | YES |
| Obs. | 29,238 | 28,562 | 9,905 | 2,500 |
| $R^2$ | 0.208 | 0.207 | 0.223 | 0.312 |

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Table 7 – *Continued from previous page*

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

**Table 8:**
## Realized Flood Disasters

This table reports results from regressing bank equity returns on the main flood risk exposure and controlling for realized flood disasters. Disasters data come from SHELDUS. Scaled Damages 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 Damage Exposure is in the top quartile. Total Damage is the unweighted dollar amount of damage that occurred in the United States in a given month. All regressions include bank-level controls Tier 1 leverage, log(assets), loan ratio, mortgage loan ratio, log(market equity), and lagged return. Macro controls are log(GDP), CPI, PCPI, and the unemployment rate. The dependent variable is the difference between the bank's stock return and the risk-free rate. Bank balance sheet data come from Call Reports. Equity data are from CRSP. Standard errors are clustered at bank level. Statistical significance is given by $*$: $p < 0.10$; $**$:$p < 0.05$; $***$:$p < 0.01$

Panel A: All Banks

| | Excess Returns | | | | Return Residuals |
|---|---|---|---|---|---|
| Scaled 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) |
| Scaled Damages | -0.085*** | -0.084*** | -0.238* | -0.199*** | |
| | (-3.81) | (-2.72) | (-1.69) | (-9.46) | |
| Flood Risk Exposure × Scaled Damages | | -0.001 | 0.338** | -0.016 | |
| | | (-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 | |

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Table 8 – *Continued from previous page*

| | | | | | |
|---|---|---|---|---|---|
| × Flood Damages | | (-0.254) | (1.87) | (0.077) | |
| Obs. | 24,677 | 24,677 | 24,677 | 24,677 | 24,677 |
| $R^2$ | 0.059 | 0.059 | 0.059 | 0.059 | 0.038 |

Panel B: Large Banks

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

**Table 9:**
## Risk-adjusted Returns on Flood Risk-sorted Portfolios

This table presents estimates from OLS regressions of monthly value-weighted excess returns on each Flood Risk Exposure-sorted portfolio of banks 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 10:**

## 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, a portfolio that goes long a high-exposure portfolio and short a low flood-exposure portfolio. 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 Newey-West adjusted with three lags. $t$-statistics are in parentheses. 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:
## Flood Disasters and 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. 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 within the top decile. In column (3), *Total Damage* are damage estimates for all hazard types. 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

| | Flood Factor | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| (Intercept) | -0.211 | -0.165 | -0.212 |
| | (-1.54) | (-1.06) | (-1.55) |
| $\Delta$log(Flood Damage) | -0.107** | | |
| | (-2.32) | | |
| High Damage | | -0.389 | |
| | | (-1.08) | |
| $\Delta$ 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) |
| $\Delta$ log(Flood Damage) | -0.071 | | |
| | (-0.887) | | |
| High Damage | | -0.306 | |
| | | (-0.391) | |
| $\Delta$ log(Total Damage) | | | -0.066 |
| | | | (-0.873) |
| Obs. | 180 | 180 | 180 |
| $R^2$ | 0.005 | 0.001 | 0.005 |

**Table 12:**
## 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, $\Delta CC$. SVI variables are from the Google Search Volume Index for the topics "Climate Change" and "Flood". UMC are defined as unexpected media climate change concerns and are prediction errors from an AR(1) regression model following Ardia et al. (2022). Measures are constructed from newspaper and newswire articles for different climate change topics. The aggregated measure captures the full concerns, while the measures on flood and summits proxy for risk from floods and regulatory risks, respectively. The dependent variable is the difference between the bank's stock return and the risk-free rate. All regressions include bank controls—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 $\Delta$VIX). Standard errors are clustered at bank level. Statistical significance is given by $*$: $p < 0.10$; $**$:$p < 0.05$; $***$:$p < 0.01$

Panel A: Full Sample

| | Excess Returns | | | | |
|---|---|---|---|---|---|
| $\Delta CC$: | 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) |
| $\Delta CC$ | -0.139*** | -0.761*** | -0.461*** | -0.032 | -0.424*** |
| | (-3.22) | (-11.8) | (-6.86) | (-0.600) | (-4.98) |
| Flood Risk Exposure $\times$ $\Delta CC$ | 0.005 | -0.161*** | 0.085 | 0.104* | 0.078 |
| | (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) |
| $\Delta CC$ | -0.054 | -0.350*** | -0.634*** | -0.348*** | -0.750*** |
| | (-0.824) | (-4.23) | (-7.01) | (-4.45) | (-6.57) |
| Flood Risk Exposure $\times$ $\Delta CC$ | -0.042 | -0.187*** | 0.002 | 0.024 | -0.010 |
| | (-0.759) | (-2.85) | (0.016) | (0.331) | (-0.088) |
| Obs. | 24,010 | 24,010 | 20,423 | 20,423 | 20,423 |
| $R^2$ | 0.073 | 0.074 | 0.078 | 0.077 | 0.079 |

