Is Flood Risk Priced in Bank Returns?

Valentin Schubert*

June 20, 2024

Abstract

I quantify the costs of flood disasters for banks and develop a novel measure of bank-level flood risk exposure using expected flood risk estimates and mortgage lending data. Banks with significant mortgage exposure in affected areas show reduced profits and capital ratios post-flood. In the cross-section of stocks, small banks with high flood risk exposure underperform by up to 2.6% annually, indicating that flood risk is not fully priced. This underperformance persists even after accounting for realized disaster impacts on returns and investors' climate change concerns, highlighting regulatory concerns about banks' physical risk from climate change.

Keywords: Banks, Stock returns, Climate change
JEL Classification Codes: E44, G21, G12, Q54

*Sveriges Riksbank. I am indebted to my thesis committee members, Adrien d'Avernas, Mariassunta Giannetti (advisor), and Marcus Opp for guidance and support. I thank my discussants Martin Gustavsson, Ivan Ivanov, Roberto Tubaldi, Yingjie Qi, and Tamas Vadasz for helping me improve this paper. I am grateful to Bo Becker, Cristina Cella, Alvin Chen, Merhan Ilhan, Vincent Maurin, Steven Ongena, Oliver Rehbein, Riccardo Sabbatucci, Farzad Saidi, Tobias Sichert, Jan Starmans, Robin Tietz, Martin Waibel, and Dong Yan, seminar participants at Banco de España, Bank of England, Banque de France, De Nederlandsche Bank, Erasmus School of Economics, IMF RESMF, LUISS University, Norwegian School of Economics, NOVA School of Business and Economics, Rotterdam School of Management, Stockholm School of Economics, Sveriges Riksbank, and Utrecht School of Economics, as well as participants at the AREUEA Annual Meeting in Washington, 5th Benelux Banking Research Day, 2022 EEA/ESEM Meeting, 2023 EFA Meeting, Nordic Finance Network Ph.D. Workshop, Nordic Finance Network Young Scholar Workshop, 10th Swedish National Ph.D. Workshop, and Sveriges Riksbank Conference on Climate Change and the Financial System for helpful comments and suggestions. Any errors are my own. For any questions, please contact me at valentin.schubert@riksbank.se. The opinions expressed in this article are the sole responsibility of the author and should not be interpreted as reflecting the views of Sveriges Riksbank.

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, and 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 US 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 novel flood risk exposure measure for banks. Since climate and environmental risks are fundamentally downside risks for most firms (Seltzer, Starks, and Zhu, 2022a), exposed banks should, if the risk is aggregate, command a higher expected return—and thus

[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 US 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.

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: Small banks with high exposure to flood risk underperform non-exposed small banks, on average, by 2.6% 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 US 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 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.

[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.

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

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 counties affected by the hurricane had abnormal returns of -15% compared with banks lending to unaffected counties in the US Gulf Coast region.

I examine the cross-sectional relation between ex ante flood risk exposure and US 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-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 increase in flood risk exposure is associated with a 2.6 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

[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 US stocks.

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

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 56 bps per month, or over 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 60% 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).

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 US experienced a series of bad shocks, which is picked up by the flood risk exposure. This implies that the 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.

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 coincides 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

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

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 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 a measure of expected returns, the coefficient on the flood risk exposure is positive but insignificant. This partly alleviates concerns 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-by-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 US 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

[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.

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 details the data sources and key explanatory variables used in the analysis. The analysis focuses on floods and hurricanes, the costliest disasters in the United States (Davenport et al., 2021). Since 2010, weather disasters have caused over $1 trillion in property damage, with nearly $300 billion attributed to floods and storms. The consensus is that without significant measures, costs from climate change-related disasters will increase, exacerbated by sea level rise (Intergovernmental Panel on Climate Change, 2015). Some estimates predict property damage from floods could increase by over 60% in the next 30 years (First Street Foundation, 2021).

The ECB (2019) highlights that increased frequency and severity of climate disasters heighten the risk of abrupt asset value losses in climate-sensitive areas. Real estate, inherently linked to its geographic location, is vulnerable to such disasters. Financial institutions lending in these areas face increased risks to collateral and asset values. Annually, mortgage lenders in the I.S. still originate between $200-250 billion in new mortgages in FEMA-designated flood zones, representing roughly 12.5% of total bank equity (Ouazad, 2020). 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. 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). Hence, the effect on bank performance and bank stability is not clear. Moreover, evidence on whether banks account for disaster risks in lending decisions is mixed (e.g., Garbarino and Guin, 2021).

To test the link between bank performance and flood disasters, I combine banks' mortgage lending with different measures of flood disasters. I use data on US mortgages obtained from the publicly available part of the Home Mortgage Disclosure Act (HMDA) data.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 one- to four-family home purchase loans that were originated. The data is 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.

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.[10] For this study, the data are restricted to major floodings and storms. Figure 1(a) plots the total estimated damage from floods in each US 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.

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 US 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. 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 also capture banks that are mostly 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 1(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.

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

2.1 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 the county level. Therefore, county-level variables must be aggregated at the 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:

$$\text{Share}_{b,c,y} = \frac{\text{Originated}_{b,c,y}}{\sum_c \text{Originated}_{b,c,y}}, \tag{1}$$

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:

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

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:

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

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.

2.2 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.

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 US 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

$$E[R_{b,t}] = \hat{\alpha}_b + \hat{\boldsymbol{\beta}}_{\boldsymbol{b}}' \boldsymbol{F}, \tag{5}$$

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

$$R_{b,t} = \alpha_b + \boldsymbol{\beta_b'} \boldsymbol{F} + \epsilon_{b,t}. \tag{6}$$

I follow Schüwer et al. (2019) to classify banks as affected and unaffected (control) by Hurricane Katrina. Their identification strategy yields 19 affected banks and 27 unaffected banks. Figure 2(b) shows the daily cumulative abnormal returns (CAR) of the value-weighted portfolios of the affected and unaffected banks from July to October 2005. Hurricane Katrina formed on August 24 and crossed the southern tip of Florida on August 26. The storm's intensity and its trajectory was revised to hit the coast of Mississippi (United States Department of Commerce, 2006). The CAR of the affected banks starts to decline relative to the control group on August 26. On August 28, the National Weather Service warned 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 the affected banks dropped by almost 15% within days. This corresponds to a $4.5 billion loss in the market value of the affected banks. The CAR of the affected banks remained negative for a long time and never recovered over the sample period. This suggests that the market reacted to the natural disaster risk when the threat became imminent and salient. The unaffected banks, which were also active in the extended coastal region, did not experience a similar decline in their CAR. This indicates that the market correctly identified the banks' exposures to the hurricane.

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:

$$\begin{aligned} Y_{b,t} = \beta_0 &+ \beta_1 \text{Scaled Damages}_{bt-1} + \beta_2 \text{Capital Ratio}_{b,t-1} \\ &+ \beta_3 \log(\text{Employees})_{b,t-1} + \beta_4 \log(\text{Assets})_{b,t-1} \\ &+ \beta_5 \text{ROA}_{b,t-1} + \boldsymbol{\gamma X} + \epsilon_{b,t}, \end{aligned} \tag{7}$$

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 reports estimates of equation 7 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 been standardized for ease of interpretation. 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 —or, given an average of 0.4%, 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 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 as property damage estimates weighted by the amount of retained mortgages. 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.

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.[11] 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).

Table 3 reports the results from equation 7 for a set of accounting variables. Column (1) replicates the baseline results for ROA. Columns (2) and (3) focus on prudential

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

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 the estimate from a regression of the Z-Score, which is negative and significant. The estimate implies flood damages increase the default likelihood of a bank. The effects on NPLs, residential real estate loan charge-offs, and loan-loss provisions are positive (columns (6) to (7)). 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 A3.1 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 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:

$$
\begin{aligned}
Y_{b,t+h} = \beta_0 &+ \beta_1^h \text{Scaled Damages}_{b,t-1} + \beta_2^h Y_{b,t-1} + \beta_3^h \text{Capital Ratio}_{b,t-1} \\
&+ \beta_4^h \log(\text{Employees})_{b,t-1} + \beta_5^h \log(\text{Assets})_{b,t-1} \\
&+ \beta_6 \text{ROA}_{b,t-1} + \boldsymbol{\gamma X} + \epsilon_{b,t}^h,
\end{aligned} \tag{8}
$$

where h goes from -3 to +4 quarters. I report the coefficients β_1^h on *Scaled Damages* for the two bank performance variables—ROA and the Tier 1 leverage ratio—in Figure 3. In both panels, the solid line (with circles) represents point estimates of β_1^h from equation 8, and dashed lines (with triangles) represent 95% confidence intervals for this estimate. Standard errors are clustered at the bank level.

Figure 3(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 3(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 3 is consistent with banks' experiencing significant losses from floods that require them to offset losses with their equity.

Figure 4 conducts a similar analysis using two loan portfolio variables as the outcomes of interest. As seen in Section **??**, 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 β_1^h from equation 8, 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 4(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 4(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.

The evidence in Figures 3 and 4 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:

$$
\begin{aligned}
r_{b,t} - r_{f,t} = \alpha &+ \beta_1 \text{Flood Risk Exposure}_{b,t-1} \\
&+ \beta_2 \log(\text{Assets})_{b,t-1} + \beta_3 \log(\text{BE/ME})_{b,t-1} \\
&+ \beta_4 \text{Leverage}_{b,t-1} + \beta_5 \text{Loan Ratio}_{b,t-1} \\
&+ \beta_6 \text{Mortgage Ratio}_{b,t-1} + beta_7 r_{b,t-1} + \epsilon_{b,t},
\end{aligned} \tag{9}
$$

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 β_1 on *Flood Risk Exposure*, which captures a bank's balance sheet exposure to flood risk. A positive β_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 4 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.

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 4 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 β_1 between -0.18 and -0.13 and

t-statistics ranging from -3.3 to -2.1. These results echo the coefficient in the baseline regression of column (1).

Notably, the different measures all capture very similar exposure. The last column of Table 4 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 5 presents separate estimates of equation 9 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.

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 6 reports results for four subsamples of the data. First, major disasters are removed from the sample. In column (1) of Table 6, 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.

