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Abstract

How does competition affect banks' adaptation to emergent risks for which there is limited supervisory oversight? The analysis matches detailed supervisory data on home equity lines of credit with high resolution flood projections to identify climate risks. Following Hurricane Harvey, banks updated their internal risk models to better reflect flood risk projections, even in areas unaffected by the disaster. These updates are only detected in banks with exposures to the disaster, indicating heterogeneous bank learning. We use this heterogeneity to identify how bank adaptation is affected by competition. Exposed banks reduce lending to areas with higher flood risks, but only in less competitive markets, suggesting that competition fosters risk-taking over risk mitigation. Additionally, banks are less likely to adapt in markets where competitors are also less likely to do so, suggesting a strategic complementarity in bank adaptation. More broadly, our paper sheds light on the role of competitive forces in how banks manage emerging risks and relevant supervisory challenges.

JEL codes: D14, E6, G21, Q54.

Keywords: Banks, climate risk, real estate, natural disasters, competition, moral hazard.

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1. Introduction

A rapidly growing literature examines how financial institutions and markets are affected by and respond to climate change. The effects of climate-related financial risks are of increasing relevance to policymakers.[1] However, our understanding of how banks, who play a critical role in the financial system, are adapting to climate change is still limited (Correa et al. 2022; Ouazad and Kahn 2022, 2023; Meisenzahl 2023).

This paper studies the role of a potentially important consideration in whether banks *strategically* adapt to climate change: competition in the banking industry. There is a rich literature that explores how competition amongst banks can affect how banks choose to manage risks.[2] However, we still lack a clear understanding of how competition affects the management of new sources of risks, such as emerging climate risks. Conceptually, climate change makes the distribution of disaster risks—e.g., hurricanes and flooding—nonstationary, and learning about nonstationary processes is difficult.[3] On the one hand, the management of climate risks can be complicated by additional stages of acquiring information about evolving risks and quantifying the bank's exposure to them (Bouvard and Lee 2020).[4] On the other hand, bank regulators also face similar challenges, making it difficult to monitor and supervise the management of such risks. Precisely because oversight of unknown risks is lacking, banks that are relatively more informed may in turn exploit limited supervision by shifting risk on this margin. This behavior may be more prevalent for banks facing higher competitive pressures.

Confidential data on internal risk models and lending activities by banks allow us to investigate these issues. Using internal risk model disclosures, we can identify learning through the heterogeneity in how banks update their beliefs about climate risks in response to Hurricane

[1] For example, see recent reports on climate change and financial stability by the Network for Greening the Financial System in 2019, by the Financial Stability Oversight Council in 2021, by the U.S. Commodity Futures Trading Commission (Litterman et al. 2020), by the Federal Reserve (Brunetti et al. 2021), and the January 27, 2021, Executive Order on Tackling the Climate Crisis by the White House.
[2] There are various channels including limited commitment (Froot et al. 1993; Petersen and Rajan 1995; Dinç 2000; Rampini and Viswanathan 2010), information imperfection (Akerlof 1970; Grossman and Stiglitz 1980; Stiglitz and Weiss 1981; Hellmann et al. 2000), mispriced deposit insurance (Keeley 1990; Allen and Gale 2000, 2004), and feedback across business lines (Boyd and De Nicolo 2005; Boyd et al. 2009). See the related literature section.
[3] See Hsiang (2016) on the challenges in climate econometrics. More generally, see Weitzman (2009, 2014, 2020) on the challenges in the learning process when there is limited prior knowledge and limited historical observations.
[4] Costly information acquisitions can take the form of purchasing data platforms (such as propriety high-resolution flood risk projections) or hiring data analysts/climate scientists to create in-house projections of flood risks (which also tend to be time-consuming) that can be incorporated into the bank's internal risk management model.

Harvey in August 2017. With detailed loan portfolio information, we are able to directly identify adaptation: banks impacted by the disaster are more likely to internalize and subsequently reduce portfolio exposures to future flood risks in areas unaffected by the hurricane. We find that local loan competition has a dampening effect on bank adaptation behavior—the reductions in risky lending disappear when there is more competition in the local loan market. Additionally, we document a competitive externality associated with adaptation: banks are less likely to reduce their portfolio exposures to climate risks when competitors in the local loan market are also less likely to do so. This suggests a *strategic complementarity* in climate adaptation by financial institutions. These findings support the view that limited oversight of unknown risks reduces incentives for risk management. This account of regulatory leakage may be particularly relevant for banks face greater competition, as our evidence suggests. For example, issuing risky loans may help banks better maintain valuable deposit franchises in competitive markets due to product bundling (DeYoung and Rice 2004).

Overall, our findings have relevant policy implications. For instance, much of the regulatory proposals and policy experiments currently being considered on climate risks have focused on microprudential considerations.[5] This paper highlights the need to also consider macroprudential consequences, as an individual bank's risk management strategy may spill over on to those of its competitors.

Data and methods. We join confidential, loan-level information from bank regulatory filings to high resolution data on climate-related shocks and future risk exposures for the analysis. The regulatory data used was created after the Global Financial Crisis to support bank stress testing under the Dodd-Frank Act and the Comprehensive Capital and Analysis Review (CCAR) regulatory framework. We leverage several important aspects of this data. First, we look "under the hood" at internal bank risk models to directly identify how each bank updates its models, or beliefs. We observe the probability of default (PD), the output of these internal models, for each individual loan and track it over time. Second, we use satellite imagery data to pinpoint properties used as collateral in bank loan portfolios that crossed the path of the hurricane. This allows us to identify which banks were impacted by the hurricane and to what magnitude. Finally, we match

[5] An example is the focus on individual banks' climate risk-management practices in the Federal Reserve Board's Pilot Climate Scenario Analysis. https://www.federalreserve.gov/publications/files/csa-instructions-20230117.pdf.

details about the loan collateral to exposures to future climate risk. We combine the regulatory data with detailed data on flood risk projections between 2020 and 2050 from First Street Foundation (FSF), providing us with information on bank risk exposures to the loan's collateral property.[6]

The data and our analysis focus on the home equity line of credit (HELOC) market, for which banks account for a large share of overall activities. HELOCs not only play an important role in the stability of the financial system (e.g., Mian and Sufi 2011), but also provide an excellent environment to study climate adaptation due to several institutional details. Like mortgage loans, HELOC loans are collateralized by real estate assets, which are particularly exposed to future climate-related risks due to their durability and immobility. Unlike mortgage loans, HELOC loans cannot be readily securitized and sold off the banks' balance sheets due to a relatively limited secondary market. Focusing on HELOC loans help us better identify the ways that banks may adapt to climate risks and alleviate potential selection issues associated with the option to originate and sell a loan to a secondary market where market participants tend to have heterogeneous information and beliefs (Ouazad and Kahn 2022; Bakkensen et al. 2023).[7]

Our empirical strategy exploits heterogeneity in bank learning about and adaptation to climate risks following Hurricane Harvey. We start by identifying learning by banks through changes in the weights on climate risk factors to their internal risk models and checking for corresponding changes in lending behavior. Heterogeneity in learning about climate risks is identified by exploiting differential bank exposures to the hurricane. In this manner, we can distinguish behaviors based upon whether learning took place. This framework is used to analyze how the linkage between learning and behavior is moderated by bank competition. To isolate effects from potentially confounding factors from local economic responses to the direct damage

[6] Notably, the FSF data takes into account hyperlocal geographic characteristics (such as elevation, slope, and ground surface perviousness), climate change factors (such as sea level rise and changes in precipitation, river overflow, coastal storm surges, and sea level rise), and existing community flood protection measures (such as dunes, wetlands, and seawalls)

[7] For example, the option to sell a loan to a secondary market can have complicated effects on the incentives to originate the loan in the first place (Dubey and Geanakoplos 2002; Dubey et al. 2005), leading to a potential selection bias in the sample of mortgage loans (since we do not observe loans that were not originated). This selection bias would be much less of a concern for our sample of HELOC loans.

of the hurricane, we focus on only bank lending to unaffected regions (i.e., *outside* of Texas).[8] To distinguish the potentially confounding effects associated with credit demand in the estimates, we adopt an approach similar to Khwaja and Mian (2008) by employing high-dimensional fixed effects to account for time-varying local demand shocks as well as other unobservable factors associated with the borrower.

Summary of findings. We offer two key sets of evidence related to bank learning and adaptation. First, we document a structural break in how banks consider climate risks in their internal risk models following Hurricane Harvey, consistent with learning. Second, we not only show that banks that are more likely to be associated with learning exhibit adaptation behavior, but also, we provide evidence of *strategic adaptation* (i.e., adaptation outcomes are dependent on the influences of competitive forces in local markets).

For the first set of tests, we begin by showing that banks revise their beliefs by incorporating future flood risks following the hurricane. We estimate how the weight used for flood risk factors changes in banks' internal risk models from before to after the disaster. We detect a positive, statistically, and economically significant relationship between the flood risk factor of the loan's underlying collateral and the bank's internal risk model assessment, as measured by the loan's default probability. Interestingly, we only find this effect after the event; we cannot detect a non-zero weight in the internal risk models in prior periods. Together, these results suggest broader learning about climate risks outside of the areas directly affected by the hurricane.

We next document a heterogeneity in bank learning due to the differences in exposures to the hurricane. A bank's exposure to Hurricane Harvey is measured as the fraction of the bank's HELOC portfolio that is collateralized by houses located near the path of the hurricane. We find that the main effects are concentrated in banks with higher exposures to the hurricane; the effects are statistically and economically insignificant for banks with no exposure. These results cannot be due to shocks associated with the hurricane on bank balance sheets for various reasons, including the inclusion of time-varying bank fixed effects in the estimators.

[8] In particular, this exclusion restriction allows us to avoid potential complications associated with the different paths of the recovery dynamics in the aftermath of a natural disaster (Gallagher and Hartley 2017; Roth, Tran and Wilson 2020).

There are at least two different mechanisms that we consider that may be underlying the learning results. On the one hand, banks with greater exposures may have been associated with local informational advantages related to the severity of losses due to climate events.[9] This form of soft information may have been used to inform internal risk models. These informational advantages are durable and so are unlikely to reverse or be "unlearned." On the other hand, proximity to the natural disaster may correspond with behavioral responses related to a salience bias.[10] That is, operations in the affected areas may make banks more attentive to flood risks, which in turn may make banks more likely to overestimate the likelihood of such events. As such, these effects are expected to reverse as more time elapses following the event. To distinguish these two mechanisms, we decompose the effects in terms of quarters before and since the event. We show that the flood risk weights follow a concave pattern, increasing through four quarters following the event before stabilizing. In other words, the results do not reverse over time, suggesting that the results are attributable to informational advantages rather than salience.