**Table 13:**

## Political Landscape

This table reports results from pooled-OLS regressions with fixed effects. The main explanatory variable is *Flood Risk Exposure*, which captures banks' exposure to expected flood risk. The dependent variable is excess return. All regressions include bank-level controls—log(market value), Tier 1 leverage, mortgage ratio, loan ratio, log(assets), past-month return, and mortgage exposure. The political indicator is an indicator that equals one if the majority of the counties in which a given bank originated mortgages has Republican during the most recent federal election or the president is Republican. Standard errors are clustered at bank level. $t$-statistics are in parentheses. 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 14:
## Flood Risk Exposure and Federal Control

This table reports 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* equal one if the House of Representatives, Senate, or the presidency is controlled by Republicans. The variables *Congress*; *Senate*; or *House* equal one if Republicans control the Congress, only the 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 bank level. $t$-statistics are in parentheses. 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 15:**
## Institutional Investors

This table reports results from pooled-OLS regressions with fixed effects. The main explanatory variable is *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 (columns (5) and (6)). The political indicator is an indicator that equals one if the president is a Republican. Standard errors are clustered at bank level. *t*-statistics are in parentheses. Statistical significance is given by $*$: $p < 0.10$; $**$:$p < 0.05$; $***$:$p < 0.01$

| | Excess Returns | | | | | |
|---|---|---|---|---|---|---|
| Investor Indicator | Negative $\Delta$ 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 $\times$ 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 $\times$ Pol. Indicator | | 0.148 | 0.083 | 0.238 | | 0.258$^{**}$ |
| | | (1.38) | (0.672) | (1.44) | | (2.21) |
| Flood Risk Exposure $\times$ Pol. Indicator $\times$ 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 $\times$ Investor Indicator | | 0.310 | -0.057 | 0.683$^{*}$ | | 0.466$^{***}$ |

*Continued on next page*

Table 15 – *Continued from previous page*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | | (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 |

# Internet Appendix for "Is Flood Risk Priced in Bank Returns?"

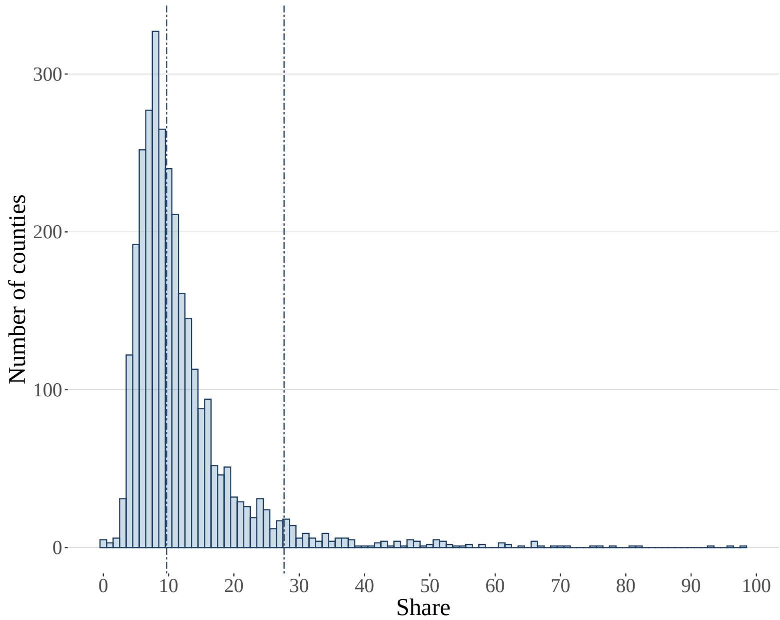
Valentin Schubert*

November 21, 2022

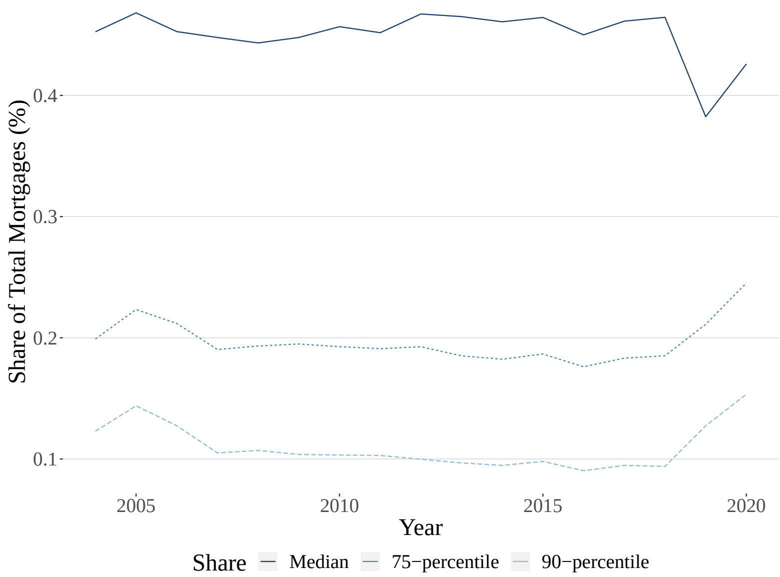
*Department of Finance, Stockholm School of Economics. All errors are my own. For any questions, please contact me at valentin.schubert@phdstudent.hhs.se