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:

$$
\begin{aligned}
r_{bt} - r_{ft} = \alpha &+ \beta_1 \text{Flood Risk Exposure}_{bt} + \beta_2 \text{Scaled Damagess}_{bt} \\
&+ \beta_3 \text{Flood Risk Exposure}_{bt} \times \text{Scaled Damagess}_{bt} \\
&+ \beta_4 \log(\text{Assets})_{bt} + \beta_5 \log(\text{ME})_{bt} \\
&+ \beta_6 \text{Leverage}_{bt} + \beta_7 r_{bt-1} + \epsilon_{bt}.
\end{aligned} \tag{10}
$$

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

Table 7 reports estimates from equation 10 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 7 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 7. 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 7 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.

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

Figure 5(a) 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 around 40% over the period 2010 to 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 8. 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.

Nevertheless, as size heterogeneity played an important role in the previous analysis, Panel B of Table 8 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 8 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 5(b) 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 50% over the sample. 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 a few outliers. 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. Interestingly, the High-Low portfolio based on the 25% largest banks displays almost the exact inverse shape: the equal-weighted and exposure-weighted portfolios increase until late 2015 to reach a 20% gain, before the exposure-weighted portfolio drops sharply, erasing all its previous gains. The figure also plots the day of ratification of the Paris Climate Agreement in December 2015. The drop in the cumulative return very closely coincides with the signing of the agreement. It is plausible that larger banks were expected to be differently affected by the agreement than smaller institutions. For instance, in the recent past, macroprudential regulations mostly focused on the largest institutions, thus further regulations such as targeted disclosure requirements or increased capital requirements for climate-exposed assets were more likely for large banks.

4.5 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 the 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 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).[12] Second, I use a similar measure from Engle et al. (2020) based on articles from the Wall Street Journal. Third, I download frequency data from the Google Search Volume Index (SVI) for the topic of "Climate Change" and the topic "Flood" more specifically.[13] It is available at the national level at the monthly frequency for the entire sample from 2004 to 2020. Finally, I use survey data from the Yale Program for Climate Change (YPCC). The data give information about the share of respondents agreeing (or disagree-

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

[13]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.

ing) with a number of climate change-related statements. For instance, I use state-level share of respondents believing in climate change and agreeing that it represents a direct harm to the US.[14] I aggregate the state-level data using banks' mortgage lending as in previous sections.

So, using the different proxies for climate change concerns, the following regression is estimated:

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

where $\mathit{\Delta CC}$ 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 (β_3) is negative, and β_1 should become insignificant or even positive.

Estimates from these regressions are reported in Table 9. The coefficient on the interaction between the flood risk exposure and the climate change attention proxy is positive in all, but one case. Moreover, they are statistically significant in several regressions. Only the coefficient on the measure based on Google's search for *Flood* is negative. However, this measure is highly tied to flood and storm realizations. Thus, it appears, that not only does climate change attention not explain the negative coefficient on the level of flood risk exposure, but the sign on the interacted effect is in opposition to the conjecture: in periods of higher climate change attention the return of flood-risk-exposed banks is higher than for non-exposed banks. Importantly, the result is not driven by a general trend in the climate attention measure as they are either averaged-out or even capture specifically unexpected climate regulation risk (e.g., Ardia et al., 2022). Furthermore, the level measure of climate change concern enters positively in almost all specifications and is significant. The estimates provide evidence that the effect of climate change concerns holds for all banks (exposed and non-exposed) and is even stronger for exposed banks as captured in the interaction term. This finding suggests that investors might view banks as a good hedge against climate change-related risks in general. Coefficients on *Flood Risk Exposure* are always negative and significant, with t-statistics below -2.6.

The evidence shows that climate change concerns matter for the performance of bank

[14] I use state-level because county-level data is sparsely populated

stocks, but not with the expected sign. A higher uncertainty is typically associated with higher returns of flood-risk-exposed banks. Thus, attention fails to explain the negative return predictability of the flood risk exposure.

4.6 Regulatory Risks

Flood-risk-exposed banks may be more likely to also be exposed to changes in climate regulations. For instance, a number of financial regulators have been discussing the possibility of increasing risk-weights for assets exposed to climate risks. In the context of this paper, this could mean that mortgages in flood zones enter capital ratios with higher risk weights, which overwhelmingly affects banks that are also exposed to physical risks from disasters. Having shown that the negative coefficient on the flood risk exposure is not driven by realized flood disasters, nor from climate attention from investors, in this section, I study the the interaction between regulatory risks and physical risks from climate change. As briefly portrayed, the conjecture is that different risks related to climate change may amplify the shocks.

To test this conjecture, I estimate following regression:

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

where β_2 is the coefficient of interest that captures the interaction between exposure to physical risks from climate change and exposure to regulatory risks from climate change. Thus, I require a measure of regulatory risks from climate change. For instance, 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 Democrat 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. Thus, as a first measure, I proxy for climate regulation risk (CRR) with the office of the US presidency.[15] Second, following Seltzer et al. (2022b), I use state-level enforcement stringency of the Environmental Protection Agency (EPA). Third, as highlighted by the abrupt decrease in the CAR in Figure 2(b) after the ratification of the Paris Climate Agreement in 2015, I use this as a simple event study. Fourth, I use the Climate Policy Uncertainty measure constructed in Gavriilidis (2021). Finally, the YPCC also provides information about respondents' inclination to favor climate change-related regulation.

The estimate on the interaction term is negative if regulatory risks increase the underperformance associated with flood risk exposure. Results from the regression are tabulated in Table 10. As conjectured, the estimate on the interaction term is negative in all regressions, albeit not always statistically significant. This result suggests that both types of risks likely amplify each other. Specifically, in Column (1), I proxy for regulatory risks with the office of the US president. Thus in the years of a Democrat President, flood-exposed banks significantly underperform other banks. In Columns (2) and (3), climate regulation risk is measured by the state-level EPA stringency. Interestingly, when using the entire sample, the coefficient on the interaction term is not statistically significant. If, however, the sample is restricted to years, when Republicans have a majority in Congress, the coefficient on the state-level EPA stringency is negative and significant. This is noteworthy because it reflects the intricacies of climate regulation in the US Typically, EPA enforces its regulations at the state level. Thus, in years when regulation is dictated by Democrats at the Federal level, state-level differences in EPA enforcement matter less, while during years when the federal agenda is dictated by Republicans and climate regulation is less likely, the risks associated with climate regulation depend on the EPA. In Column (4),) I restrict the sample to the two years around the Paris Climate Agreement. The coefficient on the interaction term suggests that the ratification of the agreement lead to quite significant underperformance of exposed banks. Interestingly, in this regression, the coefficient on the level of the flood risk exposure is positive and significant, suggesting that in the year prior to the agreement, flood risk exposure earned a positive premium. Finally, Columns (5) and (6) use CPU and YPCC data. In both regressions, the coefficient on the interaction remains negative but insignificant, which may be due to the noisy nature of the measures.

Overall, the evidence in this section supports the view that climate regulation risk

[15] Alternatively, I can use state-level election results or outcomes in the Senate and Congress with similar results.

and physical risks interact and amplify each other. Thus regulatory shocks lead to the underperformance of assets that are more exposed to other 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 A2.4 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 A3.3. 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

To examine the importance of heterogeneity for the return predictability, Table A3.4 presents separate estimates of equation 9 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 A3.4 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 A3.4 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 US flood insurance market and test for potential bias in the results by explicitly controlling for different insurance proxies.

Columns (1) and (2) of Table A3.5 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 A3.5 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 A3.6. 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 2.1. 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 A3.6 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 2.6-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 56 bps per month (or 6 p.p. per year) when 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 positive predictability for bank stock returns, regardless of the bank's exposure to flood risk, suggesting that investors in general believe that banks may allow for climate risk hedging. However, the negative predictability of flood risk exposure persists. In a final exercise, I find that the climate regulation risk likely amplifies the physical risk component of the flood risk exposure. The underperformance is strongest during President Obama's administration, while it generally increases in periods of heightened climate regulation uncertainty as proxied by several different measures including Seltzer et al. (2022b) EPA stringency measure and the Paris Climate Agreement.

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 from a number of policymakers, whereby exposure to physical risks from climate change should be monitored.

References

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

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

Baker, Scott R, Nicholas Bloom, and Steven J Davis, 2016, Measuring economic policy uncertainty, *The Quarterly Journal of Economics* 131, 1593–1636.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Davenport, Frances V., Marshall Burke, and Noah S. Diffenbaugh, 2021, Contribution of historical precipitation change to US flood damages, *Proceedings of the National Academy of Sciences* 118, 1–7.

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

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

Dick-Nielsen, Jens, Jacob Gyntelberg, and Christoffer Thimsen, forthcoming, The cost of capital for banks: Evidence from analyst earnings forecasts, *Journal of Finance* n/a.

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

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

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

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

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

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

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

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

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

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

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

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

Gavriilidis, Konstantinos, 2021, Measuring climate policy uncertainty, *Working Paper* .

Gebhardt, William R., Charles M. C. Lee, and Bhaskaran Swaminathan, 2001, Toward an implied cost of capital, *Journal of Accounting Research* 39, 135–176.

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

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

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

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

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

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

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

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

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

Ivanov, Ivan T., Marco Macchiavelli, and João A. C. Santos, 2022, Bank lending networks and the propagation of natural disasters, *Financial Management* 1–25.

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

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

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

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

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

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

National Weather Service New Orleans, 2005, Urgent\textemdash Weather Message.

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

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

Ouazad, Amine, 2020, Coastal flood risk in the mortgage market: Storm surge models' predictions vs. flood insurance maps, Working Paper.