For the second set of tests, we perform cross-sectional analysis of the role of competition in bank adaptation strategies. Banks with greater exposures are more likely to adapt by reducing lending on properties associated with higher flood risks following Hurricane Harvey. That is, banks that are more likely to have learned are more likely to adapt. As with the learning tests, these results are not necessarily driven by losses at banks with higher exposures given that the tests focus on intra-bank variation across markets that lie outside of the areas affected by the hurricane. Importantly, we show that competition moderates this bank adaptation response despite learning. Banks with higher exposures to the hurricane curtail risky lending only in concentrated markets, or where the loan market Herfindahl-Hirschman Index (HHI) is high. We do not detect a significant response in these banks in competitive markets.

[9] The effects of Hurricane Harvey and trends in the frequency of large-scale natural disasters were broadly discussed in industry trade journals at the time, and so were arguably highly visible regardless of proximity to the event. Instead, local informational advantages associated with the exposures are likely to be durable and so are more likely to correspond with permanent shifts in internal bank risk models.

[10] Studies that examine the effects of natural disasters on the behaviors of households and investors show a reversal in initial effects over time, suggesting behavioral biases associated with overreaction, specifically the theory of salience bias. The theory of salience bias, developed by Tversky and Kahneman (1973) and more recently by Bordalo et al. (2012, 2013, 2020), posits a decision maker who overweighs the probability of salient risks. This theory predicts that as salient events pass into the past, their impact on the decision makers decreases with time (Alok et al. 2020). Consistent with this predictions, Dessaint and Matray (2017), Alok et al. (2020), and Correa et al. (2020) find that the effects of climate-related disasters on investors' choices tend to diminish after one year.

A view that has been well-studied in the banking literature is that greater competition, by eroding bank charter values, exacerbates bank incentives to take excessive risks. Banks face reduced profitability due to greater competition as banks pay higher deposit rates, and so worsening moral hazard issues. Consequently, banks may have less to lose from failing, diminishing incentives to act prudently (Keeley 1990; Hellmann et al. 2000; Allen and Gale 2000; Hellmann et al. 2000; Repullo 2004; Allen and Gale 2004). These predictions are generally applicable on the bank-level rather than on the bank-market-level. However, there may be heterogeneity in risk-shifting behavior across markets for the same bank. For example, recent studies demonstrate the importance of bank deposit franchises (Drechsler et al. 2017). Local competition erodes the value of these franchises, and banks may bundle product offerings, such as HELOCs, to retain depositors (DeYoung and Rice 2004). In markets where competition is low, banks may not be as reliant on bundling to preserve deposit franchises.

Further tests are constructed to distinguish specific mechanisms that may be underlying the results. Specifically, we investigate whether there is a potential spillover in banks' climate adaptation strategies. The presence of spillover is key in understanding whether there are potential inefficiencies in how banks manage climate-related risks. We are interested in a particular form of spillover that is at the heart of the rich theoretical literature on bank failure and financial stability: strategic complementarity (Bryant 1980; Diamond and Dybvig 1983; Morris and Shin 1998; Rochet and Vive 2004; Goldstein and Pauzner 2005; Vives 2014). In our context, a strategic complementarity arises if the marginal benefit of a bank from adaptation increases in the level of adaptation by its peers or rivals. To evaluate this channel, we study the effects of competitor exposures to the hurricane within the same local market. This allows us to evaluate cases where the competing banks are informed and uninformed, separately. Competitor exposures is measured by the fraction of competitors with non-zero exposures to Hurricane Harvey within a local HELOC market. We find evidence of strategic complementarities in bank adaptation behavior. The results indicate that a bank with exposures to the hurricane is less likely to curtail risky lending in local markets in which local competitors do not have exposures, and hence are unlikely to adapt themselves. Likewise, we show that an exposed bank is more likely to curtail risky lending when local competitors also have exposures, and so are likely to adapt themselves. A potential explanation for this complementarity is less of a "race to the bottom" in such markets: a bank is more likely to reduce its lending to a risky market segment if it expects that its local competitors are also likely to do so, since the bank is less concerned about preserving their market shares in this scenario.

Paper organization. The balance of the paper is organized as follows. Section 2 presents the literature review. Section 3 describes our data sources. Section 4 provides details on the empirical methodology. Section 5 presents and discusses our results on bank learning. Section 6 presents our evidence on bank adaptation and competitive dynamics. Section 7 provides further analysis on competitive mechanisms. Section 8 presents the conclusions.

2. Literature Review

To the best of our knowledge, our paper is the first to connect two important strands of research: (1) a rapidly growing literature on climate finance and the large (2) extant literature on how competition affects outcomes in financial markets.

Our study contributes to the developing literature that studies the effects of climate change on financial markets.[11] It is most related to the branch that focuses on the effects of climate-related disasters on bank balance sheets (Blickle et al. 2021), bank lending (Correa et al. 2022; Nguyen et al. 2022), and loan performance (Kousky et al. 2020; Issler et al. 2021; Biswas et al. 2023). Of particular relevance is Meisenzahl (2023), who also use the same regulatory database to document that in recent years, especially after 2015, large U.S. banks have reallocated their loan portfolios away from counties with increased climate-related disaster risks. Our paper complements this by adding an additional layer to the empirical investigation: competition in the banking industry. In documenting the strategic dimension of bank adaptation, our paper is related to Ouazad and Kahn (2022, 2023), who document that after big flooding events, banks tend to strategically shift climate risks by securitizing at-risk mortgages under the conforming loan limits and selling them to the government-sponsored enterprises. Our study complements theirs by showing that risk-shifting incentives are also present, but in a different form, in the home-equity loan market, where the securitization option is generally not available. Our paper is additionally related to the branch that focuses on the effects of climate-related risks, especially flooding, on the housing market (Bernstein et al. 2019; Baldauf et al. 2020; Murfin and Spiegel 2020; Bakkensen and Barrage 2022;

[11] Hong et al. (2020), Furukawa et al. (2020), and Giglio et al. (2021) provide excellent overviews.

Keys and Mulder 2022) and the mortgage market (Bakkensen et al. 2023). Finally, our paper is also related to the literature on learning from extreme events (Kousky 2010; Gallagher and Hartley 2017; Kozlowski et al. 2020). Our paper complements these studies, which focus on households, by documenting how financial institutions learn from a natural disaster. Moreover, we are the first paper to document a strategic complementarity in adaptation to climate change. Finally, we are the first paper to provide evidence on bank learning and belief formation in the context of climate change.

Our study also contributes to the expansive banking literature that examines different mechanisms through which competition in deposit and loan markets affects banks' risk-shifting incentives.[12] Our paper is more related to the recent empirical work in this literature, including Keys et al. (2009), Drechsler et al. (2017); Egan et al. (2017); Whited et al. (2021); and Wang et al. (2022). Most related is Yannelis and Zhang (2023), who study how competition affects banks' incentives to acquire information. Their model predicts that when there is a fixed cost of information acquisition, increased competition reduces lenders' market shares, and thus lowers their incentive to invest in screening borrowers, and they find supporting evidence using TransUnion credit panel data for auto loans. In analyzing a spillover in bank adaptation, our paper is also related to Di Maggio et al. (2019), who provide evidence of a race to the bottom between regulated and unregulated banks to issue risky complex mortgages, by exploiting a quasi-experiment surrounding the exemption of national banks from state laws against predatory lending by the Office of the Comptroller of the Currency. Our paper is the first, to our knowledge, to examine the relationship between competition and the management of unknown risks, such as climate change.

3. Data

3.1 Data Sources

We use a confidential, supervisory dataset that is collected for the purpose of stress testing the largest U.S. bank holding companies. Specifically, the data is from Schedule B.1 of the Federal

[12] Boyd and De Nicolo (2005) and Boyd et al. (2009) provide excellent summaries of the earlier theoretical and empirical literature.

Reserve Board's FR Y-14M from January 2014 through December 2019. The data is reported monthly by large banks who hold or service home equity loan products and includes loan-level information on the respondent bank's loan portfolio associated with domestic home equity loans and home equity lines of credit. We require the availability of certain fields used in the analysis, including those related to a bank's internal risk model, in order for the loan to be included in the sample. The data provides unique loan identifiers allowing us to track the loan at a monthly frequency. Importantly, the data provides the exact address of the underlying collateral, allowing us to precisely match the loan with physical risk attributes at the property-level. The data also includes information related to the loan, including loan terms and utilization, as well as borrower characteristics at origination.

The resulting dataset includes almost 180 million observations of 6.9 million households located across 2,962 counties. **Figure 1** shows the geographic distribution of home equity line balances represented in the data, by county. The choropleth is formatted such that lower (higher) density is shaded blue (orange). The figure indicates broad geographic coverage of the dataset. This is unsurprising as the banks in the dataset are the predominant lenders in the home equity loan market. To ensure that the data is representative for the broader market, we obtain data from Equifax that provides home equity loan stock by county issued by any credit institution. The information is displayed in **Figure 2**. It is formatted similarly to Figure 1. The loan distributions between our sample and the Equifax sample are highly correlated, or 92.8%, confirming the representativeness of the confidential data.

[See Figure 1]

[See Figure 2]

We use high resolution satellite data that provides information on the path of the hurricane from the National Oceanic and Atmospheric Administration (NOAA) HURDAT2, specifically the Atlantic hurricane database. The data provides six-hourly information on the precise coordinates, maximum winds, central pressure, and the size of all tropical and subtropical cyclones since 2004. We collapse data from August 16, 2017, through September 9, 2017, to identify the ZIP codes that intersect with Hurricane Harvey's path based upon the wind radii of its focal point. **Figure 3** displays a visualization of areas affected by Hurricane Harvey. Like Ouazad and Kahn (2022), we focus on portions of the hurricane path that exhibit tropical storm intensities or stronger, or at least

34 knot wind speeds. This excludes the parts of Louisiana that were on the hurricane path. We impose this restriction in order to capture the most powerful portion of the storm associated with the bulk of the damages. The data is merged with the bank regulatory data to identify households that were in the ZIP codes that were crossed by the hurricane path.

[See Figure 3]

The regulatory data is also merged with flood exposure projection data from the First Street Foundation. The First Street Foundation provides property-level estimates of flood risk, called the flood factor. The factor, defined from 1 to 10, is a composite score reflecting both the severity and cumulative likelihood of flooding over a 30-year period from 2021 to 2050. The flood factor is generated by the First Street Foundation Flood Model. This model considers four major flood contributors: rainfall, river overflow, high tide, and coastal storm surge. It also adjusts for local variables such as elevation, ground surface perviousness, and existing community flood protection measures like dunes, wetlands, and seawalls. Importantly, the model is forward-looking, explicitly considering projected climate change effects, including sea-level rise. In addition to the property-level data, First Street also provides the proportion of properties in a 5-digit ZIP code that are classified by the Federal Emergency Management Agency (FEMA) as being in a Special Flood Hazard Area (SFHA).