# Table of Contents

# A1 Additional Figures

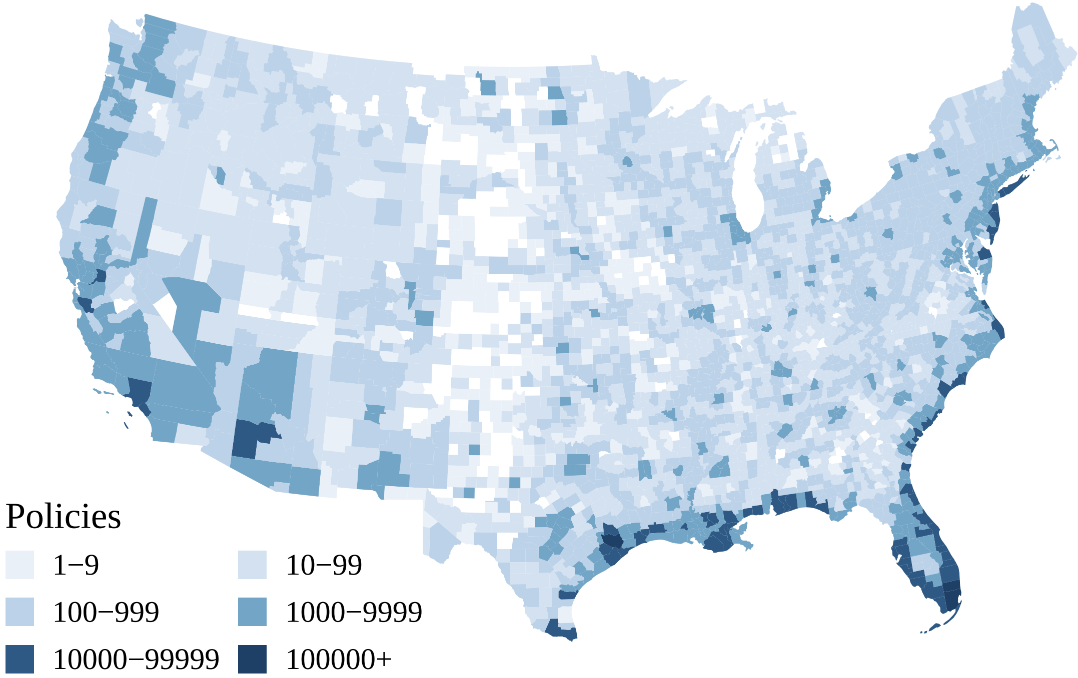



**(a)** Number of Counties by Risk Group

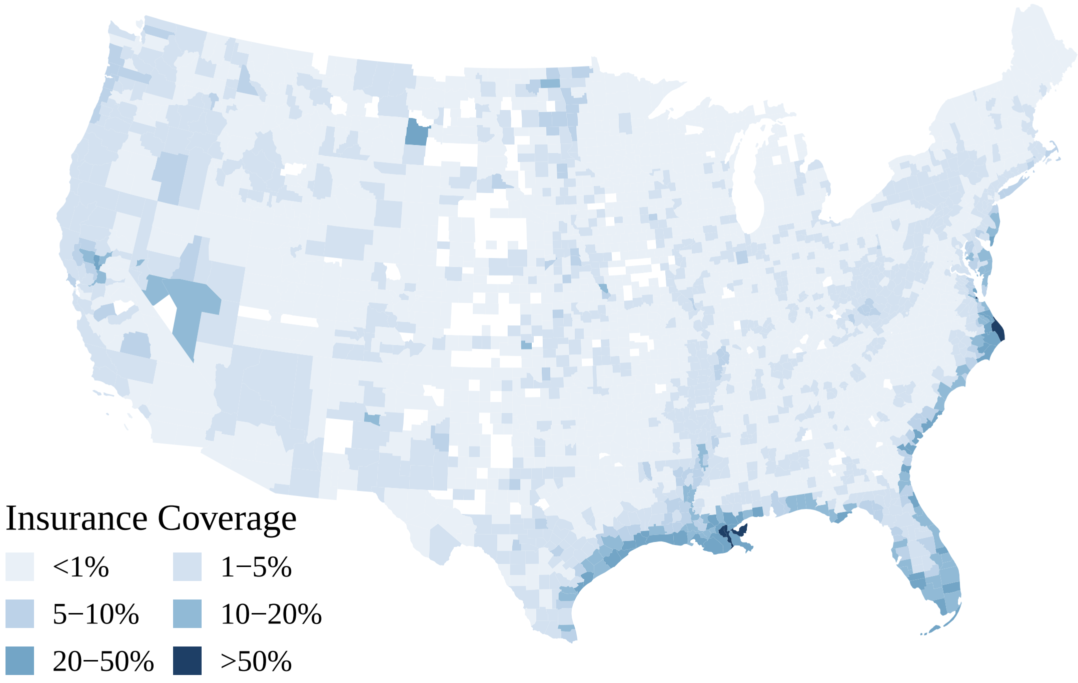



**(b)** Share of Mortgage Amounts by Risk Percentiles

**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.

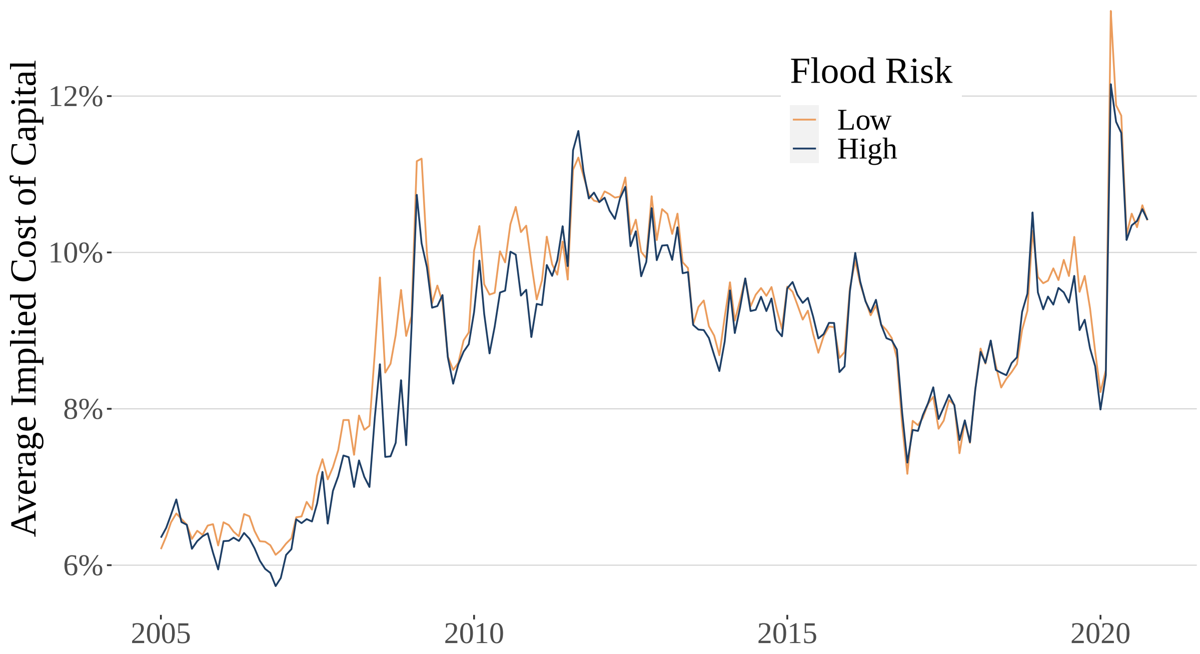



**(a)** Number of Active Insurance Policies

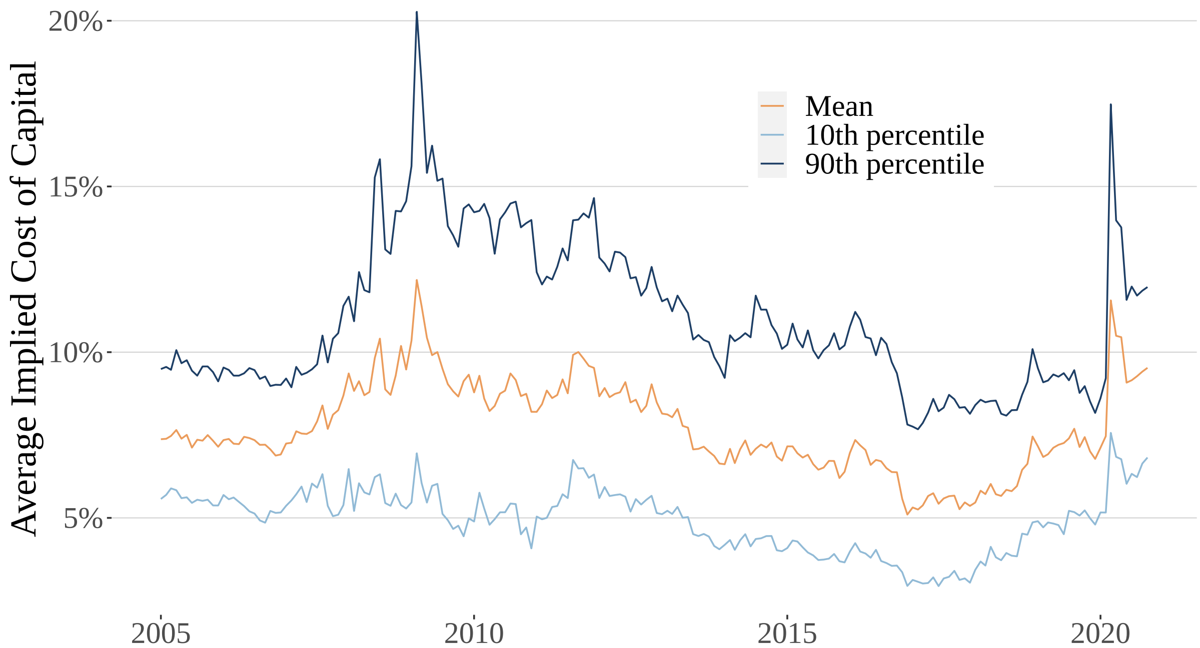



**(b)** Insurance Coverage

**Figure A1.2: NFIP Insurance Data**. Panel (a) plots the total number of active insurance policies from the National Flood Insurance Program (NFIP) by county. Panel (b) plots the average insurance coverage calculated as the number of active NFIP policies divided by the total housing stock from the Census data.