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

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

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

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

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

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

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

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

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

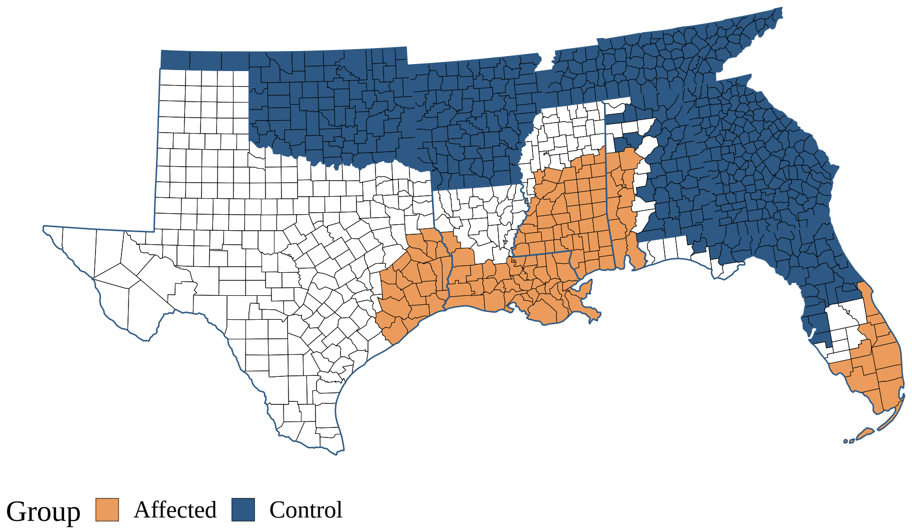
Seltzer, Lee, Laura T Starks, and Qifei Zhu, 2022b, Climate Regulatory Risks and Corporate Bonds.

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

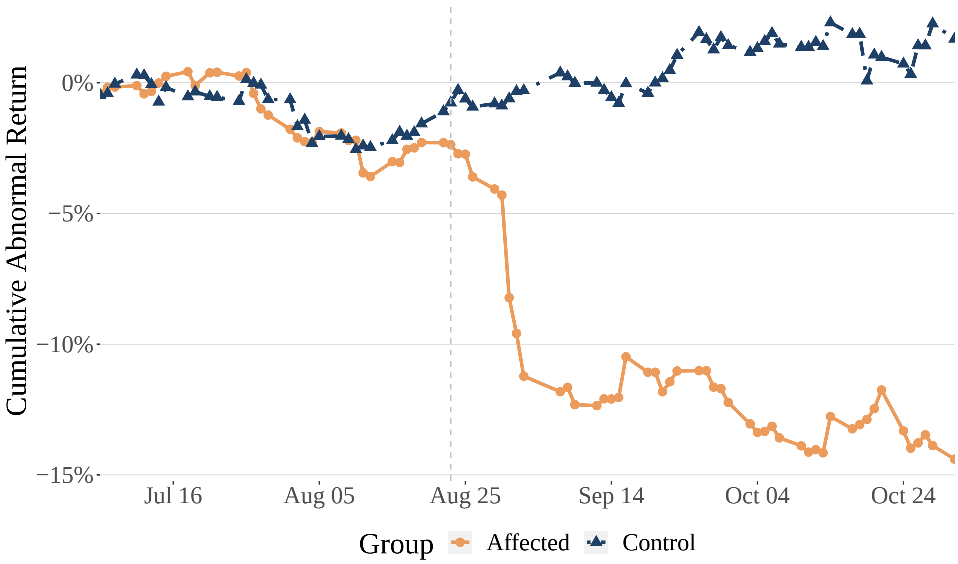
7 Figures

Figure 2: 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 light-shaded areas in Panel (a). Banks active in dark-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 (circles) and control group (triangles).



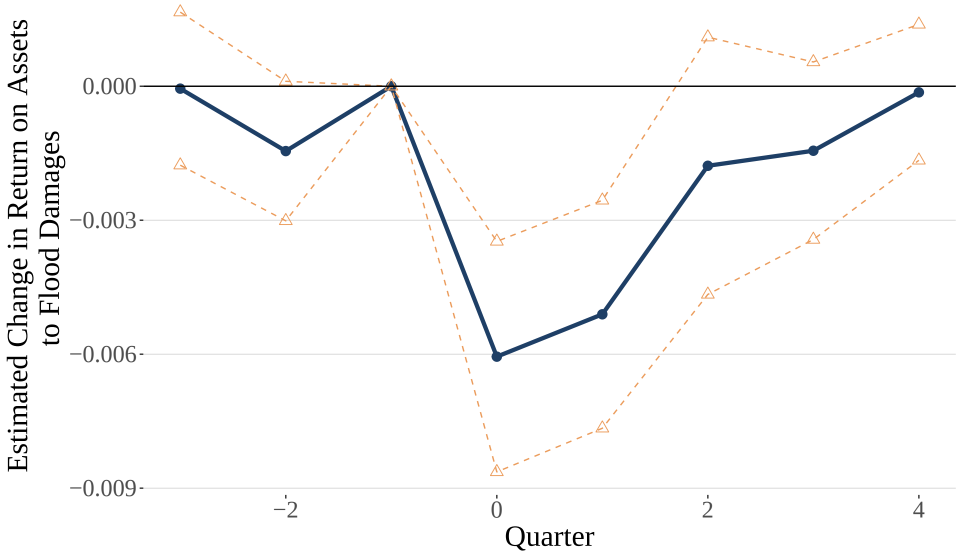
(a) Affected Areas



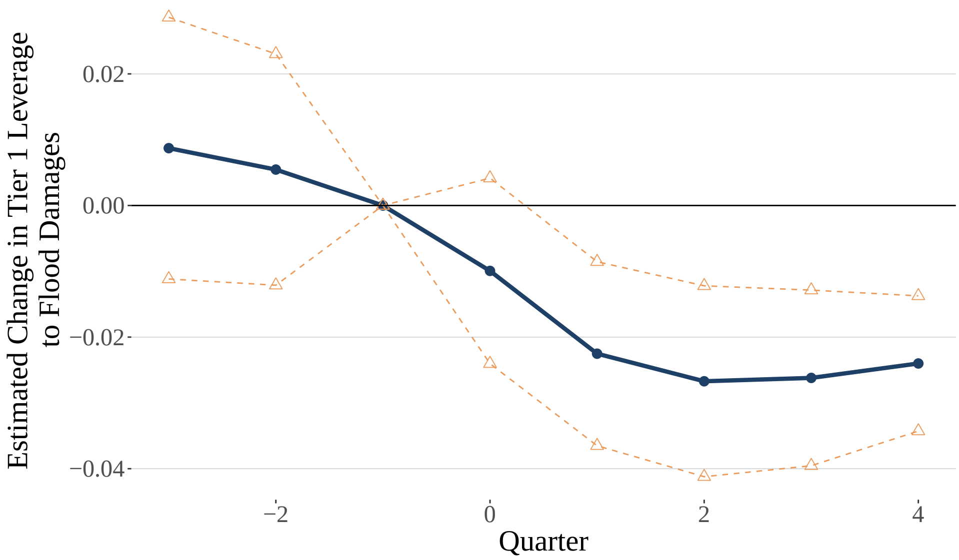
(b) Cumulative Abnormal Return

Figure 3: 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 (with triangles) denote 97.5% confidence intervals for this estimate.



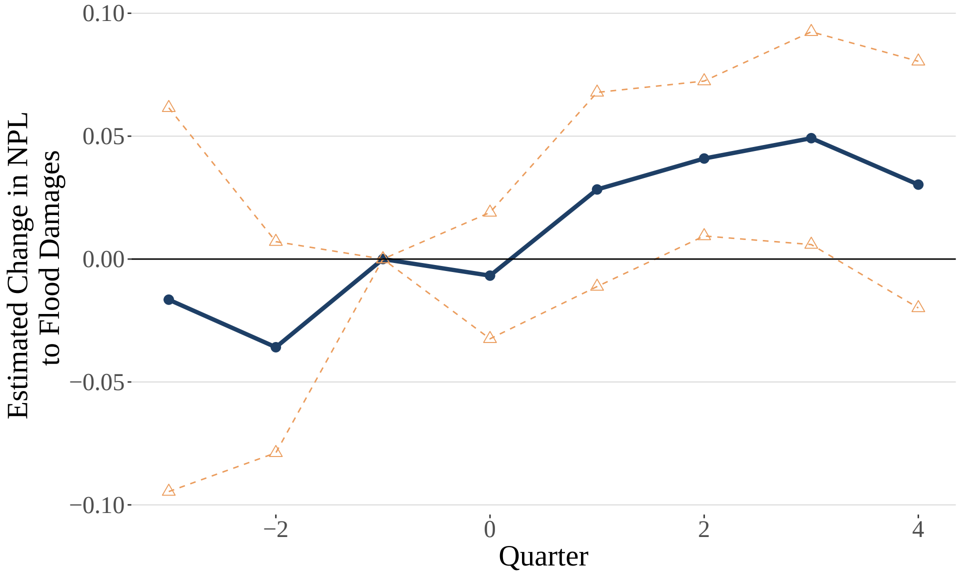
(a) Return on Assets



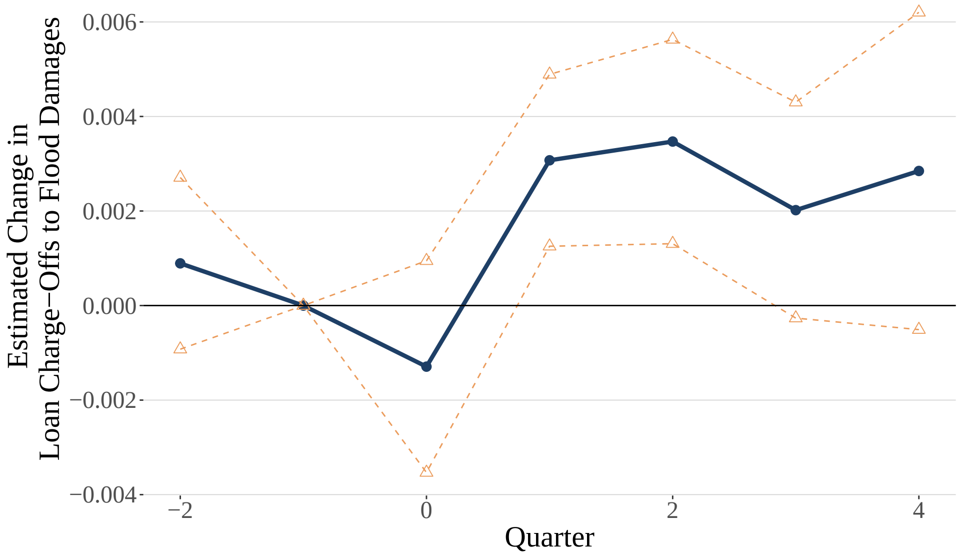
(b) Tier 1 Leverage Ratio

Figure 4: 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 (with triangles) denote 95% confidence intervals for this estimate.