3.2 Data Description

Table 1 displays the summary statistics. The primary outcome measure, the probability of default, is highly right skewed; it has a mean of 4.5% and a median of 0.2%. In the analysis, we address this issue by using the natural log transformation of one plus the default probability in points. The flood risk measure from First Street Foundation also exhibits right skewness and is transformed similarly for the analysis. **Figure 4** displays the geographic distribution of the flood risk measure by ZIP code. The choropleth is formatted such that lower (higher) risk levels are shaded blue (red).

[See Table 1]

[See Figure 4]

Table 2 displays the histogram of the flood risk measure. A vast majority of the properties (85.7%) are rated as the lowest risk level. In contrast, those with score above five account for 5.9% of all properties. The flood risk scores generally correspond with other measures of flood risk. The table also displays the average proportion of homes within a ZIP code that are located in an SFHA conditional on the First Street Foundation flood risk score associated with the property. This fraction increases monotonically in the flood risk measure. The highest flood risk score is associated with ZIP codes where an average of 34.4% of homes are located in an SFHA. The correlation between the flood factor and SFHA measure is 63.4%. The table also displays the coefficient of variation of the SFHA measure for each risk score. For all values, the coefficient of variation exceeds 1.0, and is pronounced for lower risk score values.

[See Table 2]

There is considerable heterogeneity in the bank-level exposures to Hurricane Harvey. More importantly for the analysis, there is geographic variation within and across markets for which banks with and without exposures to Hurricane Harvey operate. **Figure 5** displays counties where all banks have no exposure (light grey), there are both banks with and without exposures (dark grey), and all banks with exposure (orange). As explained in the next section, Texas is excluded in our analysis and so is not included in the chart. Most counties feature both banks with and without exposures. Most of the counties where all banks have exposures are concentrated in midwestern and northeastern states. These counties include both cases where there is only a single exposed bank operating and multiple exposed banks that may differ in the extent to which they were exposed.

[See Figure 5]

4. Empirical Design

We first focus on identifying which banks learn about climate risks following a natural disaster. We conjecture that banks with larger ex ante exposures are more likely to learn and therefore incorporate climate risks into their internal risk models. Once identified, we trace bank responses in the period following the disaster across geographic markets that were not directly affected. Importantly, we examine how bank responses are conditioned by competitive conditions.

4.1. Learning and Exposures to Natural Disaster

Our experimental setting focuses on bank learning about climate risks following a natural disaster. Natural disasters are generally visible to all banks, yet there may still be heterogeneity in bank learning about associated risks. In this section, we motivate our instrument that captures heterogeneity in learning about climate risks: the exposure of a bank's loan portfolio to a natural disaster.

Banks may have better access to information due to proximity to the natural disaster that would be otherwise costly to obtain. In the context of climate risks, the occurrence of a natural disaster may inform the frequency of such disasters from happening again. This type of information is highly localized and so only pertains to borrowers in specific regions. The severity of the damages due to the disaster may not only be informative for assessing credit risks for borrowers following certain types of natural disasters, but also may provide insights into losses associated with a broader set of events. For example, the damage during a hurricane may provide information about losses due to heavy rainfalls in other regions as well. The magnitude of the losses, in turn, may directly inform the borrower's ability to repay in the event of such events. These informational advantages may represent more durable and meaningful changes in bank beliefs as they are more pervasive.

There is an alternative channel by which proximity to natural disasters can affect belief formation: salience bias. Banks may overreact to the event by assigning a greater likelihood to similar events of occurring again. Proximity to the event may increase the salience of these effects. We distinguish salience from the informational channel above in the following ways. The effects should be transient such that beliefs should revert to their pre-event levels as the salience of the event wanes over time. In contrast, the relevance of soft information learned from the event should be relatively durable and not diminish over time. Moreover, the effect of the bias should be localized. The occurrence of a natural disaster in one region need not be linked to the likelihood of similar events occurring in other regions. As such, these effects are expected to impact most the areas directly affected as opposed to unaffected areas.

There may be other important channels by which banks change their behavior following a natural disaster that are unrelated to changes in their beliefs. These channels are associated with the shock of the natural disaster to the balance sheet of banks in affected regions. Banks that are constrained because of the shock may change their behavior, not only in areas directly impacted by the event but also in other regions in which they have operations. To directly account for these issues, we include high dimensional fixed effects that account for time-varying bank factors to rule out these non-learning channels. Moreover, our tests focus on differential climate risk exposures within the same region. While constrained banks may choose to curtail lending irrespective of climate risk exposures, banks that learn will become more sensitive to climate risks in their lending decisions.

Identifying bank learning is oftentimes inferred indirectly by examining changes in ex post behavior, and so is challenging to directly identify. To overcome these challenges, our empirical strategy focuses on changes in bank internal risk models that are directly used in lending decisions. Earlier literature shows considerable heterogeneity across banks in internal risk ratings for the same borrower (Carey 2002; Jacobson et al. 2006). This may be the case given that banks are likely to employ different types of approaches and models that may systematically bias risk assessments from one bank to another (Behn et al. 2014). Other studies find evidence of systematic differences in risk assessments associated with specific loan characteristics. For example, Firestone and Rezende (2016) show systematically lower risk assessments for loans for which banks hold larger shares in loan syndicates. Plosser and Santos (2018) find evidence that banks with lower capital ratios systemically report lower risk assessments.

4.2. Bank Learning Tests

Our first task is to validate whether bank exposures to Hurricane Harvey correspond with learning about climate risks. Towards that end, we construct tests that recover weights from internal bank risk models related to climate risk factors and measure how they change in response to the hurricane. In order to avoid the influence of the direct impact of the hurricane itself, we exclude the subsample of properties in states that intersect the path of Hurricane Harvey from the analysis.

There are a host of time-invariant as well as time-varying factors unrelated to learning that may potentially confound the analysis. As such, we use a similar approach to Khwaja and Mian (2008) by saturating the models with high dimensional fixed effects to isolate the learning effects. First, household fixed effects allow us to restrict the model to time variation for the same household, which mitigates the influence of household characteristics associated with assortative matching factors that may lead to selection bias. Second, interactive fixed effects on the county and date levels allow us to purge any effects related to local demand or regional heterogeneity. Finally, as noted earlier, the interactive fixed effects on bank and date levels enables the analysis to focus on intra-bank variation at each point in time to account for potential shocks associated with the hurricane on bank balance sheets. They also account for any supervisory factors corresponding with changes in the regulatory environment that may affect each bank differentially during the period of the analysis.

We employ a difference-in-differences estimator, using an estimation window from two years before to two years after Hurricane Harvey. For the approach to be valid, the parallel trends assumption is required to hold. That is, the differences in the effects between low and high flood risk properties must not change over the sample period in the absence of the hurricane. In examining bank rather than household outcomes, we are primarily interested in whether there were systematic differences in internal bank risk models across areas with low and high flood risks prior to the event. While we include household fixed effects to mitigate these concerns, we also provide tests in the next section that inform to what extent this identifying assumption holds.

For household i, bank j, county g, and date t, the regression model takes the following form:

$$PD_{i,j,g,t} = \alpha_1 \times FloodRisk_i + \alpha_2 \times Post_t + \alpha_3 \times FloodRisk_i \times Post_t + \phi_i + \phi_{g\times t} + \phi_{j\times t} + \epsilon_{i,j,g,t}$$

The dependent variable $PD_{i,j,g,t}$ is the natural log of one plus the probability of default for property i (located in county g) for bank j at date t. $FloodRisk$ is the natural log of one plus the flood factor score for property i. $Post$ is a dummy that takes value one if date t occurs after August 2017 and zero otherwise. ϕ denotes the fixed effects associated with the household, county × date and bank × date levels. Robust standard errors are clustered on the household, county-date and bank-date levels.

To examine heterogeneity in bank learning, we use the proportion of bank j's home equity loan portfolio that intersects with the hurricane path as of July 2017, or $BankExposure$. We choose to measure exposures before the hurricane to avoid potential charge-offs that the bank may have incurred after the event. We use the proportion as dollar amounts of affected properties may be mechanically larger due to the size of a bank's lending operations. We augment the model with interaction terms associated with $BankExposure$ in the following manner:

$$
\begin{aligned}
PD_{i,j,g,t} = {} & \beta_1 \times FloodRisk_i + \beta_2 \times Post_t + \beta_3 \times BankExposure_j \\
& + \beta_4 \times FloodRisk_i \times Post_t + \beta_5 \times FloodRisk_i \times BankExposure_j \\
& + \beta_6 \times FloodRisk_i \times Post_j \times BankExposure_j + \phi_i + \phi_{g\times t} + \phi_{j\times t} + \xi_{i,j,g,t}
\end{aligned}
$$

Our focus will be on the triple interaction term (β_6). We expect the coefficient to be statistically significant if there is any heterogeneity in bank learning. A positive coefficient would indicate that banks with higher exposures to the event place greater weight on climate factors following the event relative to banks with lower exposures. A negative coefficient can be interpreted as banks with higher exposures decrease risk assessments of properties after the event.

4.3. Market Share Tests

We next describe the market share tests. We examine the competitive response of treated and untreated banks in the aftermath of Hurricane Harvey outside of the affected areas. Critically, we focus on the differential responses for loans that have higher and lower climate risks within a particular market. As with the learning tests, the richness of the data allows us to employ high dimensional fixed effects that help us account for a host of different sources of potentially omitted factors.

The baseline specification will be a triple-difference estimator where the dependent variable is the change in local market share from December 2014 to December 2019. The data is aggregated to the level of a bank, a county, and a flood risk bucket. For each county, we create three risk buckets based on the tercile rankings of the property-level flood risk score. The market share is calculated as the share of loans associated with bank *j* across all loans in county *g* and risk bucket *k*. The triple-difference estimator captures: (1) the changes in the log market share from before the Hurricane Harvey to 24 months after the event (2) across banks with low and high exposures to the natural disaster, and (3) across low and high-risk properties.

$$
\begin{aligned}
\Delta MktShr_{j,g,k} = {} & \gamma_1 \times MedRisk_{g,k} + \gamma_2 \times HighRisk_{g,k} + \gamma_3 \times BankExposure_j \\
& + \gamma_4 \times MedRisk_{g,k} \times BankExposure_j + \gamma_5 \times HighRisk_{g,k} \times BankExposure_j \\
& + \phi_j + \phi_g + \xi_{j,g,k}
\end{aligned}
$$

The dependent variable, $\Delta MktShr_{j,g,k}$, is the change in the natural log of one plus the market share for bank j in county g for risk bucket k. The focus of the analysis will be on the coefficient for the double interaction term $HighRisk_{g,k} \times BankExposure_j$, or γ_5. This coefficient captures the differential change in the market share across low versus high-risk areas for banks that have high versus low exposures to the natural disasters. We also include the terms associated with $MedRisk_{g,k}$ for comparison. To account for demand-based factors specific to a particular market, we include county fixed effects (ϕ_g). To account for other bank-level factors that may be contaminating the results, we include bank fixed effects (ϕ_j). Standard errors are clustered on the county level.