**(a)** ICC of high and low flood exposed banks




**(b)** ICC by Percentiles

**Figure A1.3: Implied Cost of Capital**. The equity cost of capital is calculated using the ICC estimate based on analyst earnings forecasts. The mean estimate is across all banks in a given month. The figure also shows the 10% and 90% percentiles in the monthly distribution. The cost of capital is measured in percentage points.

# A2 Additional Tables

**Table A2.1:**
**Flood Damages and Denied Mortgage Placebo**

This table reports the results from pooled-OLS regressions with fixed effects. The main explanatory variable is the *Scaled Damages*, which captures banks' costs of realized floods. Column (1) uses the baseline risk exposure based on originated mortgages. Columns (2) and (3) are based on denied mortgages. Column (4) normalizes the denied mortgage amount by application amount. The dependent variable is 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 $*$: $p < 0.10$; $**$:$p < 0.05$; $***$:$p < 0.01$

| | ROA | | | |
|---|---|---|---|---|
| Sample | Full | | Small | |
| | Baseline | Denied-Exposure | Denied-Exposure | Normalized Denied |
| | (1) | (2) | (3) | (4) |
| Scaled Damages | -0.002** | -0.001 | -0.002 | -0.0010 |
| | (-2.46) | (-0.991) | (-0.998) | (-0.296) |
| Tier 1 Ratio | 0.001*** | 0.001*** | 0.002*** | 0.002*** |
| | (3.36) | (3.36) | (3.82) | (3.82) |
| log(Assets) | -0.755*** | -0.755*** | -0.805*** | -0.805*** |
| | (-14.1) | (-14.1) | (-10.6) | (-10.6) |
| Loan Ratio | -0.360* | -0.360* | -0.274 | -0.274 |
| | (-1.73) | (-1.73) | (-1.02) | (-1.02) |
| Mortgage Ratio | -0.337 | -0.337 | -0.437 | -0.437 |
| | (-1.47) | (-1.47) | (-1.54) | (-1.54) |
| log(ME) | 0.736*** | 0.736*** | 0.724*** | 0.724*** |
| | (17.9) | (17.9) | (14.8) | (14.8) |
| lagged Return | 0.003*** | 0.003*** | 0.004*** | 0.004*** |
| | (5.73) | (5.73) | (5.39) | (5.39) |
| Average Retained Amount | -0.137 | -0.137 | -0.178 | -0.177 |
| | (-0.962) | (-0.962) | (-1.08) | (-1.07) |
| HQ State-Month FE | YES | YES | YES | YES |
| Bank FE | YES | YES | YES | YES |
| Observations | 48,548 | 48,548 | 35,021 | 35,021 |
| $R^2$ | 0.645 | 0.645 | 0.635 | 0.635 |

## Table A2.2:
## Flood Risk Exposure and Denied Mortgage Placebo

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. Column (1) uses the baseline risk exposure based on originated mortgages. Columns (2) and (3) are based on denied mortgages. Column (4) normalizes the denied mortgage amount by application amount. The dependent variable is 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 $*$: $p < 0.10$; $**$:$p < 0.05$; $***$:$p < 0.01$

| | Excess Return | | | |
|---|---|---|---|---|
| | Full Sample | | Small Banks | |
| | Baseline | Denied-Exposure | Denied-Exposure | Normalized Denied |
| | (1) | (2) | (3) | (4) |
| Flood Risk Exposure | -0.016** | -0.044 | -0.068 | 0.151 |
| | (-2.15) | (-0.811) | (-1.09) | (0.594) |
| Tier 1 Ratio | -0.003 | -0.003 | -0.002 | -0.002 |
| | (-1.05) | (-1.21) | (-1.07) | (-1.04) |
| log(Assets) | -2.67*** | -2.66*** | -3.37*** | -3.38*** |
| | (-13.2) | (-13.2) | (-12.7) | (-12.7) |
| Loan Ratio | -0.761 | -0.762 | -0.158 | -0.119 |
| | (-1.15) | (-1.15) | (-0.174) | (-0.131) |
| Mortgage Ratio | 0.505 | 0.460 | 0.565 | 0.513 |
| | (0.893) | (0.816) | (0.853) | (0.773) |
| log(ME) | 2.52*** | 2.51*** | 2.78*** | 2.77*** |
| | (13.5) | (13.5) | (13.3) | (13.3) |
| lagged Return | -0.105*** | -0.105*** | -0.123*** | -0.123*** |
| | (-10.6) | (-10.6) | (-11.0) | (-11.0) |
| Average Retained Amount | -0.367 | -0.289 | -0.684 | -0.635 |
| | (-0.802) | (-0.642) | (-1.23) | (-1.14) |
| HQ State-Month | YES | YES | YES | YES |
| Obs. | 57,126 | 57,126 | 42,668 | 42,668 |
| $R^2$ | 0.395 | 0.395 | 0.382 | 0.382 |