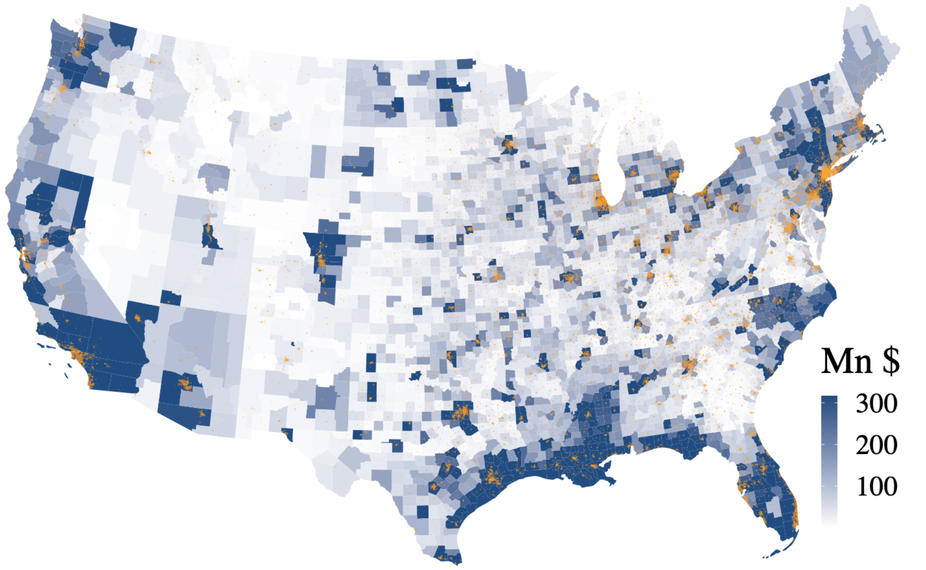
(a) Non-performing Loans



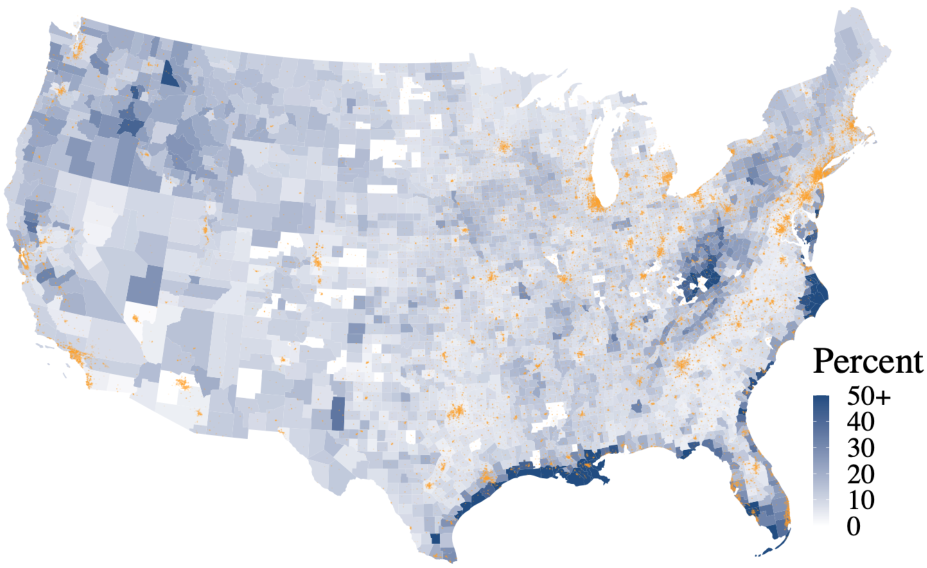
(b) Loan Charge-offs

Figure 1: 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. Darker areas report higher property damages from floods (a) or higher probabilities of floods (b). In both figures, dots represent bank branches and are obtained from FDIC Summary of Deposits for the year 2020.



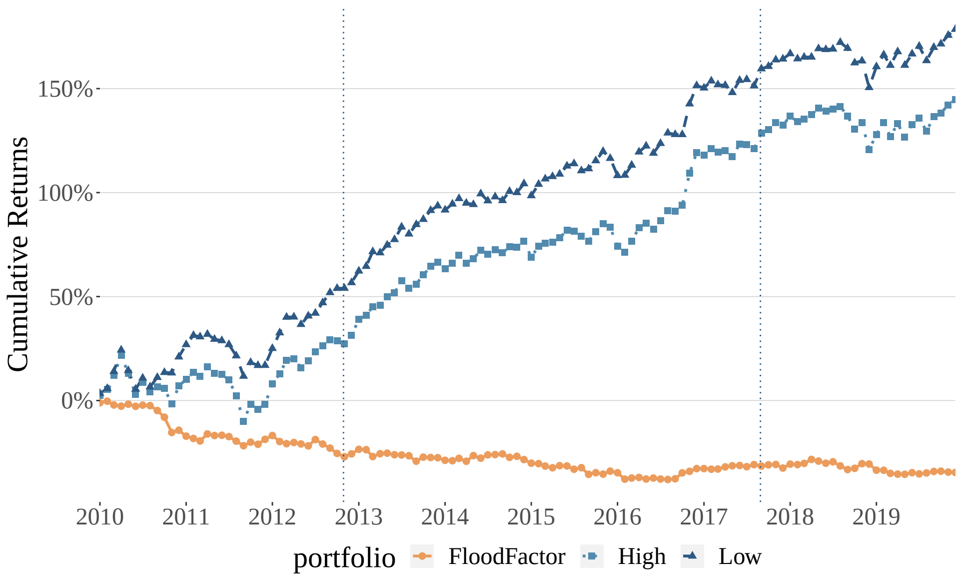
(a) Flood Damage Map



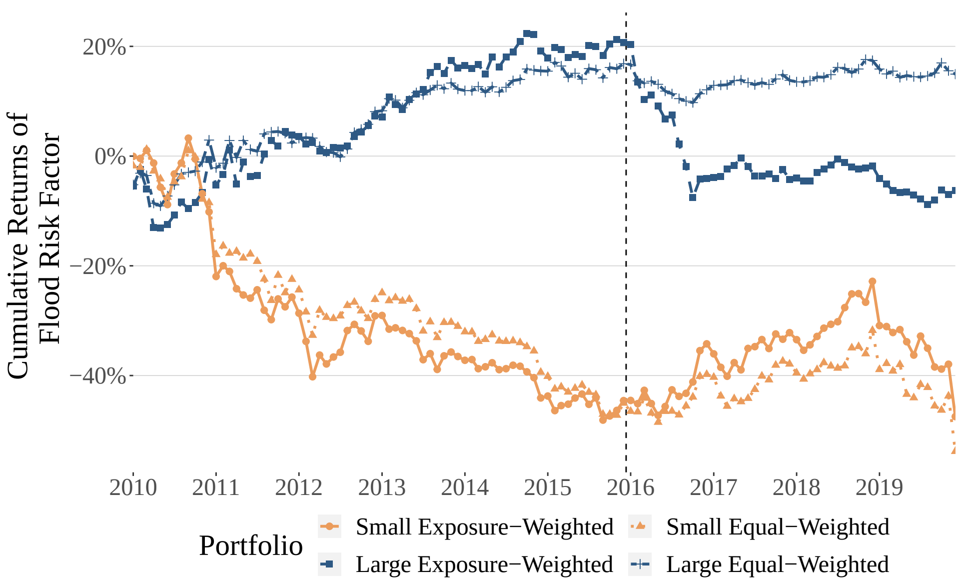
(b) Flood Risk Map

Figure 5: Cumulative Return of the Flood Factor

The figures plot the cumulative return of the flood factor constructed with banksś flood risk exposure for the full sample (a) and size-sorted samples (b).



(a) Full sample



(b) Size-sorted Samples

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 $)	0.1	1,721	0.1	5,157	−0.03	−1.4	
Flood Risk Exposure (2050)	20.7	1,721	7.9	5,157	12.8	49.9	***
Flood Risk Exposure (2035)	19.0	1,721	7.6	5,157	11.5	55.3	***
Flood Risk (Score-based)	2.4	1,721	1.4	5,157	1.0	53.6	***
Insurance Policies	11,293.2	1,721	3,563.7	5,157	7,729.6	11.5	***
Insurance Sum (Mn$)	2,322.5	1,721	725.8	5,157	1,596.7	11.6	***

Continued on next page

Table 1 – *Continued from previous page*

	High Exposure		Low Exposure				
	Mean	Obs	Mean	Obs.	Diff.	t-Stat.	Signif.
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)
Observations	19,126	19,126	19,125	19,126	19,126
R^2	0.498	0.498	0.498	0.498	0.498
Bank FE	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓

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 the 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 $*$: $p < 0.10$; $**$:$p < 0.05$; $***$:$p < 0.01$

	ROA_{t+1}	Leverage_{t+1}	Capital Ratio_{t+1}	SWFR_{t+1}	Z-Score_{t+1}	NPL_{t+1}	Charge-Offs_{t+1}	Loan Loss_{t+1}
	(1)	(2)	(3)	(4)	(5)	(6)	(7) c	(8)
Scaled Damages	-0.005***	-0.022***	-0.018**	-0.049***	-0.011***	0.002	0.0002	0.013***
	(-3.92)	(-3.16)	(-2.56)	(-11.3)	(-2.93)	(0.405)	(0.902)	(3.44)
ROA	0.248***							
	(4.78)							
Capital Ratio			1.13***					
			(21.3)					
SWFR				0.638***				
				(40.3)				
Z-Score					0.859***			
					(26.8)			
NPL						0.843***		
						(31.4)		
Charge-Offs							0.369***	