To directly evaluate the effects of competition, we augment this specification to condition on prevailing competitive conditions. To capture competition, the Herfindahl-Hirschman Index (HHI) on home equity loans is calculated for each county *g* as of December 2014. We take two different approaches to estimate the conditioning effects. First, we estimate the market share tests from the above specification on samples spliton the median county HHI. Second, we augment the model above with the inclusion of triple-interaction terms based upon HHI. We employ both approaches not only for interpretability purposes but also to assess robustness of the results.

5. Bank Learning Results

5.1. Flood Risk and Internal Bank Models

We start with simple tests based on univariate regression models where the dependent variable is the loan default probability, PD, and the explanatory variable is the flood risk measure, FloodRisk. **Figure 6** displays the results visually. The figure displays the marginal effects based on the regression coefficients for each quarterly regression from eight quarters prior through eight quarters following the event. Overlaid on top of the figure are 95% confidence bands. The standard errors used to calculate the confidence bands are clustered on the ZIP code level. We estimate the marginal effects by estimating the change in the dependent variable. For example, for the +8-quarter subsample, the marginal effect is 1.3%, compared to the sample median of 15.2%.

[See Figure 6]

Several interesting patterns emerge. First, the effects are not significant until after one quarter following Hurricane Harvey. This suggests that the sensitivity in the flood risk measure is in response to the event. It may take some time to develop and incorporate climate risk into internal bank risk models, potentially explaining the delay in the effects. Second, the effect does not reverse over time but rather increases during the first year before levelling off. This suggests that the effect is not transient. That is, banks do not overreact to the event by overweighting the climate factor initially. If anything, banks appear to take a conservative approach, increasing the sensitivity over time. This provides support for the internal validity of the difference-in-differences estimator. This is also consistent with other studies (e.g., Meisenzahl 2023) that find a change in bank behavior in response to climate risk around the same period. One potential explanation is that technological advances during this period enabled development of climate-based models that could be reliably incorporated into internal risk assessments. In other words, even though banks may have recognized climate risks from past natural disasters, such as Hurricane Katrina, they were unable to measure these risks due to technological limitations.

The univariate test results suggest that banks, on average, respond to the natural disaster by updating their internal risk models to account for flood risks. We next turn our attention to the baseline regression model specifications, which address various endogeneity issues described in the previous section. The results are displayed in **Table 3**.

[See Table 3]

We present the results iteratively including additional factors in each specification to help assess their importance. Column (1) only include household fixed effects. The estimate on the interaction term is statistically significant at the 1% level and the magnitudes are comparable to the univariate tests. When including time-varying bank and county fixed effects in Column (2), the coefficient remains significant, though attenuates considerably. This suggests that the influence of other factors is quite large, providing some validation to the empirical design. Column (3) decomposes the post-event period by quarter.

The results from these specifications are consistent with the univariate regression model results. The flood risk measure is again insignificant prior to Hurricane Harvey, suggesting that banks did not initially take account of flood risks in their internal models. Following the hurricane, the weight on flood risk factors steadily increases. As the estimates are an average effect, this suggests heterogeneous adoption of flood risks in their internal models. These results are consistent with the bank learning interpretation. While it is possible that banks also may have updated their beliefs about risks pertaining to the prevalence of natural disasters in both the affected and unaffected regions, our analysis focuses on more general climate risks related to flooding. In the next section, we further examine learning heterogeneity and how it impacts bank decision-making.

5.2. Heterogenous Bank Learning: Proximity to Natural Disaster

We next examine heterogeneity in how internal bank risk models are updated in response to bank exposures to Hurricane Harvey. How do the results in the previous section differ based on bank exposures to the natural disaster? If there is no new information learned by the bank, there should be no changes in the internal risk models used by the affected banks. While it is possible that greater exposure may correspond with a larger impact on the bank's profitability, this should not necessarily affect the bank's internal risk models outside the affected areas. The results are consistent with the interpretation that the models are updated to reflect learning from local informational advantages.

To examine the role of bank exposures to the natural disaster, we augment the baseline specification with the exposure measure as described earlier. **Table 4** displays the results. Column (1) only includes household fixed effects. The triple interaction term coefficient is positive and statistically significant at the 1% level. This suggests that the increased weight on flood risks in bank internal risk models are more pronounced for banks with a larger proportion of its loan portfolios in the affected regions. Column (2) also includes time-varying bank and county fixed effects. The triple interaction remains positive and significant, but also increases in magnitude by more than one-third. The larger coefficient could be due to either regional or bank factors that may be attenuating the estimates. For example, banks with greater exposures may have been subject to greater supervisory influence following the natural disaster to address potential losses that may not have directly coincided with the banks' internal risk models. The inclusion of the additional fixed effects may have mitigated the attenuation.

[See Table 4]

We next consider the extent to which the results are due to local information advantages versus a salience bias. We start by noting that the prevalence of large natural disasters began to increase prior to our sample period. **Figure 7** displays the cost and frequency of billion-dollar disasters over time.[13] The average annual frequency from 1980 to 1999 is 3.3 events, compared to 6.6 events during 2000 to 2014. These events are highly visible, and the associated damages were widely reported in trade journals. This casts at least some doubt that banks without any exposures to the event were unaware of the event. Moreover, we exclude areas directly affected by the disaster, where we would expect a salience bias to be most pronounced, from the testing sample.

[See Figure 7]

We next provide tests for overreaction associated with the behavioral channel. **Figure 8** plots out the marginal effects from a model that decomposes the results in Table 4 based on the quarters following the event. Rather than reversing, the results indicate that the effects remain positive and stable up through eight quarters following the event. The marginal effect of changes to the bank exposure and flood risk measures through quarter eight on the default probability is 3.9%, which is economically significant compared to the sample median of 15.2%. These results support the interpretation that the effects are due to learning through informational advantages of the affected banks.

[See Figure 8]

5.2.1. Alternative Explanations

To what extent are the results sensitive to the flood risk measure used in the baseline specifications? Up until this point in the analysis, we have used a relatively sophisticated measure of flood risk. There may be concerns that banks did not have access to technologies that would allow them to observe flood risks at such a level of granularity. To alleviate this concern, we repeat the analysis using one measure that was available to banks before the event–the SFHA classifications. **Table AI** displays the results. The results are qualitatively identical and quantitatively similar. They suggest that our findings are not sensitive to the choice of flood risk measure.

We further examine bank sophistication related to climate risks in the internal risk models by performing tests on separate subsamples based on the SFHA classifications. Specially, we

[13] Specifically, we only include flooding, severe storms, tropical storms, and winter storms in the calculation. The data can be found at: https://www.ncei.noaa.gov/access/billions/time-series.

divide the full sample into two subsamples based on the proportion of homes in an associated ZIP codes that are classified as SFHA. This should break any mechanical correlation between the two measures and allow us to examine to what extent they use information correlated with the more sophisticated measure after conditioning on the SFHA information. **Table A2** displays the results. Across both subsamples, the estimates are very similar. This suggests that the information that banks used to update their models was relatively sophisticated and went beyond sole reliance on the SFHA classifications.

We next assess the robustness of the results when excluding specific states from the analysis. These states may be associated with higher climate risks, and our tests assess their importance in driving the main results. In addition to the areas directly affected by the hurricane, we iteratively drop loans located in the following states: California, Florida, Louisiana, New York, and Texas. **Table A3** displays the results. Across the subsamples, the estimates are all statistically significant at the 1% level. This suggests that the main results are not sensitive to the exclusion of any of these states.

In other robustness checks, we assess the influence of extreme values of the flood factor measure by considering an alternative specification that maps it to a dummy variable. We find the results remain significant (**Table A4**).

5.3. Bank Lending Tests

We next analyze bank adaptation by checking if the effect of learning corresponds with changes in drawdown behavior and credit line provisioning. Higher risk reflected in the internal risk models due to learning about climate factors should lead banks to curtail lending in areas associated with higher climate risks. We directly test this conjecture by using additional information from the regulatory filings that allows us to track the loan activity before and after the event. For these tests, we use a similar empirical approach while alternating the outcome of interest.

Table 5 displays the results. Across all specifications, the triple interaction term is statistically significant at the 1% level. Column (1) shows that households in areas with higher flood risks were less able to drawdown on their existing lines of credit following Hurricane Harvey. Column (2) provides a possible explanation, that households in riskier areas received reductions to the credit limit available to them, and that the effect is pronounced for banks with higher exposures. Moreover, any local shocks that may have been coincident with the event are already accounted for by the time-varying county fixed effects.

[See Table 5]

The results indicate that the effects of the event on internal bank risk models impact households through credit availability. While it may be desirable to properly manage such risks by reducing credit issued, there may be adverse consequences that affect constrained households living in areas of elevated climate risks. While it would be interesting to examine loan pricing as well, it may be difficult to detect an effect. The pricing of home equity loans is complicated by the fact that loan rates are determined by other loan terms that cannot be accounted for with the information available in the data. Moreover, loan rates are often fixed over the life of the loan and are inversely related to any up-front fees that are not available in the data. As such, we expect the bulk of the effects to transmit through adjustments to commitment sizes rather than through price terms for existing customers.

6. Bank Competition

This section presents the test results on competition and adaption outcomes. In the previous section, we provided evidence demonstrating that exposures are associated with heterogeneous learning: some banks will learn about emergent risks before others. In response to the risks, some banks may adapt to these risks; they may pull out of certain markets or decrease exposures to riskier segments of the market. We next examine whether competition may influence banks to choose not to adapt despite learning. In particular, the choice not to adapt to climate risk may be consistent with one account of risk-taking.

Table 6 displays evidence on bank adaptation. The dependent variable is the change in the natural log of one plus the market share from December 2014 to December 2019. The explanatory variables are as follows: dummies associated with regions where properties are in the mid- and high-tercile in terms of flood risk; the bank's exposure to Hurricane Harvey; and interaction terms between the flood risk dummies and the bank exposure measure. The key variables of interest are the double interaction terms. We expect to see a negative (positive) coefficient if banks who learn faster decrease (increase) their market share following the event.

[See Table 6]

To begin, Columns (1), (2), and (3) display specifications with the *BankExposure* measure but for sample splits associated with the bottom, middle, and top flood risk region terciles, respectively. These specifications allow us to directly evaluate the differential reaction between informed and uninformed banks with respect to climate risks. The results show that the *BankExposure* coefficient is significant across all the specifications. More importantly, the magnitude of the coefficient is largest for the high-risk areas. These patterns are consistent with bank adaptation to climate risks.