**Table A2.3:**
## Implied Cost of Capital

This table reports the results from pooled-OLS regressions with fixed effects with the implied cost of capital as the dependent variable. The main explanatory variable is the *Flood Risk Exposure*, which captures banks' exposure to expected flood risk. The measure is based on expected flood risk estimates from FSF available at the county level and is aggregated at the bank level using a bank's mortgage lending activity. Standard errors are clustered at the bank level. $t$-statistics are in parenthesis. Statistical significance is given by $*$: $p < 0.10$; $**$:$p < 0.05$; $***$:$p < 0.01$

| | ICC-$r^F$ | | | | |
|---|---|---|---|---|---|
| | Full | High Mortgage Share | Small Size | Large | High Flood |
| | (1) | (2) | (3) | (4) | (5) |
| Flood Risk Exposure | -0.036 | 0.140 | -0.036 | -0.005 | 0.069 |
| | (-0.243) | (0.567) | (-0.158) | (-0.038) | (0.413) |
| Leverage | -0.311*** | -0.236* | -0.312** | -0.260* | -0.317** |
| | (-3.31) | (-1.87) | (-2.51) | (-1.72) | (-2.36) |
| log(Assets) | 1.73*** | 2.11** | 1.85* | 1.24** | 1.68** |
| | (3.31) | (2.16) | (1.80) | (2.06) | (2.54) |
| Loan Ratio | 1.17 | 4.23 | 4.12* | -0.825 | 1.27 |
| | (1.08) | (1.52) | (1.91) | (-0.724) | (1.16) |
| Mortgage Ratio | -0.838 | -0.329 | -0.855 | -0.387 | -0.553 |
| | (-0.730) | (-0.217) | (-0.386) | (-0.450) | (-0.368) |
| log(BE/ME) | -1.82*** | -2.10** | -2.01*** | -1.37** | -1.74*** |
| | (-3.50) | (-2.31) | (-2.62) | (-2.20) | (-2.73) |
| $\text{Return}_{bt-1}$ | -0.011 | -0.003 | -0.011 | -0.014 | -0.020* |
| | (-1.27) | (-0.190) | (-1.02) | (-1.02) | (-1.96) |
| Mortgage Exposure | 0.852 | 2.33 | 0.645 | 1.15 | 0.462 |
| | (0.751) | (1.40) | (0.427) | (0.723) | (0.264) |
| Month | YES | YES | YES | YES | YES |
| Obs. | 37,265 | 18,310 | 18,552 | 18,713 | 18,848 |
| $R^2$ | 0.048 | 0.052 | 0.057 | 0.047 | 0.046 |

**Table A2.4:**
## Examination of Heterogeneity in Stock Returns

This table reports the results from pooled-OLS regressions with month fixed effects. The main explanatory variable *Flood Risk Exposure* captures banks' exposure to flood risk. The measure is based on a flood probability map and is aggregated at the bank level using a bank's mortgage lending activity. The dependent variable is the excess stock return over the risk-free rate. In Panel A, the sample is split in banks with high and low share of mortgage loans to total assets. Panel B splits the sample into banks with above and below median exposure to flood risk. All regressions control for log(market equity), Tier 1 capital ratio, 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<br>(1) | Low<br>(2) | Full<br>(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: Flood Risk Exposure

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

## Table A2.5:
## 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. Data on flood policies and claims come from NFIP. Policies are the number of active policies divided by the number of homes in a county, weighted by a bank's mortgage lending. Claim amounts are monthly insurance claims after floods divided by total personal income in a county. The claims are mapped to the different banks using mortgage lending patterns. All regressions including bank controls and month fixed effects. The bank-level controls include log(market equity), Tier 1 capital ratio, mortgage ratio, loan ratio, log(assets), past-month return, and mortgage exposure. 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) | |

*Continued on next page*

Table A2.5 – *Continued from previous page*

| | | | | |
|---|---|---|---|---|
| Defaults | | | | -0.010 |
| | | | | (-0.389) |
| Bank Controls | YES | YES | YES | YES |
| Month FE | YES | YES | YES | YES |
| Obs. | 23,648 | 23,648 | 19,126 | 19,126 |
| $R^2$ | 0.20 | 0.20 | 0.20 | 0.20 |

Panel C: Large Banks

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

## A3 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 have been assumed to be the connecting link between realized floods and bank performance. The first 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.

**Table A2.6:**
## Regional Factors

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 |

### A3.1 Relized Flood Disasters and Delinquencies

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:

$$\begin{aligned} \mathrm{Y}_{c,t+h} = \quad & \beta_0^h + \beta_1^h \mathit{Flood\ Damages}_{c,t} \\ & + \beta_2^h Y_{c,t-1} + \boldsymbol{\gamma} \boldsymbol{X} + \epsilon_{c,t+k}, \end{aligned} \tag{A3.1}$$

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 A3.1(a) reports the coefficients $\beta_1^h$ 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 A3.1(b) reports the coefficients $\beta_1^h$ 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.