Continued on next page

Table 3 – *Continued from previous page*

	ROA_{t+1}	$Leverage_{t+1}$	Capital $Ratio_{t+1}$	$SWFR_{t+1}$	Z-$Score_{t+1}$	NPL_{t+1}	Charge-$Offs_{t+1}$	Loan $Loss_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
							(15.5)	
Loan Loss								0.362***
								(9.28)
Leverage	0.002	0.023	-1.19***	-0.003	-0.009	-0.0002	-0.0002	-0.001
	(0.975)	(0.470)	(-13.0)	(-0.887)	(-0.973)	(-0.120)	(-0.942)	(-0.869)
log(Assets)	-0.227***	-1.62***	-1.31***	1.36***	-0.007	0.430***	0.0004	0.251***
	(-4.25)	(-4.68)	(-3.88)	(6.56)	(-0.093)	(6.34)	(0.068)	(5.95)
Loan Ratio	0.060	2.28	6.87***	-3.09***	-0.550	1.11***	-0.004	0.706***
	(0.283)	(1.53)	(3.22)	(-3.15)	(-1.13)	(3.60)	(-0.152)	(4.06)
Mortgage Ratio	-0.033	-6.78*	-10.1**	-0.530	0.051	-0.661	0.086**	-0.622***
	(-0.106)	(-1.66)	(-2.22)	(-0.349)	(0.105)	(-1.62)	(2.27)	(-2.93)
Observations	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
Bank FE	✓	✓	✓	✓	✓	✓	✓	✓
Year-quarter FE	✓	✓	✓	✓	✓	✓	✓	✓

Table 4: 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	2035 Flood Risk	Flood Risk Score	Number-weighted	Origination-weighted	Rolling Retained	Rolling Origination	Competition-weighted
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Flood Risk Exposure	-0.174***	-0.178***	-0.133**	-0.185***	-0.173***	-0.159**	-0.182***	0.019
	(-3.03)	(-3.11)	(-2.05)	(-3.21)	(-3.28)	(-2.46)	(-3.10)	(0.657)
Leverage	-0.002	-0.002	-0.003	-0.002	-0.002	-0.002	-0.002	-0.003
	(-0.662)	(-0.747)	(-0.913)	(-0.632)	(-0.691)	(-0.678)	(-0.696)	(-0.955)
log(Assets)	-3.02***	-3.03***	-3.02***	-3.03***	-3.03***	-3.02***	-3.03***	-3.01***
	(-15.1)	(-15.1)	(-15.1)	(-15.1)	(-15.2)	(-15.1)	(-15.1)	(-15.2)
Loan Ratio	-1.14	-1.14	-1.13	-1.16	-1.15	-1.14	-1.16	-1.13
	(-1.56)	(-1.56)	(-1.55)	(-1.58)	(-1.59)	(-1.56)	(-1.59)	(-1.59)
Mortgage Ratio	1.54***	1.55***	1.55***	1.55***	1.54***	1.58***	1.58***	1.47**

Continued on next page

Table 4 – *Continued from previous page*

	Excess Returns							
	2050 Risk	2035 Risk	Risk Score	Number-weighted	Origination-weighted	Rolling Retained	Rolling Origination	Competition-weighted
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(2.66)	(2.69)	(2.67)	(2.68)	(2.66)	(2.73)	(2.75)	(2.50)
log(BE/ME)	2.86***	2.87***	2.86***	2.87***	2.86***	2.86***	2.87***	2.84***
	(15.8)	(15.8)	(15.7)	(15.7)	(15.9)	(15.7)	(15.7)	(15.9)
Return	-0.089***	-0.089***	-0.089***	-0.089***	-0.089***	-0.089***	-0.089***	-0.089***
	(-10.1)	(-10.1)	(-10.1)	(-10.1)	(-10.1)	(-10.1)	(-10.1)	(-10.1)
Mortgage Exposure	-1.48***	-1.50***	-1.52***	-1.48***	-1.48***	-1.56***	-1.60***	-1.34***
	(-3.54)	(-3.57)	(-3.58)	(-3.54)	(-3.51)	(-3.66)	(-3.70)	(-3.23)
Observations	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
Month FE	✓	✓	✓	✓	✓	✓	✓	✓

Table 5: 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

Continued on next page

Table 5 – *Continued from previous page*

	Excess Returns					
	Small Banks			Large Banks		
	<Median	<Top Quartile	<$50 bn	>Median	>Top Quartile	>$50 bn
	(1)	(2)	(3)	(4)	(5)	(6)
	(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)
Observations	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
Month FE	✓	✓	✓	✓	✓	✓

Table 6: 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)
Observations	58,861	57,274	14,371	3,433
R^2	0.306	0.305	0.261	0.339
Bank Controls	✓	✓	✓	✓
Month FE	✓	✓	✓	✓

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)

Continued on next page

Table 6 – *Continued from previous page*

Observations	29,238	28,562	9,905	2,500
R^2	0.208	0.207	0.223	0.312
Bank Controls	✓	✓	✓	✓
Month FE	✓	✓	✓	✓

Panel C: Large Banks

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

Table 7: 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)	
Observations	50,957	50,957	50,957	50,957	50,957
R^2	0.054	0.054	0.054	0.055	0.033
Bank Controls	✓	✓	✓	✓	✓
Macro Controls	✓	✓	✓	✓	✓

Panel B: Small Banks

	Excess Returns				Return Residuals

Continued on next page

Table 7 – *Continued from previous page*

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 × Flood Damages		-0.004	0.347*	0.002	
		(-0.254)	(1.87)	(0.077)	
Observations	24,677	24,677	24,677	24,677	24,677
R^2	0.059	0.059	0.059	0.059	0.038
Bank Controls	✓	✓	✓	✓	✓
Macro Controls	✓	✓	✓	✓	✓

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 × Flood Damages		-0.021	0.220	-0.051	
		(-1.54)	(0.910)	(-1.49)	
Observations	26,280	26,280	26,280	26,280	26,280
R^2	0.057	0.057	0.057	0.058	0.033
Bank Controls	✓	✓	✓	✓	✓
Macro Controls	✓	✓	✓	✓	✓

Table 8: Performance of the Exposure-weighted Flood Factor

This table reports monthly time-series regressions using data from January 2005 to December 2020. The dependent variable is the return on the exposure-weighted flood factor, 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				
	(1)	(2)	(3)	(4)
(Intercept)	-0.237*	-0.206	-0.234*	-0.243*
	(-1.89)	(-1.60)	(-1.79)	(-1.86)
Observations	192	190	190	190
R^2		0.002	0.013	0.022
Factors	None	Mkt	Mkt, SMB, HML	Mkt, SMB, HML, Mom

Panel B: Small Banks				
	(1)	(2)	(3)	(4)
(Intercept)	-0.563**	-0.556**	-0.558**	-0.579**
	(-2.10)	(-2.46)	(-2.43)	(-2.53)
Observations	192	190	190	190
R^2		0.034	0.040	0.056
Factors	None	Mkt	Mkt, SMB, HML	Mkt, SMB, HML, Mom

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

Table 9: Climate Change Attention and Bank Returns

The sample is constructed at the bank-month level. *Excess Return*$_{b,t}$ is the monthly stock return of bank b minus risk-free rate. *CC* is a measure of climate change attention. Columns 1 and 2 use the measure from Ardia et al. (2022). Column 2 is the measures from Engle et al. (2020). *EPU* is the economic policy uncertainty from Baker et al. (2016). The measures in Columns 5 and 6 are constructed using data from Google's Search Volume Index for the topics *Climate* and *Floods*. Finally, Columns 7 and 8 are constructed using data from the Yale Program on Climate Change. *Climate Belief* is the weighted state-level share of responding believing in climate change, while *Climate Harm* is the share believing that climate change represents harm for the U.S. All regressions include log(assets), log(BE/ME), Tier 1 leverage, and the previous month's stock return. Standard errors are clustered at the bank level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Dependent Variable	Excess Return							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Flood Risk Exposure	-0.225***	-0.229***	-0.158***	-0.162***	-0.160***	-0.160***	-0.218***	-0.317***
	(-3.29)	(-3.23)	(-2.62)	(-3.09)	(-3.06)	(-3.05)	(-2.91)	(-3.45)
Flood Risk Exposure × UMC (Floods)	0.336**							
	(2.56)							
Flood Risk Exposure × UMC (Agg)		0.482**						
		(2.04)						
Flood Risk Exposure × Δlog(WSJ)			0.270					
			(1.53)					
Flood Risk Exposure × Δlog(EPU)				0.253*				
				(1.66)				
Flood Risk Exposure × Δlog(SVI Climate)					0.057			
					(0.612)			
Flood Risk Exposure × Δlog(SVI Flood)						-0.263***		
						(-3.22)		
Flood Risk Exposure × Climate Belief							0.211*	
							(1.79)	
Flood Risk Exposure × Climate Harm								0.152**
								(2.17)
Observations	46,802	46,802	48,215	57,126	57,126	57,126	35,944	37,762
R^2	0.25	0.25	0.25	0.29	0.29	0.29	0.33	0.33
Bank Controls	✓	✓	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓	✓	✓

Table 10: Climate Change Regulation Risk and Bank Returns

This table analysis the interaction between physical risk from climate change and regulation risk. The sample is constructed at the bank-month level. *Excess Return*$_{b,t}$ is the monthly stock return of bank b minus risk-free rate. In Columns 1, climate change regulation risk is proxied by the U.S. presidency. *EPA Stringency* in Columns 2 and 3 is the lending-weighted stringency of the state-level Environmental Protection Agency following Seltzer et al. (2022b). *Paris Agree.* is an indicator variable that equals 1 after the ratification of the Paris Climate Agreement in December 2015 and zero otherwise. *CPU* is the measure of climate policy uncertainty from Gavriilidis (2021) Finally, *YPCC (Regulate)* captures the share of respondent from the Yale Program on Climate Change that favor climate regulation. All regressions include log(assets), log(BE/ME), Tier 1 leverage, and the previous month's stock return. Standard errors are clustered at the bank level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Dependent Variable:	Excess Return					
Sample	Full		Repub. Congress	± 1 year from Paris Agree.	Full	
	(1)	(2)	(3)	(4)	(5)	(6)
Flood Risk Exposure	-0.085	-0.223***	-0.021	0.144**	-0.218***	-0.325**
	(-1.49)	(-3.82)	(-0.282)	(2.06)	(-3.74)	(-2.37)
Flood Risk Exposure × Dem. President	-0.259**					
	(-2.35)					
Flood Risk Exposure × EPA Stringency		-0.068	-0.205***			
		(-0.783)	(-3.64)			
Flood Risk Exposure × Paris Agree.				-0.756*		
				(-1.72)		
Flood Risk Exposure × Δlog(CPU)					-0.087	
					(-1.00)	
Flood Risk Exposure × YPCC (Regulate)						-0.729
						(-0.523)
Observations	42,668	42,345	27,652	5,360	42,668	3,177
R^2	0.25	0.26	0.26	0.42	0.25	0.68
Bank Controls	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓

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

Valentin Schubert*

June 20, 2024

*Sveriges Riksbank and Department of Finance, Stockholm School of Economics. Any errors are my own. For any questions, please contact me at valentin.schubert@riksbank.se. The opinions expressed in this article are the sole responsibility of the author and should not be interpreted as reflecting the views of Sveriges Riksbank.