We next directly test whether there are significant differences in the *BankExposure* effects across risk levels. Columns (3) and (4) present the results of the pooled specifications. The results indicate that the interaction term coefficients are negative and grow stronger in risk level. Together, the results indicate that the reductions (increases) by banks with higher (lower) exposures were most pronounced in the higher risk areas. Finally, column (4) shows the results with the bank fixed effects as well. This specification directly accounts for the possibility that the exposures may be more likely to be associated with constrained banks and so focuses on intrabank variation across markets. The interaction term coefficient remains negative and statistically significant, suggesting that the effects are likely due to adaptation rather than balance sheet effects.

Overall, we find evidence consistent with the implication that heterogeneous learning has a significant impact on bank adaptation. They suggest that, depending on when banks learn about risks, concentration in risks are formed and this has implications for broader competitive dynamics. For example, banks that learn slower may face an overhang of loans associated with higher levels of risks that were not accounted for at origination. These loans will invariably underperform given that revenues accrued from these assets will not sufficiently compensate the bank for the level of risk. Depending on the level of concentration, it is possible that banks may be forced to scale back their lending operations overall or take on greater risks to offset potential shortfalls.

The results so far square with received wisdom on the effects of learning and adaptation responses. We next examine the degree to which the effects are related to the bank's competitive position. It is possible that the results are driven by banks that do not have a heavy presence in the market. These banks may be more willing to exit the market given that it may be less costly to do so. Likewise, banks with higher market share may be less willing to adapt given that those markets may be relatively more important to the bank's operations.

Table 7 displays the results for the market share interaction tests. The table displays the results for subsamples based upon whether the market share of the bank is below (Low) or above (High) the median in Columns (1) and (2), respectively. Column (3) displays the pooled specification.

[See Table 7]

To begin, Columns (1) and (2) display the results for the sample splits. The double interaction term coefficient is significant for both subsamples. However, the results are much stronger for the High subsample. To directly test whether the results are significantly different, we examine the specification with the triple interaction term. The triple interaction term is also negative and statistically significant, indicating that the difference is indeed significant.

These results are interesting in that they reflect adaptation in markets where risk exposures are more meaningful on average. For markets where risk exposures are lower, or where existing market share is small, the decision to reduce risk exposures may not be as important or may not alter the bank's overall risk profile as much.

Finally, we consider the main tests related to competition. Namely, we use a setup that is similar to that of Table 7, though the specifications are augmented by HHI terms in place of market share. We start by calculating the HHI for each county based on the share using HELOC dollar balances for data as of June 2016. The HHI is interacted with both the risk dummies and the bank exposure interaction terms. The tests focus on the triple interaction between those three terms. We assess whether more competition offsets the effects of the interaction term between the risk dummies and the *BankExposure* measure. If this is the case, it would imply that the triple interaction coefficient should be negative. **Table 8** displays the results.

[See Table 8]

Across the specifications, the results indicate that the main effects are heightened in more concentrated markets. That is, the effects attenuate or are insignificant in markets that are most competitive. Column (3) shows the results with the *HHI* interaction terms. As expected, the triple interaction term coefficients are negative and grow stronger in risk level. Meanwhile, the interaction terms between the risk category dummies and the bank exposure measure remain negative and statistically significant. This indicates that when competition is higher (lower values of *HHI*) the effect of the double interaction term attenuates, suggesting that competition mitigates the effects of adaptation.

Overall, the results provide supportive evidence of strategic adaptation. That is, banks may choose not to adapt due to competitive considerations despite learning.

7. Identifying Competitive Mechanisms

In this section, we provide further analysis to better identify what mechanisms may be responsible for the results documented in Section 6. Specifically, we examine the role of strategic spillover in adaptation. We provide direct tests that examine how competitor bank exposures to the natural disaster affect adaptive outcomes.

We next investigate whether there is a potential spillover in banks' climate adaptation strategies. Traditionally, there are two types of spillover: strategic complementarity or strategic substitutability. In our context, there is a strategic complementarity (substitutability) if the marginal benefit of a bank from adaptation increases (decreases) in the level of adaptation by its competitors. For example, strategic substitutability could arise due to a free-rider effect: when competitors are informed, a bank’s marginal benefit of information acquisition can be reduced if the bank can instead learn from the diffusion of competitors' private information through market prices (Grossman and Stiglitz 1980). There are other channels through which these spillovers can manifest. For example, strategic complementarities could arise due to a “race to the bottom:” a bank is more likely to reduce its lending to a risky market segment if it expects that its competitors are also likely to do so, since the bank is less concerned about preserving their market shares in this scenario (Di Maggio et al 2019).

We evaluate the potential existence of spillovers in bank adaptation as follows. To alleviate the potential simultaneity bias, we proxy for peer adaptation by conditioning on the *BankExposure* values of local competitors, i.e., the fraction of competitors with exposures to Hurricane Harvey in a local HELOC market. Specifically, for each bank and market, we identify the list of competitors and rank them based on their *BankExposure* measure. We then calculate the fraction of competitors whose *BankExposure* value is above the sample mean of banks with non-zero exposures. We refer to this measure as *PeerExposure*. We augment the regression specifications in Table 6 with interactions based on *PeerExposure.* Our focus will be on the interaction between *BankExposure*, the flood risk dummies, and *PeerExposure.*

Table 9 displays the results. The first two columns show the results on the *BankExposure* interaction terms for sample splits based on *PeerExposure* levels: Low and High levels for below and above sample median levels for *PeerExposure*. Model (3) displays the results for the pooled sample.

[See Table 9]

The results provide evidence of a spillover and, more specifically, a *strategic complementarity:* a bank is less likely to adapt when its competitors do not have exposures (and hence its competitors are unlikely to adapt themselves). In Column (1), the *BankExposure* interaction term coefficient is statistically insignificant for the subsample where competitors do not have exposures. In Column (2), we find an analogous result for when competitors are exposed or are more likely to adapt: banks are also more likely to exhibit adaptation behavior. The results in Column (3) indicate that the difference in the results are statistically significant. While the results provide support for a “race to the bottom” dynamic, the results for informed competitors also suggest a positive spillover.

8. Conclusion

Using confidential supervisory data, we provide evidence on the role of competition on bank adaption to climate change. We provide evidence of adaptation in lending behavior that corresponds with changes in beliefs about climate risks in the aftermath of Hurricane Harvey. However, banks are less likely to adapt in more competitive loan markets despite learning. We also document a spillover, more specifically a strategic complementarity in adaptation: a bank is more likely to adapt when competitors are also more likely to do so. Our findings suggest that the adaptation effort of an individual bank interestingly has a positive externality on rival banks' incentives to adapt. It is important to understand the underlying reasons behind these nuanced findings and their implications, and that is what we plan to do in future iterations of the paper.

Our findings highlight the interdependence of climate adaptation among banks: an individual bank's adaptive action depends on competitive considerations. An implication of these findings is that it is not only important to incorporate market forces and strategic considerations into ongoing policy experiments, but also to develop a macroprudential framework to evaluate the systemic implications of climate risks. Such considerations may be especially beneficial to the climate scenario analysis piloted by the Federal Reserve Board of Governors in conjunction with six large banks. In parallel with nascent policy efforts by regulators around the world, the climate stress testing research literature is also in an early stage (Acharya et al. 2023). These studies had a microprudential focus on evaluating individual banks' vulnerabilities to climate-related transition risks (Jung et al. 2021).

More generally, we believe that climate adaptation in financial markets is an exciting area for future research, especially given the potential implications for financial system stability. There is a large and growing literature on climate adaptation (Kahn 2021; Hsiang et al. 2023), but very few papers have focused on strategic adaptation in financial markets (Ouazad and Kahn 2022, 2023; Bakkensen et al. 2023). Our paper suggests interdependency in the aggregation of individual adaptation strategies. In some cases, this interaction may make certain markets and systemically important institutions more vulnerable to climate shocks, and merits further investigation.

References

Acharya, V. V., Berner, R., Engle, R., Jung, H., Stroebel, J., Zeng, X., & Zhao, Y. (2023). Climate stress testing. *Annual Review of Financial Economics*, 15, 291-326.

Akerlof, G. (1970). The market for "lemons": qualitative uncertainty and the market mechanism. *Quarterly Journal of economics*, 89(3).

Allen, F. and Gale, D. (2000). *Comparing financial systems*. MIT press.

Allen, F. and Gale, D. (2004). Competition and financial stability. *Journal of Money, Credit and Banking*, pages 453–480.

Alok, S., Kumar, N., and Wermers, R. (2020). Do fund managers misestimate climatic disaster risk. *The Review of Financial Studies*, 33(3):1146–1183.

Alvarez, J. L. C. and Rossi-Hansberg, E. (2021). The economic geography of global warming. Technical report, *National Bureau of Economic Research*.

Auffhammer, M. and Schlenker, W. (2014). Empirical studies on agricultural impacts and adaptation. *Energy Economics*, 46:555–561.

Bakkensen, L. A. and Barrage, L. (2022). Going underwater? flood risk belief heterogeneity and coastal home price dynamics. *The Review of Financial Studies*, 35(8):3666–3709.

Bakkensen, L., Phan, T., and Wong, T.-N. (2023). Leveraging the disagreement on climate change: Theory and evidence. *Richmond Fed Working Paper*.

Bakkensen, L. A. and Mendelsohn, R. O. (2016). Risk and adaptation: Evidence from global hurricane damages and fatalities. *Journal of the Association of Environmental and Resource Economists*, 3(3):555–587.

Barreca, A., Clay, K., Deschenes, O., Greenstone, M., and Shapiro, J. S. (2016). Adapting to climate change: The remarkable decline in the us temperature-mortality relationship over the twentieth century. *Journal of Political Economy*, 124(1):105–159.

Baldauf, M., Garlappi, L., and Yannelis, C. (2020). Does climate change affect real estate prices? only if you believe in it. *The Review of Financial Studies*, 33(3):1256– 1295.

Bernstein, A., Gustafson, M. T., and Lewis, R. (2019). Disaster on the horizon: The price effect of sea level rise. *Journal of Financial Economics*, 134(2):253–272.

Biswas, S., Hossain, M., and Zink, D. (2023). California wildfires, property damage, and mortgage repayment.

Blickle, K., Hamerling, S. N., and Morgan, D. P. (2021). How bad are weather disasters for banks? *FRB of New York Staff Report*, (990).

Bordalo, P., Gennaioli, N., and Shleifer, A. (2012). Salience theory of choice under risk. *The Quarterly journal of economics*, 127(3):1243–1285.

Bordalo, P., Gennaioli, N., and Shleifer, A. (2013). Salience and asset prices. *American Economic Review*, 103(3):623–628.