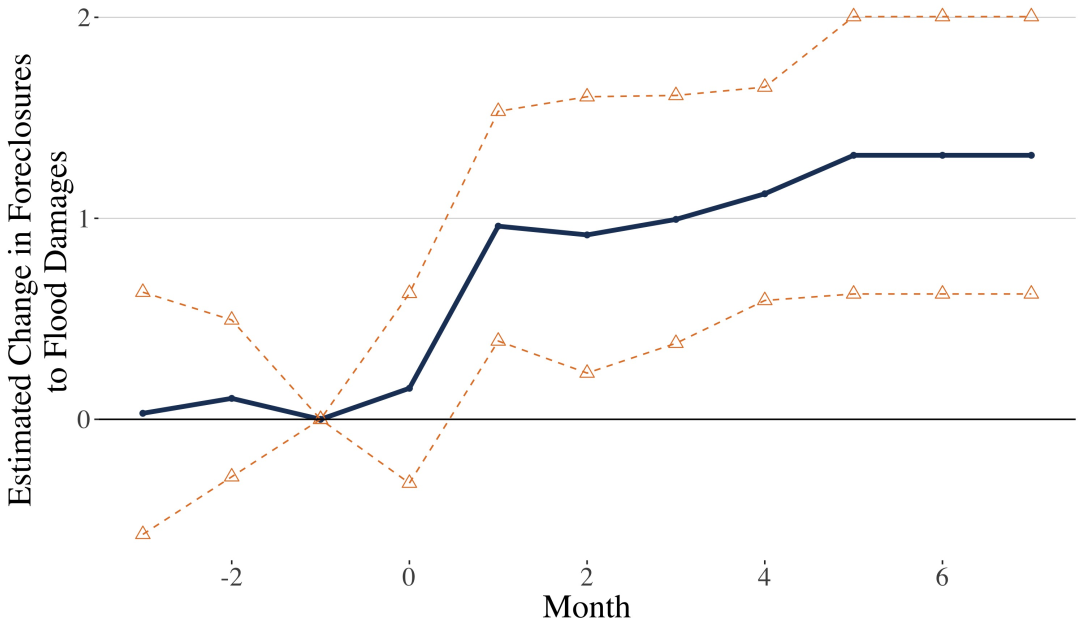
## A3.2 Accounting Performance and Delinquencies

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:

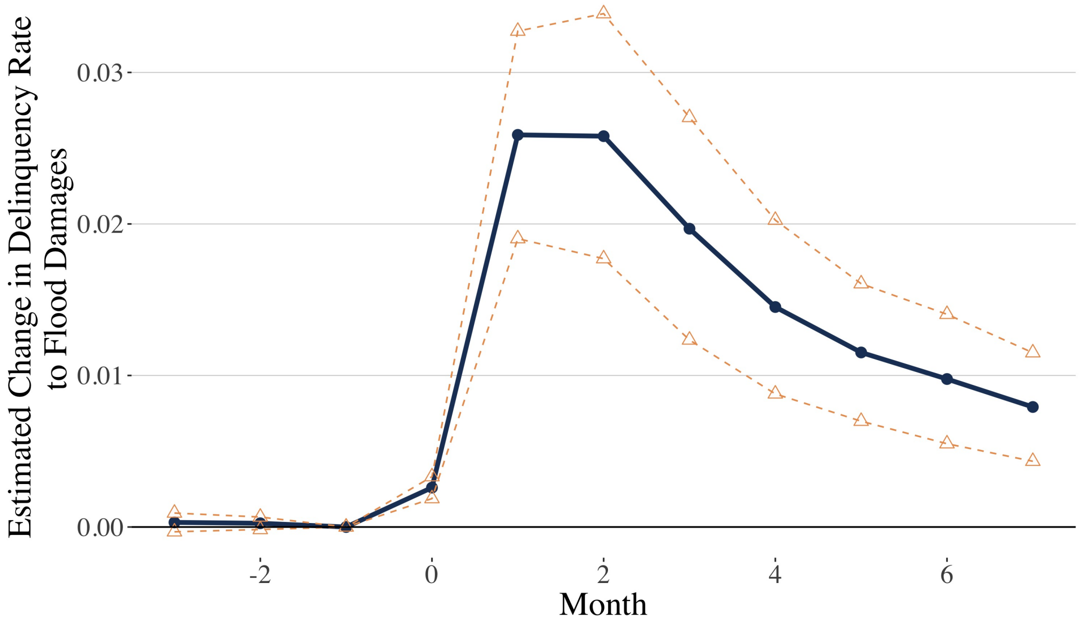
$$\begin{aligned} Y_{b,t} = \beta_0 &+ \beta_1 \mathit{Market\ Exposure}_{b,t} + \beta_2 \mathit{Capital\ Ratio}_{b,t-1} \\ &+ \beta_3 \mathit{log(Employees)}_{b,t-1} + \beta_4 \mathit{log(Assets)}_{b,t-1} \\ &+ \beta_5 \mathit{ROA}_{b,t-1} + \boldsymbol{\gamma X} + \epsilon_{b,t}, \end{aligned} \tag{A3.2}$$

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.

Panel A of Table A3.1 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 A3.1. 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.




**(a)** Mortgage Foreclosures




**(b)** Mortgage Delinquencies

**Figure A3.1: Effect of flood disasters on loan performance**. This figure presents the relation between bank-level exposure to current flood damages and mortgage foreclosures (Panel A) and mortgage delinquency rates (Panel B). Mortgage foreclosure data is from RealtyTrac and is available from 2004 to 2012 at the county level. Mortgage delinquency rates are computed from Fannie Mae's Loans Performance data from 2004 to 2020 at the ZIP3 level. The solid line presents the point estimates for *Flood Damages*. The short dashed lines present 95% confidence intervals on this estimate.