Table of Contents

A1 Data Construction **A.2**

A2 Additional Figures **A.5**

A3 Additional Tables **A.7**

A4 The Role of Mortgage Market in Propagating Flood Disasters **A.13**

A4.1 Relized Flood Disasters and Delinquencies A.13

A4.2 Accounting Performance and Delinquencies A.15

A1 Data Construction

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

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

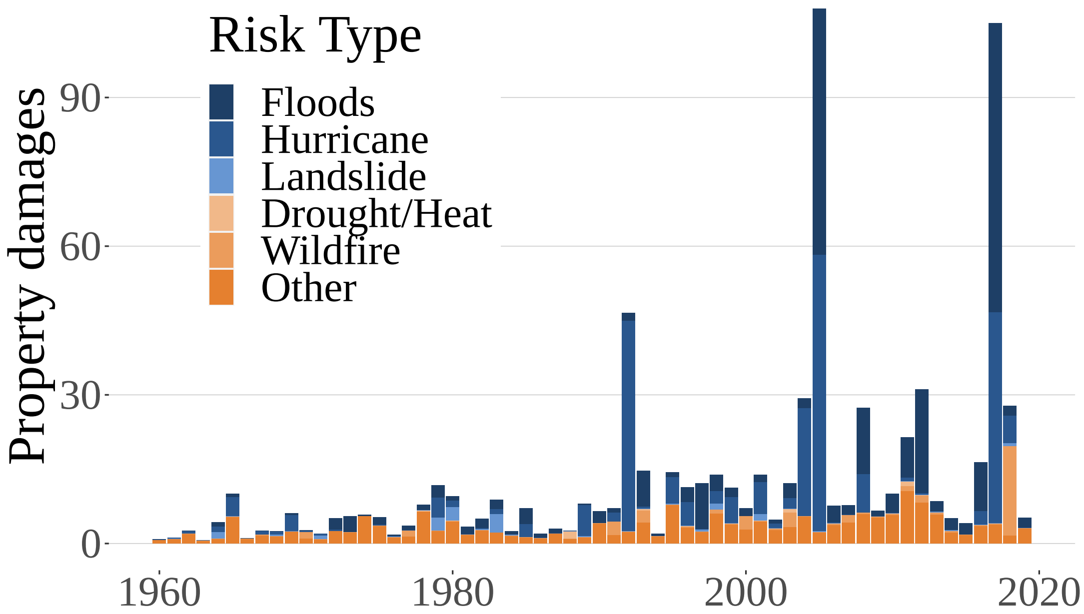
The FR Y-9C filings include detailed information about the balance sheet and income and data on loan performance. In my analysis, I extract information on balance sheet size (total assets), funding structure (deposits, Tier 1 capital, equity), and non-performing loans. As I focus on real estate for my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

Stock variables are the monthly stock returns from CRSP. 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.

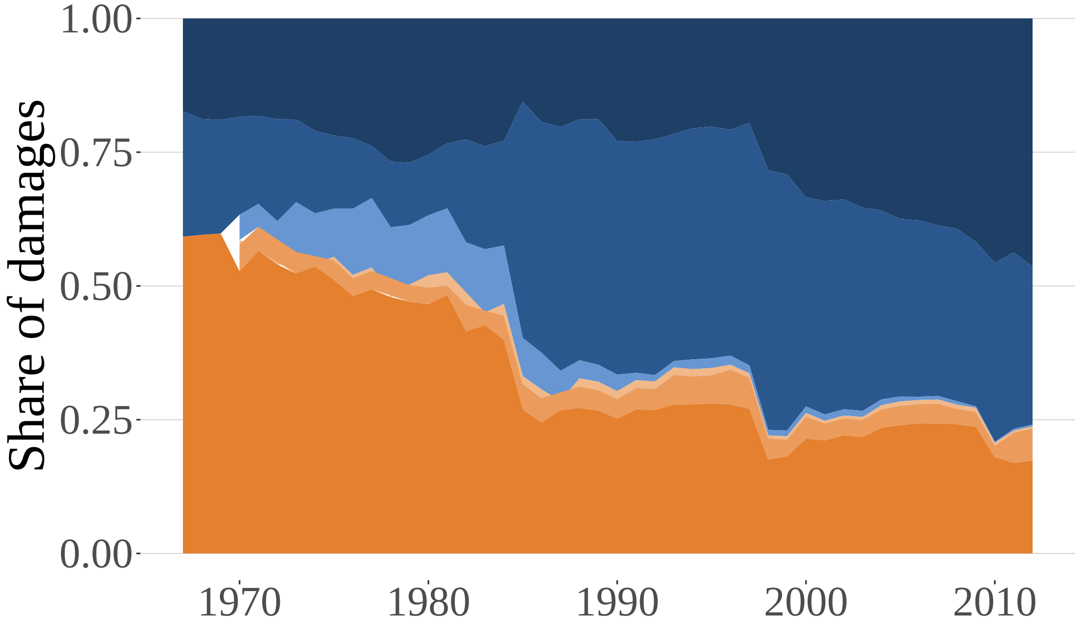
A2 Additional Figures

Figure A2.1: 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. The analysis uses the sum of "Floods" and "Hurricane" (shown in dark)



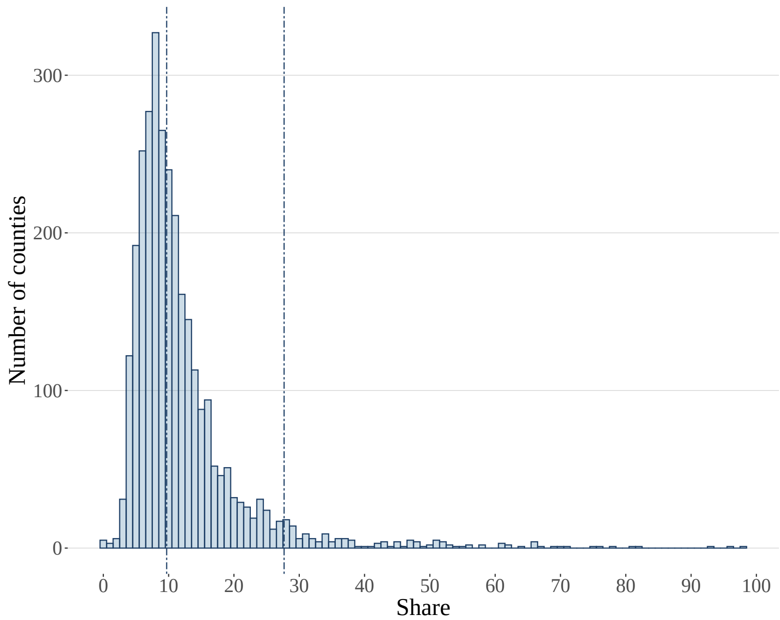
(a) Property Damage Estimates



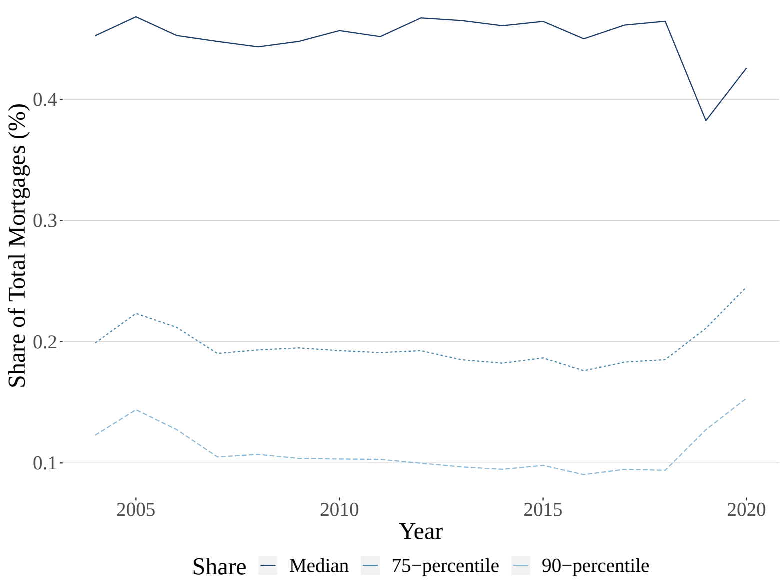
(b) Share of Damage Estimates

Figure A2.2: 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 Counties by Risk Group



(b) Share of Mortgage Amounts by Risk Percentiles

A3 Additional Tables

Table A3.1: 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)
Observations	48,548	48,548	35,021	35,021
R^2	0.645	0.645	0.635	0.635
HQ State-Month FE	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓

Table A3.2: 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)
Observations	57,126	57,126	42,668	42,668
R^2	0.395	0.395	0.382	0.382
HQ State-Month FE	✓	✓	✓	✓

Table A3.3: 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)
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)
Observations	37,265	18,310	18,552	18,713	18,848
R^2	0.048	0.052	0.057	0.047	0.046
Month FE	✓	✓	✓	✓	✓

Table A3.4: 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 (1)	Low (2)	Full (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)
Observations	20,706	22,521	43,227
R^2	0.248	0.325	0.283
Bank Controls	✓	✓	✓
Month FE	✓	✓	✓

Panel B: Flood Risk Exposure

	Excess Returns		
	High (1)	Low (2)	Full (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)

Continued on next page

Table A3.4 – *Continued from previous page*

Observations	23,273	19,954	43,227
R^2	0.311	0.266	0.283
Bank Controls	✓	✓	✓
Month FE	✓	✓	✓

Table A3.5: 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)
Observations	43,227	43,227	31,785	31,785

Continued on next page

Table A3.5 – *Continued from previous page*

R^2	0.28	0.28	0.24	0.24
Bank Controls	✓	✓	✓	✓
Month FE	✓	✓	✓	✓

Panel B: Small Banks

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

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)

Continued on next page

Table A3.5 – *Continued from previous page*

Observations	19,968	19,968	12,878	12,878
R^2	0.46	0.46	0.40	0.40
Bank Controls	✓	✓	✓	✓
Month FE	✓	✓	✓	✓

✓

A4 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.