Bordalo, P., Gennaioli, N., and Shleifer, A. (2020). Memory, attention, and choice. *The Quarterly journal of economics*, 135(3):1399–1442.

Bouvard, M. and Lee, S. (2020). Risk management failures. *The Review of Financial Studies*, 33(6):2468–2505.

Boyd, J. H. and De Nicolo, G. (2005). The theory of bank risk taking and competition revisited. *The Journal of finance*, 60(3):1329–1343.

Boyd, J. H., De Nicolo, G., and Jalal, A. M. (2009). Bank competition, risk, and asset allocations. *IMF Working Papers*, 2009(143).

Brunetti, C., Dennis, B., Gates, D., Hancock, D., Ignell, D., Kiser, E. K., Kotta, G., Kovner, A., Rosen, R. J., and Tabor, N. K. (2021). Climate change and financial stability. *FEDS Notes*, (2021-03):19–3.

Brunnermeier, M. K. and Koby, Y. (2018). The reversal interest rate. *NBER Working Paper*.

Bryant, J. (1980). A model of reserves, bank runs, and deposit insurance. *Journal of banking & finance*, 4(4):335–344.

Correa, R., He, A., Herpfer, C., and Lel, U. (2022). The rising tide lifts some interest rates: Climate change, natural disasters and loan pricing. *Working Paper*.

Council, F. S. O. (2021). FSOC report on climate-related financial risk. Technical report, *Financial Stability Oversight Council*. Deschênes, O. and Greenstone, M. (2011). Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the us. *American Economic Journal: Applied Economics*, 3(4):152–85.

Desmet, K., Kopp, R. E., Kulp, S. A., Nagy, D. K., Oppenheimer, M., Rossi-Hansberg, E., and Strauss, B. H. (2021). Evaluating the economic cost of coastal flooding. *American Economic Journal: Macroeconomics*, 13(2).

Dessaint, O. and Matray, A. (2017). Do managers overreact to salient risks? evidence from hurricane strikes. *Journal of Financial Economics*, 126(1):97–121.

DeYoung, R. and Rice, T., 2004. How do banks make money? The fallacies of fee income. Economic Perspectives-Federal Reserve Bank of Chicago, 28(4), p.34.

Di Maggio, M., Kermani, A., and Korgaonkar, S. (2019). Partial deregulation and competition: Effects on risky mortgage origination. *Management Science*, 65(10):4676–4711.

Diamond, D. W. and Dybvig, P. H. (1983). Bank runs, deposit insurance, and liquidity. *Journal of Political Economy*, 91(3):401–419.

Dinç, I. S. (2000). Bank reputation, bank commitment, and the effects of competition in credit markets. *The Review of Financial Studies*, 13(3):781–812.

Drechsler, I., Savov, A., and Schnabl, P. (2017). The deposits channel of monetary policy. *The Quarterly Journal of Economics*, 132(4):1819–1876.

Dubey, P. and Geanakoplos, J. (2002). Competitive pooling: Rothschild-Stiglitz reconsidered. *The Quarterly Journal of Economics*, 117(4):1529–1570.

Dubey, P., Geanakoplos, J., and Shubik, M. (2005). Default and punishment in general equilibrium 1. *econometrica*, 73(1):1–37.

Egan, M., Hortaçsu, A., and Matvos, G. (2017). Deposit competition and financial fragility: Evidence from the us banking sector. *American Economic Review*,107(1):169–216.

Farhi, E. and Tirole, J. (2021). Shadow banking and the four pillars of traditional financial intermediation. *The Review of Economic Studies*, 88(6):2622–2653.

Fostel, A. and Geanakoplos, J. (2008). Leverage cycles and the anxious economy. *American Economic Review*, 98(4):1211–44.

Fostel, A. and Geanakoplos, J. (2012). Tranching, cds, and asset prices: How financial innovation can cause bubbles and crashes. *American Economic Journal: Macroeconomics*, 4(1):190–225.

Freixas, X. and Rochet, J.-C. (2008). Microeconomics of banking. *MIT press*.

Fried, S. (2021). Seawalls and Stilts: A Quantitative Macro Study of Climate Adaptation. *The Review of Economic Studies*.

Froot, K. A., Scharfstein, D. S., and Stein, J. C. (1993). Risk management: Coordinating corporate investment and financing policies. *the Journal of Finance*, 48(5):1629–1658.

Furukawa, K., Ichiue, H., Shiraki, N., et al. (2020). How does climate change interact with the financial system? a survey. *Technical report, Bank of Japan*.

Gallagher, J. and Hartley, D. (2017). Household finance after a natural disaster: The case of hurricane katrina. *American Economic Journal: Economic Policy*, 9(3):199– 228.

Geanakoplos, J. (2010). The leverage cycle. NBER macroeconomics annual, 24(1):1–66.

Giglio, S., Kelly, B., and Stroebel, J. (2021). Climate finance. Annual Review of Financial Economics, 13(1):15–36.

Grossman, S. J. and Stiglitz, J. E. (1980). On the impossibility of informationally efficient markets. The American economic review, 70(3):393–408.

Hellmann, T. F., Murdock, K. C., and Stiglitz, J. E. (2000). Liberalization, moral hazard in banking, and prudential regulation: Are capital requirements enough? *American Economic Review*, 91(1):147–165.

Hellwig, C. and Veldkamp, L. (2009). Knowing what others know: Coordination motives in information acquisition. The Review of Economic Studies, 76(1):223–251.

Hong, H., Karolyi, G. A., and Scheinkman, J. A. (2020). Climate finance. The Review of Financial Studies, 33(3):1011–1023.

Hsiang, S. M. and Narita, D. (2012). Adaptation to cyclone risk: Evidence from the global cross-section. Climate Change Economics, 3(02):1250011.

Hsiang, S., S. Greenhill, J. Martinich, M. Grasso, R.M. Schuster, L. Barrage, D.B. Diaz, H. Hong, C. Kousky, T. Phan, M.C. Sarofim, W. Schlenker, B. Simon, and S.E. Sneeringer, 2023: Ch. 19. Economics. In: Fifth National Climate Assessment. U.S. Global Change Research Program.

Jung, H., Engle, R. F., & Berner, R. B. (2021). Climate stress testing (No. 977). Staff Report.

Kahn, M. E. (2021). Adapting to climate change. Yale University Press.

Keys, B. J., Mukherjee, T., Seru, A., & Vig, V. Financial regulation and securitization: Evidence from subprime loans. *Journal of Monetary Economics* 56.5 (2009): 700-720.

Keys, B.J. and Mulder, P., 2022. Neglected No More: Housing Markets, Mortgage Lending, and Sea Level Rise. *Working Paper.*

Khwaja, A.I. and Mian, A., 2008. Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *American Economic Review*, *98*(4), pp.1413-42.

Kousky, C. (2010). Learning from extreme events: Risk perceptions after the flood. *Land Economics*, 86(3):395–422.

Kozlowski, J., Veldkamp, L., and Venkateswaran, V. (2020). The tail that wags the economy: Beliefs and persistent stagnation. *Journal of Political Economy*, 128(8):2839– 2879.

Litterman, R., Anderson, C. E., Bullard, N., Caldecott, B., Cheung, M. L., Colas, J. T., Coviello, R., Davidson, P. W., Dukes, J., Duteil, H. P., et al. (2020). Managing climate risk in the us financial system: Report of the Climate-Related Market Risk Subcommittee, Market Risk Advisory Committee of the U.S. Commodity Futures Trading Commission. *Technical report*.

Meisenzahl, R., (2023). How Climate Change Shapes Bank Lending: Evidence from Portfolio Reallocation. FRB Chicago Working Paper.

Mendelsohn, R., Emanuel, K., Chonabayashi, S., and Bakkensen, L. (2012). The impact of climate change on global tropical cyclone damage. *Nature climate change*, 2(3):205– 209.

Mian, A., Rao, K., and Sufi, A. (2013). Household balance sheets, consumption, and the economic slump. *The Quarterly Journal of Economics*, 128(4):1687–1726.

Mian, A. and Sufi, A. (2011). House prices, home equity-based borrowing, and the us household leverage crisis. *American Economic Review*, 101(5):2132–56.

Mian, A. and Sufi, A. (2015). House of debt: How they (and you) caused the Great Recession, and how we can prevent it from happening again. *University of Chicago Press*.

Network for Greening the Financial System (2019). Macroeconomic and financial stability: Implications of climate change. *Technical supplement to the First comprehensive report*.

Ouazad, A. (2022). Do investors hedge against green swans? option-implied risk aversion to wildfires.

Ouazad, A. and Kahn, M. E. (2021). Mortgage finance and climate change: Securitization dynamics in the aftermath of natural disasters. *Review of Financial Studies* (forthcoming).

Phan, T. and Schwartzman, F. (2021). Climate defaults and financial adaptation. *Richmond Fed Working Paper*.

Rochet, J.-C. and Tirole, J. (1996). Interbank lending and systemic risk. *Journal of Money, credit and Banking*, 28(4):733–762.

Rothschild, M. and Stiglitz, J. (1978). Equilibrium in competitive insurance markets: An essay on the economics of imperfect information. In *Uncertainty in economics*, pages 257–280. Elsevier.

Stiglitz, J. E. and Weiss, A. (1981). Credit rationing in markets with imperfect information. The *American economic review*, 71(3):393–410.

Tirole, J. (1994). On banking and intermediation. European Economic Review, 38(3- 4):469–487.

Yannelis, C. and Zhang, A. L. (2023). Competition and selection in credit markets. *Journal of Financial Economics*, 150(2):103710.

Weitzman, M. L. (2009). On modeling and interpreting the economics of catastrophic climate change. *The review of economics and statistics*, 91(1):1–19.

Weitzman, M. L. (2014). Fat tails and the social cost of carbon. *American Economic Review*, 104(5):544–46.

Weitzman, M. L. (2020). Fat-tailed uncertainty in the economics of catastrophic climate change. *Review of Environmental Economics and Policy*.

Figure 1

Loan Coverage in Regulatory Bank Data

The figure displays a map of the log of home equity loans by county based on the regulatory bank data.