**Table A3.1:**

## 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 Tier 1 capital ratio. Nonperforming loans and charge-offs are divided by the total loans. All regressions control for log(assets), loan ratio, Tier 1 capital ratio, and mortgage loan ratio. 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 FE | YES | YES | YES | YES |
| Quarter FE | 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 FE | YES | YES | YES | YES |
| Quarter FE | YES | YES | YES | YES |
| Obs. | 15,566 | 15,037 | 15,566 | 14,429 |
| $R^2$ | 0.501 | 0.886 | 0.854 | 0.495 |

# A4 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 A4.1, where the orthogonalized risk factors and their related beta coefficients are given by $F^{\perp}_{T\times K}$ and $\beta^{\perp}$.

$$r_{j,t} - r_{f,t} = \alpha + \beta^{\perp}_j F^{\perp}_t + \epsilon_{j,t} \tag{A4.1}$$

where $j$ represents the portfolio of interest.

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

$$R^2 = \sum_{k=1}^{K} DR_k^2, \text{ where } DR_k^2 = \left(\hat{\beta}_k^{\perp} \frac{\sigma_k}{\sigma_r}\right)^2 \quad \text{(A4.2)}$$

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

$$F_{T\times K}^{\perp} = F_{T\times K} S_{K\times K} \quad \text{(A4.3)}$$

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.[2]. I estimate $F_{T\times K}^{\perp}$ 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 A4.1. 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

[2]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 A4.1 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.

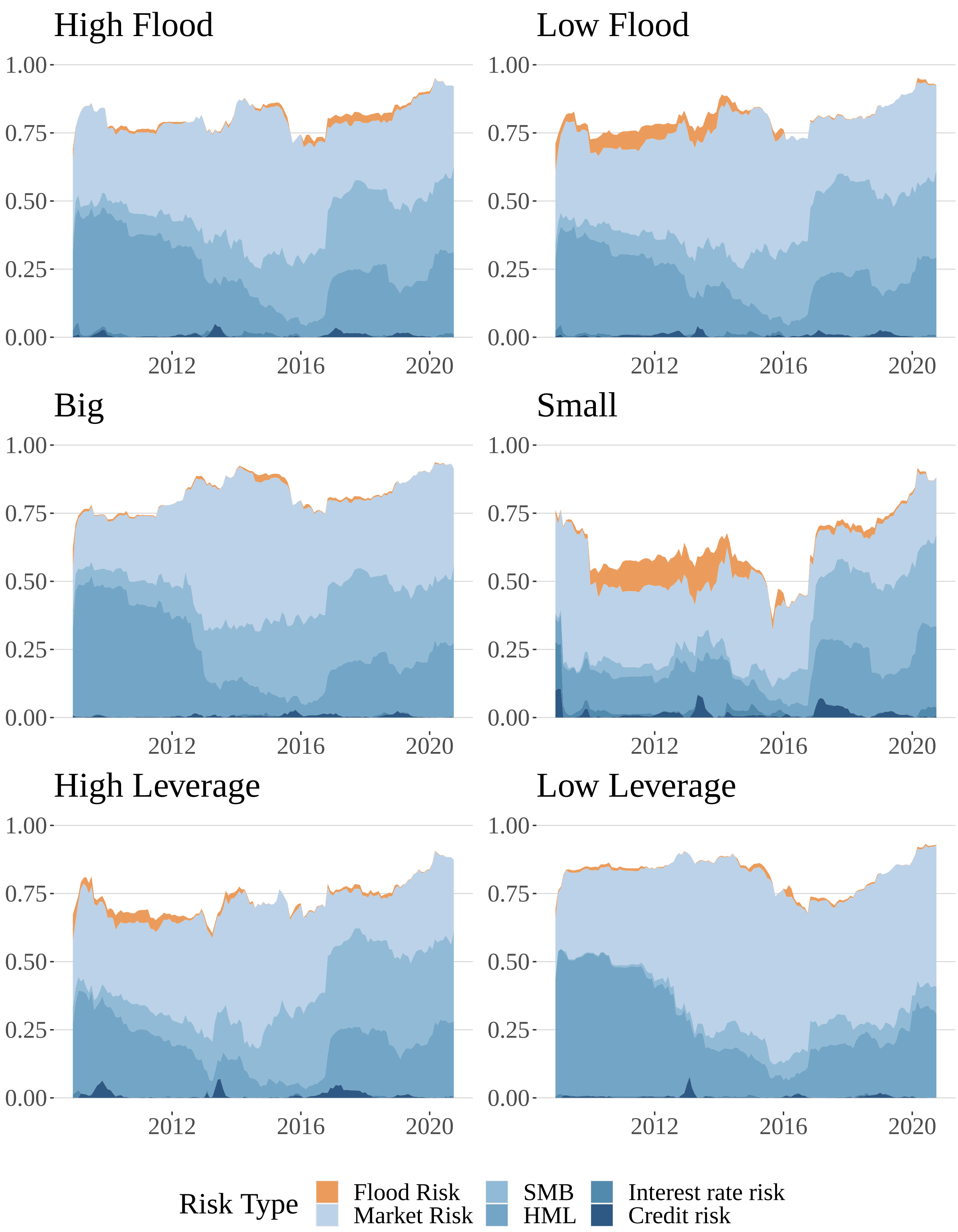



**Figure A4.1: Variance Decomposition**. Rolling variance decompositions for US bank portfolios. This figure shows variance decompositions for portfolios of US banks depending on bank characteristics. In the first row, the graphs plot the variance for the portfolio divided along their flood risk (above 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.