A4.1 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:

$$\begin{aligned} \mathrm{Y}_{c,t+h} = \quad & \beta_0^h + \beta_1^h \mathit{Flood\ Damages}_{c,t} \\ & + \beta_2^h Y_{c,t-1} + \boldsymbol{\gamma X} + \epsilon_{c,t+k}, \end{aligned} \tag{A4.1}$$

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

Table A3.6: 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 $*$: $p < 0.10$; $**$:$p < 0.05$; $***$:$p < 0.01$

Panel A: All Banks

	Excess Returns			
	(1)	(2)	(3)	(4)
Flood Risk Exposure	-0.238***	-0.148**	-0.164**	-0.122*
	(-3.49)	(-2.37)	(-2.53)	(-1.84)
Observations	38,507	43,227	43,227	43,227
R^2	0.25	0.28	0.30	0.28

Panel B: Small Banks

	Excess Returns			
	(1)	(2)	(3)	(4)
Flood Risk Exposure	-0.389***	-0.254***	-0.282***	-0.195**
	(-4.47)	(-3.02)	(-2.96)	(-2.17)
Observations	22,869	23,648	23,648	23,648
R^2	0.19	0.20	0.22	0.20

Panel C: Large Banks

	Excess Returns			
	(1)	(2)	(3)	(4)
Flood Risk Exposure	0.051	0.012	0.023	-0.031
	(0.480)	(0.133)	(0.246)	(-0.314)
Observations	16,024	19,968	19,968	19,968
R^2	0.40	0.46	0.48	0.46
Bank Controls	✓	✓	✓	✓
State Controls	✓			
State Dummies		✓		
State-Year Dummies			✓	
Month FE	✓	✓	✓	✓
HQ FE				✓

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 A4.1(a) reports the coefficients β_1^h for $h = -3 : 7$ from regressing the county-level number of foreclosures on the flood damages. The solid blue line reports the point estimates, while the 95% confidence interval is the dashed orange line. The coefficients are insignificant for the periods before the shock (proxied by the property damages). Following the shock, the coefficient increases to 1 and remains at that level over six months. The coefficient indicates that a 1 percentage point shock leads to a 1 percentage point higher number of foreclosures. Foreclosures are a powerful instrument, imply costly spillovers for a bank (Favara and Giannetti, 2017), and require active intervention from the lender. To avoid any influence by the banks and focus on the behavior of borrowers, Figure A4.1(b) reports the coefficients β_1^h from regressing the county-level delinquency rate on the flood damages. Again, the solid blue line reports the point estimates, and the 95% confidence interval is the dashed orange line over the horizon $h = -3 : 7$. The coefficients are insignificant for the periods before the shock. Following the shock, the coefficient increases to 0.025 before gradually decreasing again. The coefficients in period 1 imply that a 1 percentage point higher shock leads to a 2.5 percentage point higher delinquency rate, which given an average delinquency rate of 3.3%, is an economically meaningful increase.

A4.2 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:

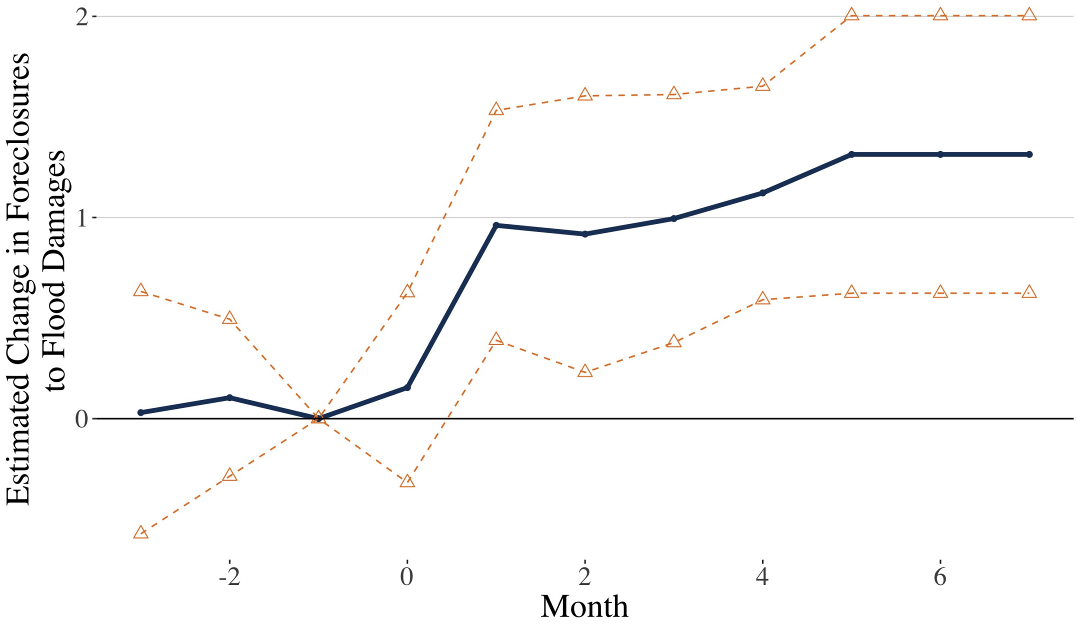
$$\begin{aligned} Y_{b,t} = {} & \beta_0 + \beta_1 \textit{Market Exposure}_{b,t} + \beta_2 \textit{Capital Ratio}_{b,t-1} \\ & + \beta_3 \textit{log(Employees)}_{b,t-1} + \beta_4 \textit{log(Assets)}_{b,t-1} \\ & + \beta_5 ROA_{b,t-1} + \boldsymbol{\gamma X} + \epsilon_{b,t}, \end{aligned} \tag{A4.2}$$

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.

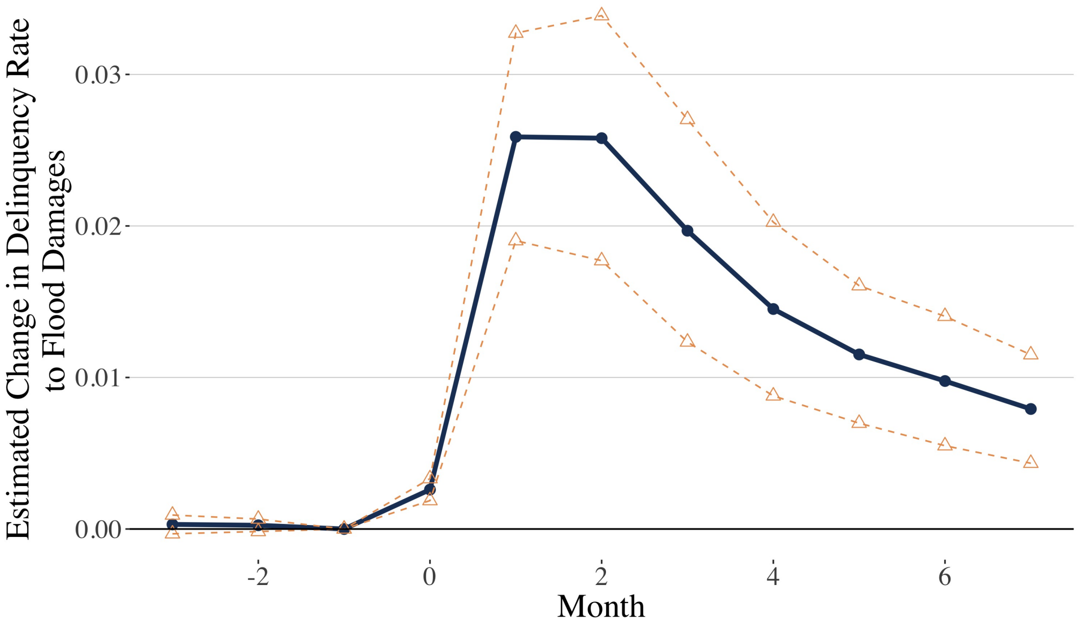
Panel A of Table A4.1 reports the estimates for the exposure to foreclosures. Across the four regressions, the estimates suggest that bank performance and foreclosures are negatively correlated. For return on assets and leverage, the coefficients on the exposure are negative and significant. Furthermore, 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 A4.1. 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.

Figure A4.1: 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.