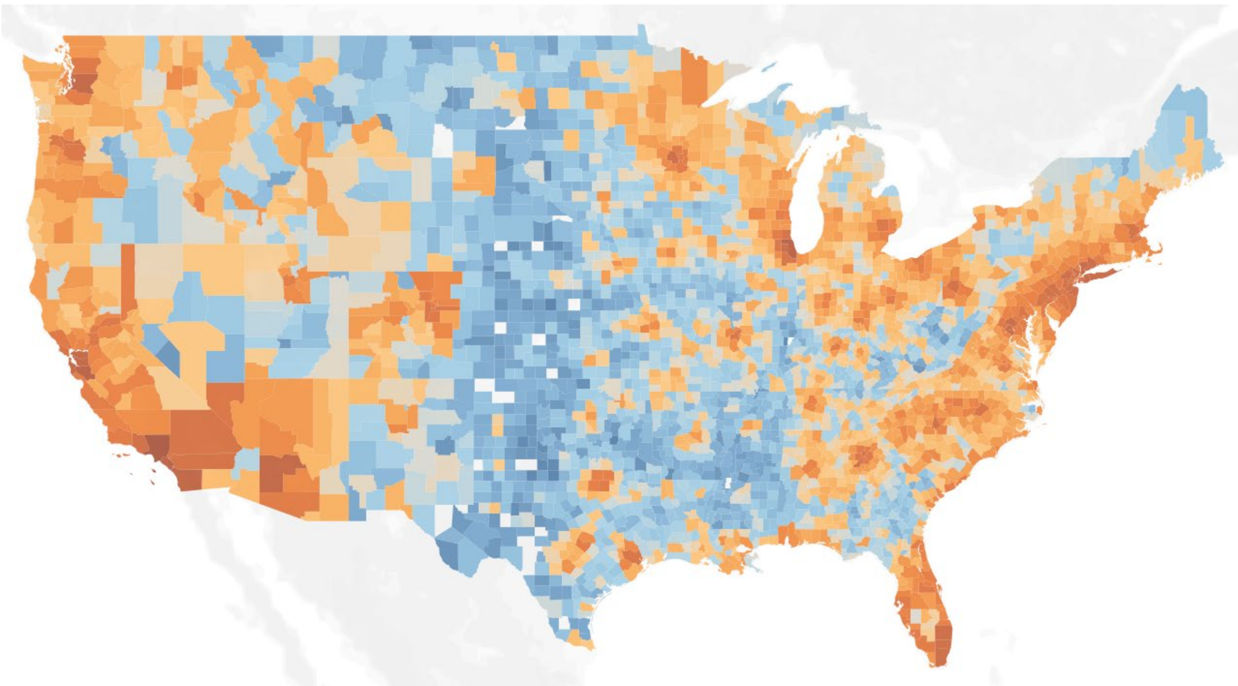

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Figure 2

Loan Coverage in Credit Bureau Data

The figure displays a map of the log of home equity loans by county based on the credit bureau data.

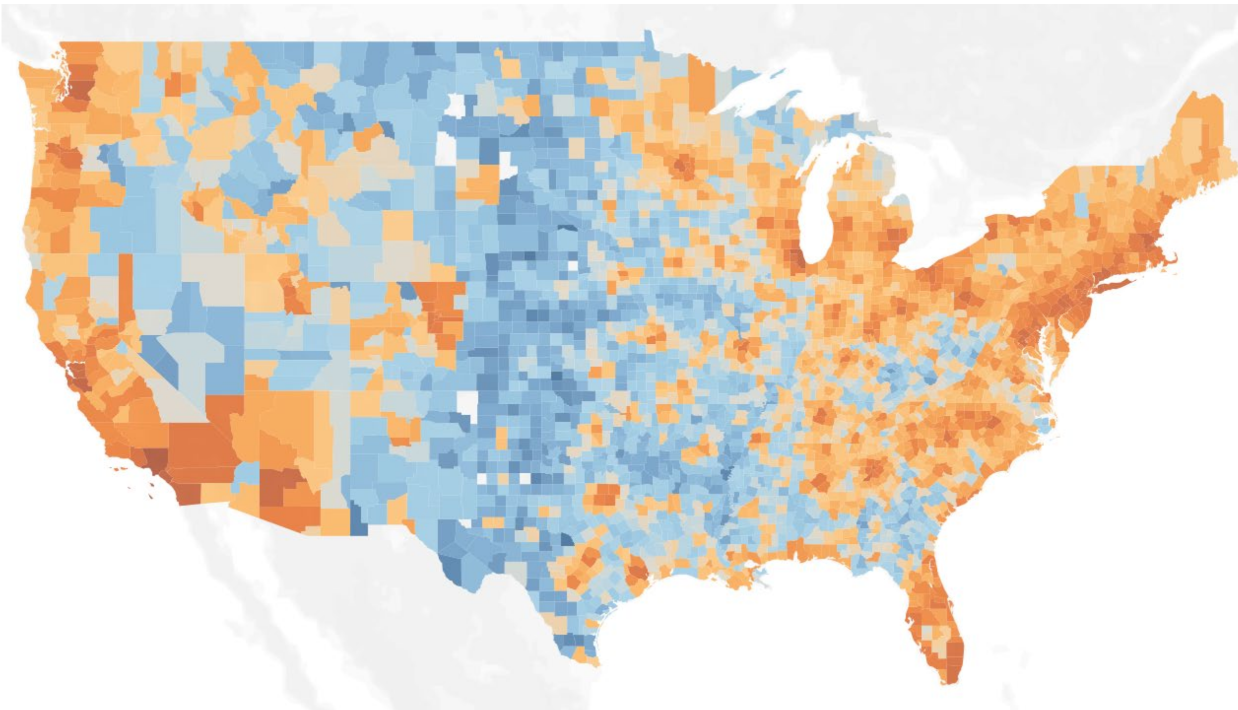

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Figure 3

Areas Affected by Hurricane Harvey

The figure displays a map of the trajectory of Hurricane Harvey.

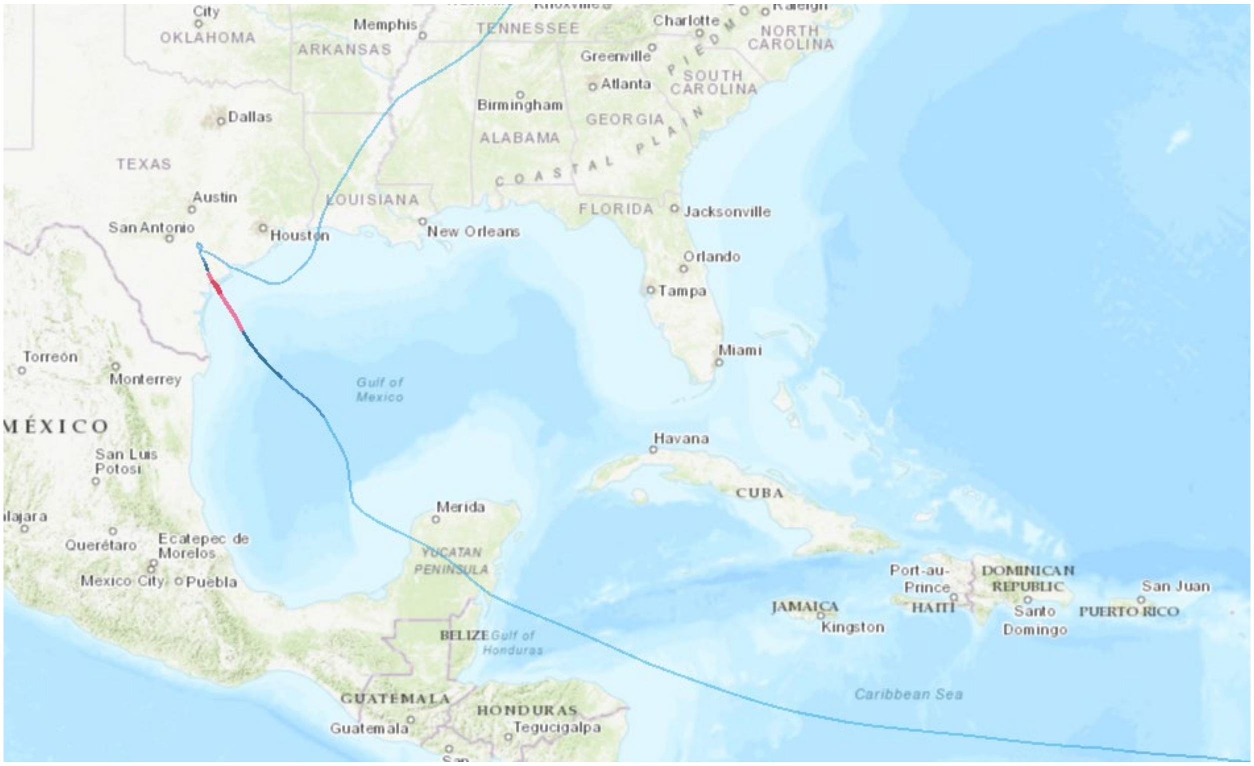

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Figure 4

Geographic Distribution of Flood Risks

The figure displays a map of log of the average *FloodRisk* using the publicly available zip code level data from the First Street Foundation.

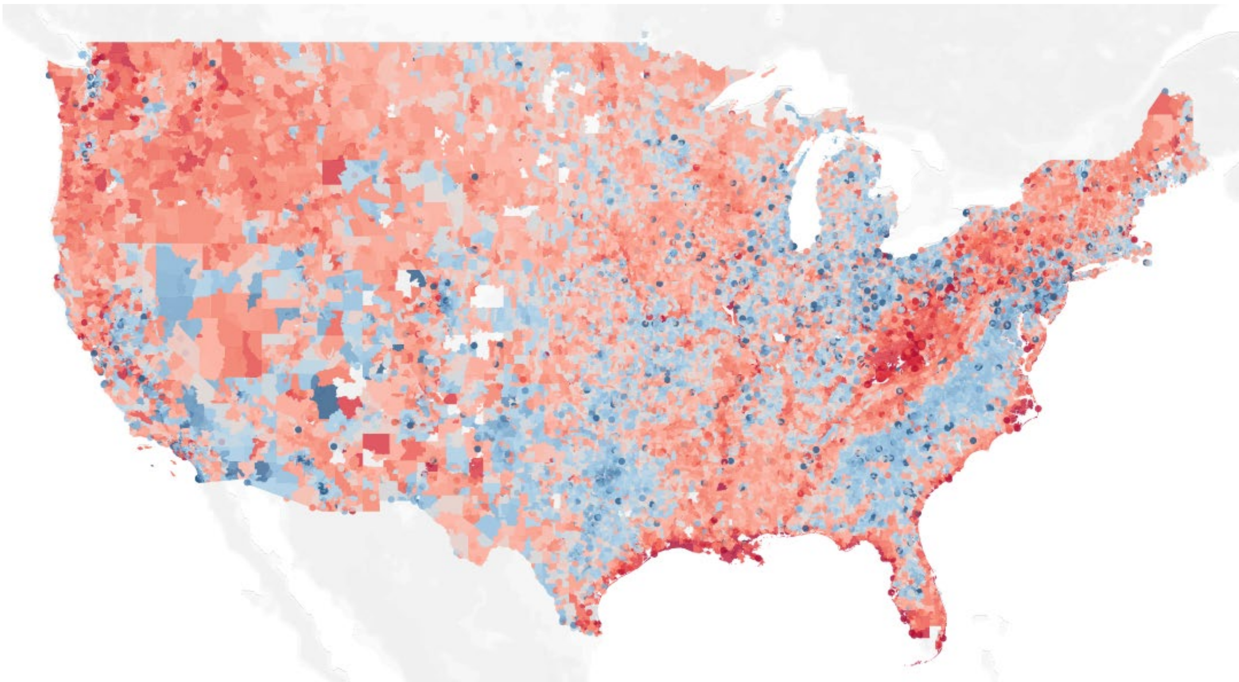

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Figure 5

Heterogeneity in Bank Exposures to Hurricane Harvey

The figure displays a map of counties to indicate variation of *BankExposure* across banks within counties in which banks lend. The choropleth is configured such that counties where all banks have no exposure are colored light grey, where there are both banks with and without exposures are colored dark grey, and where all banks with some exposure are colored orange.