(a) Mortgage Foreclosures



(b) Mortgage Delinquencies

Table A4.1:
Bank performance and Mortgage Delinquencies

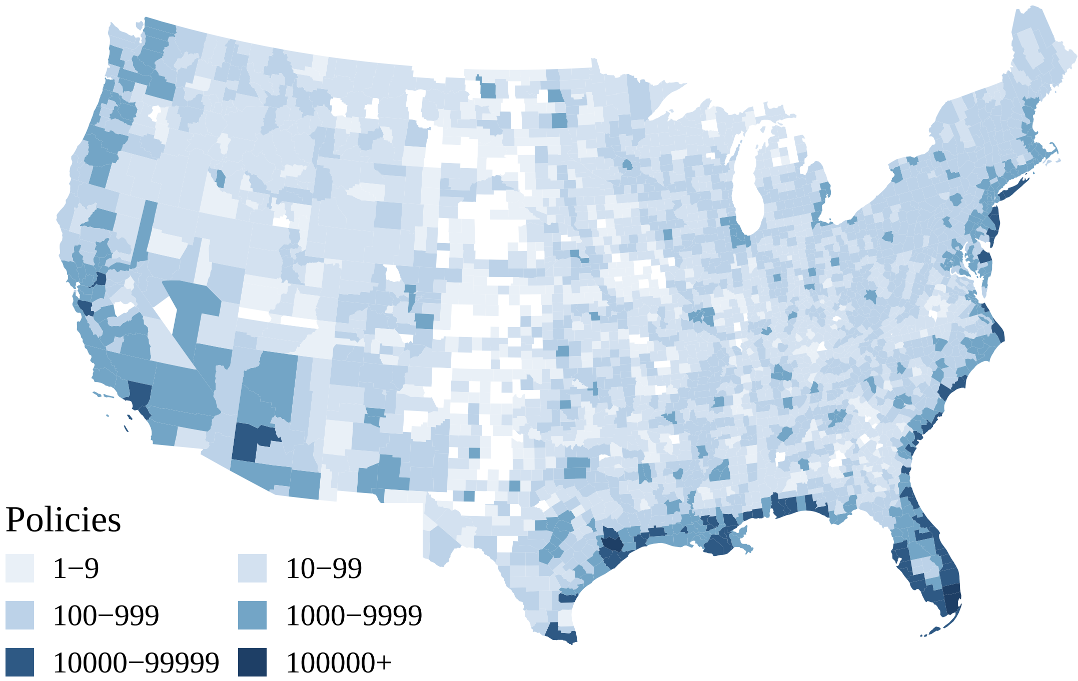
This table reports the results from the analysis of bank performance and mortgage market performance. The main explanatory variable in Panel A is the *Foreclosures Exposure*, which captures banks' exposure to local mortgage foreclosures using data from RealtyTrac for the years 2004 to 2012. In Panel 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)
Observations	15,566	15,037	15,566	14,429
R^2	0.501	0.886	0.854	0.496
Bank Controls	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓

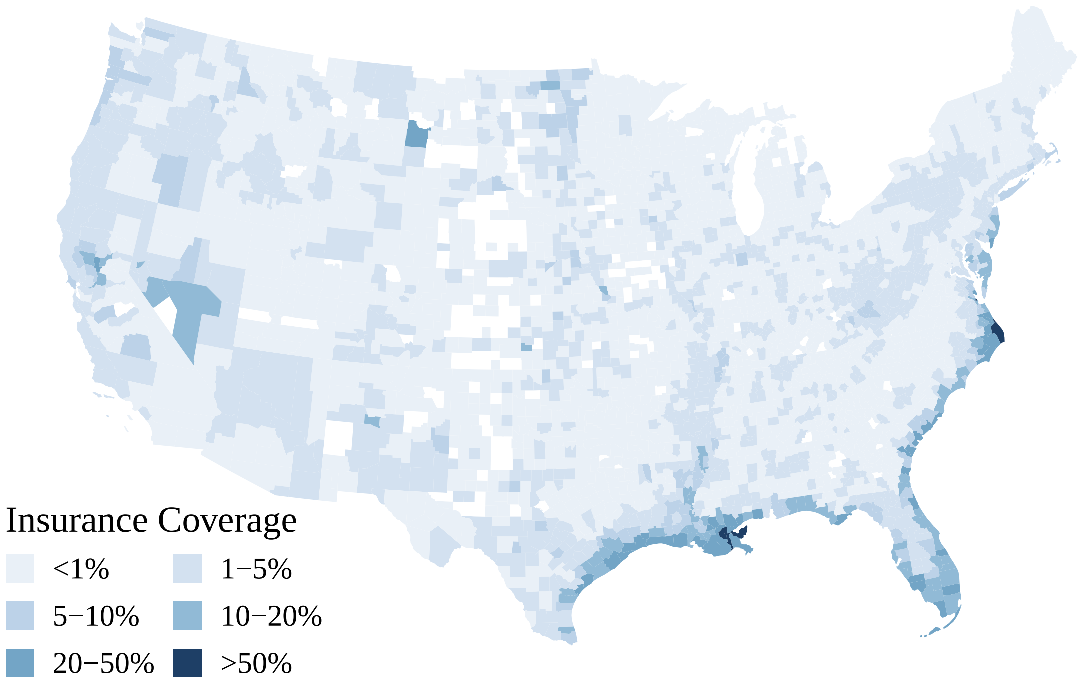
Panel B: Delinquency Exposure				
	ROA_{t+1}	$Leverage_{t+1}$	NPL_{t+1}	Charge-$Offs_{t+1}$
	(1)	(2)	(3)	(4)
Delinquency Exposure	-0.043**	-0.169**	0.069*	0.011***
	(-2.43)	(-2.15)	(1.91)	(4.20)
Observations	15,566	15,037	15,566	14,429
R^2	0.501	0.886	0.854	0.495
Bank Controls	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓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

Figure A2.3: 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.



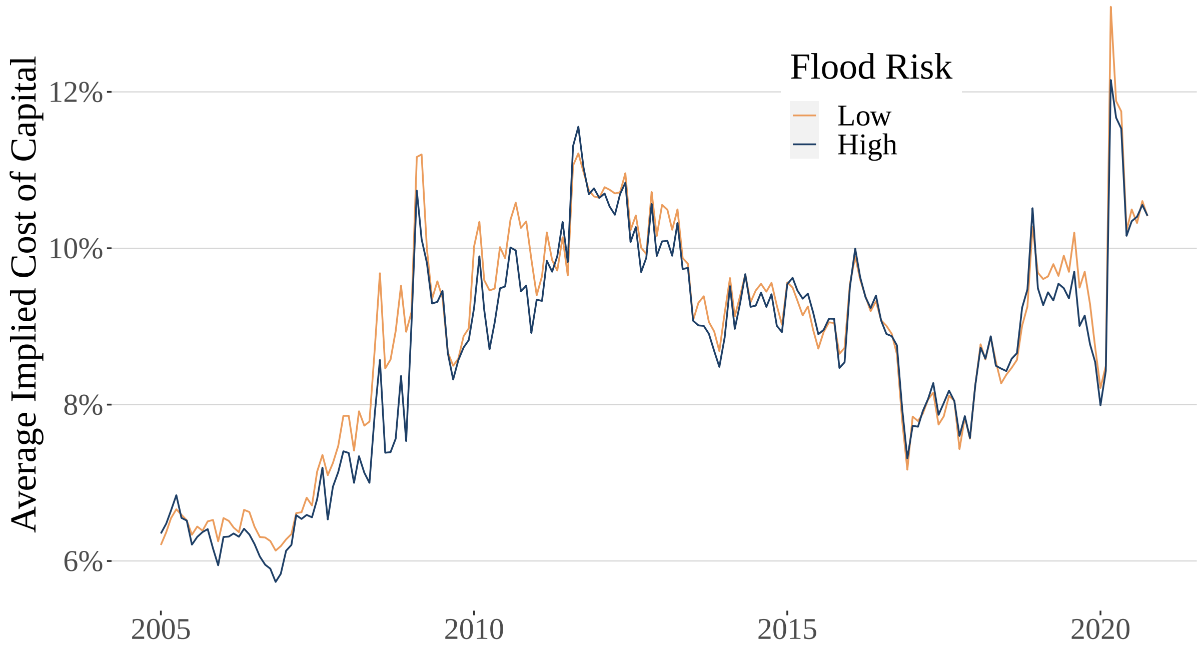
(a) Number of Active Insurance Policies



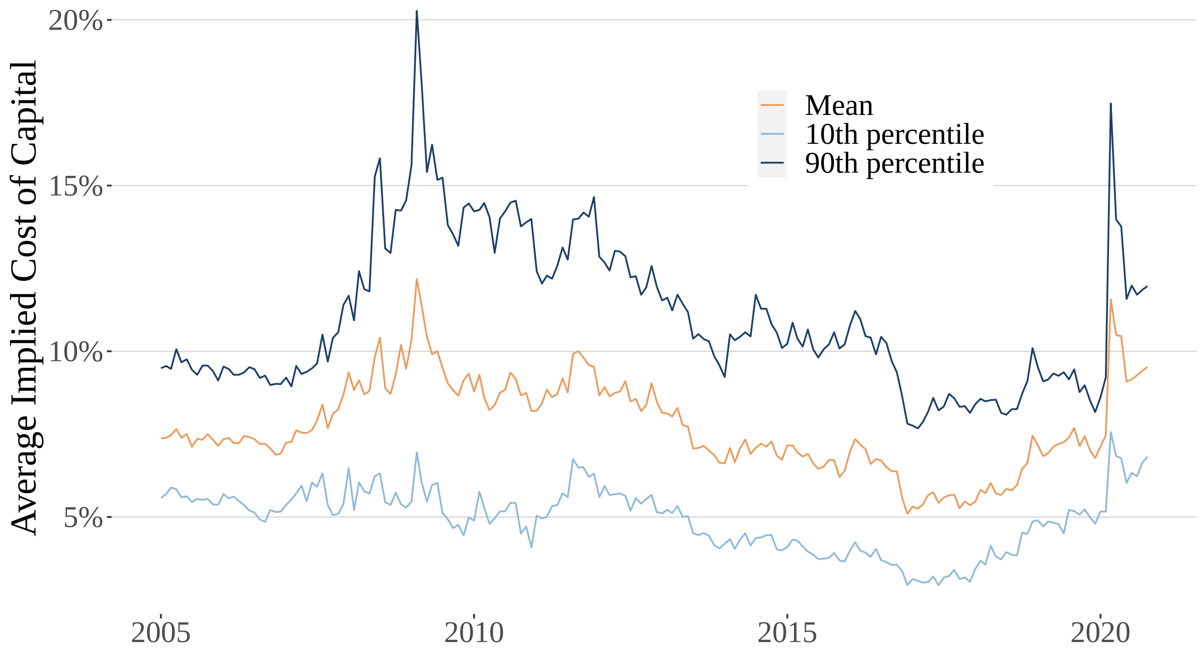
(b) Insurance Coverage

Figure A2.4: 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.



(a) ICC of high and low flood exposed banks



(b) ICC by Percentiles