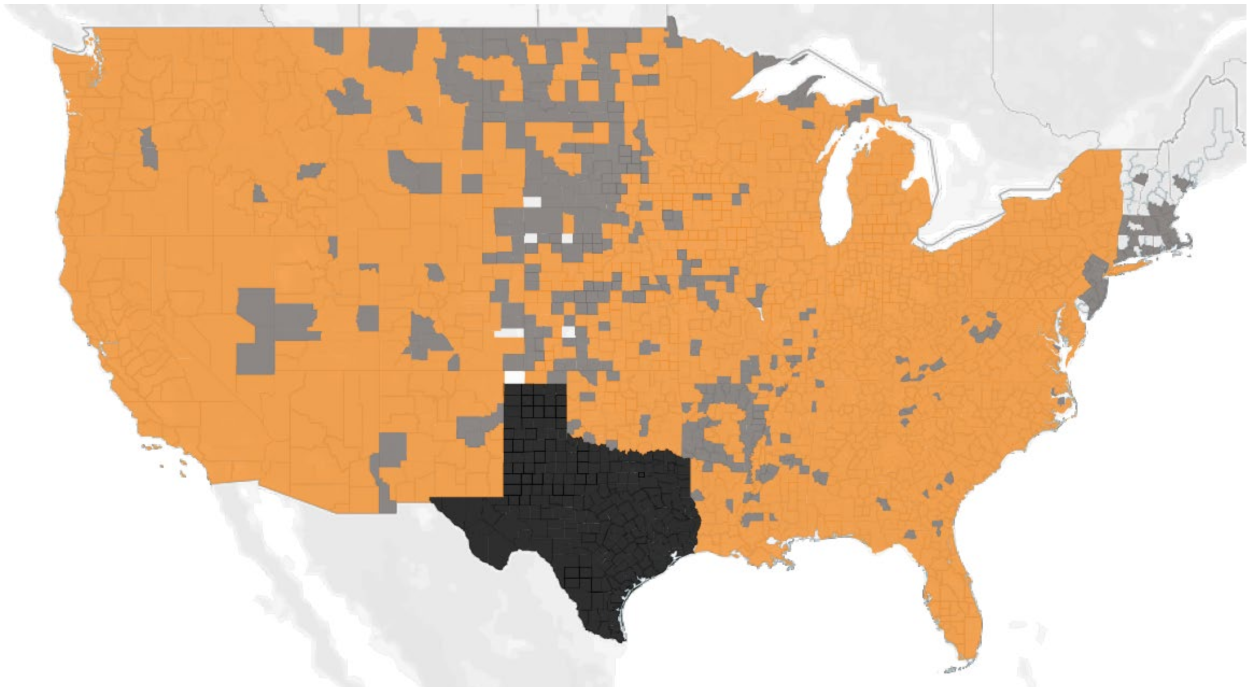

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Figure 6

Marginal Effects of Flood Risk on Default Probabilities Around Natural Disaster

The figure displays calculations from univariate regression coefficients where the dependent variable is the banks' estimates of probability of default (*PD*) for each borrower and the explanatory variable is *FloodRisk*. The figure shows the estimated average marginal effects with 95% confidence bands by quarter surrounding the event.

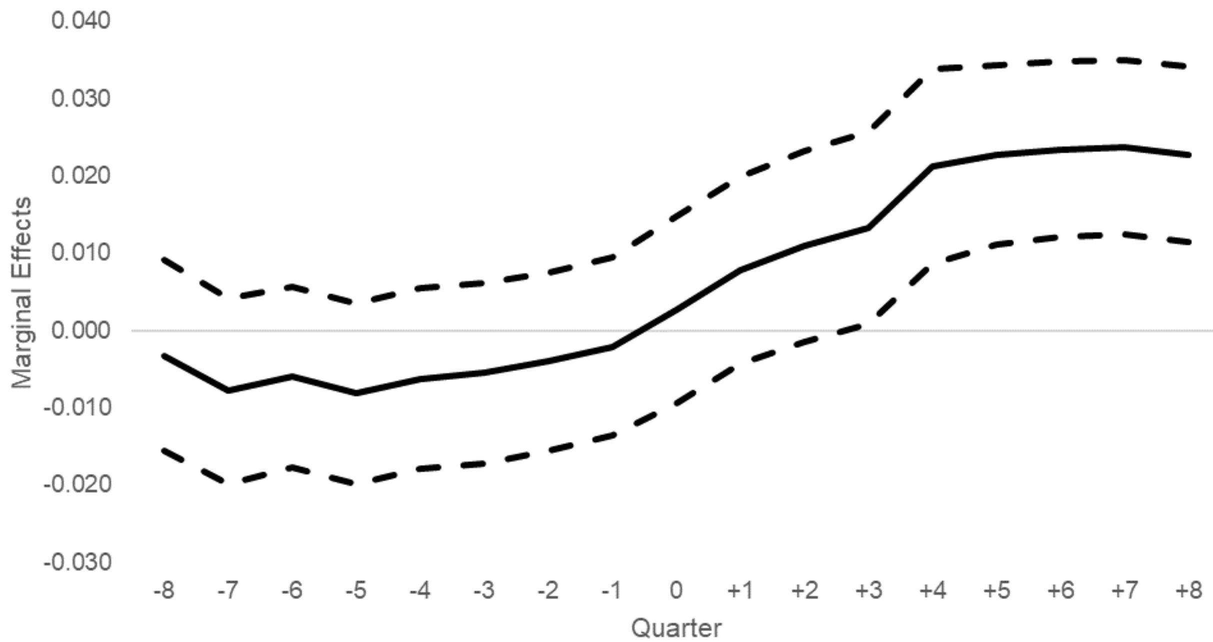

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Figure 7

Frequency and Costs of Billion Dollar Disasters over Time

The figure displays the annual frequency and total costs of storms that cause at least $1 Billion in damages, with the damage amount adjusted by the CPI.

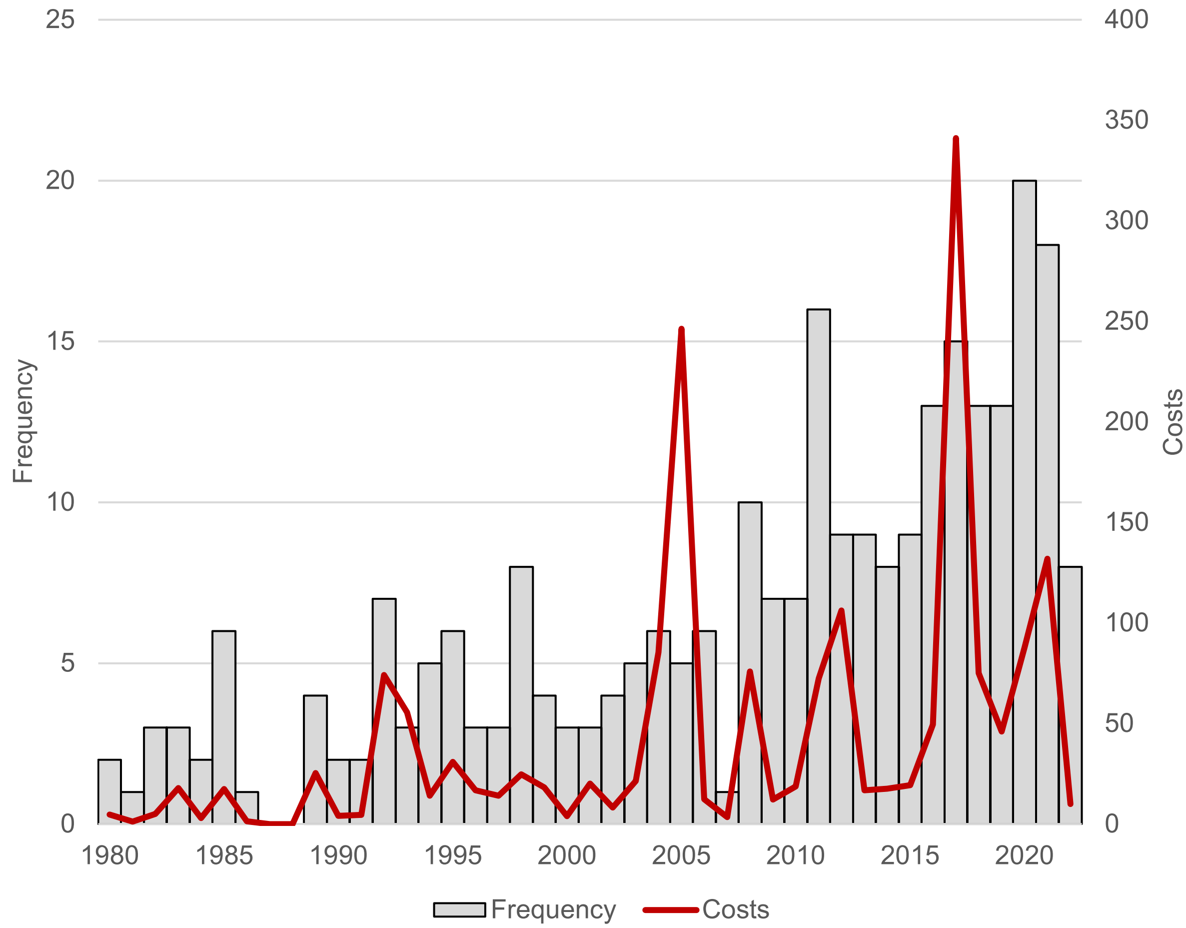

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Figure 8

Marginal Effects of Bank Exposures and Flood Risk

The figure displays a figure of regression analysis results where the dependent variable is the banks' estimates of probability of default (*PD*) for each borrower and the explanatory variables are interaction terms between quarter dummies and *FloodRisk*. The figure shows the estimated average marginal effects with 95% confidence bands by quarter surrounding the event.

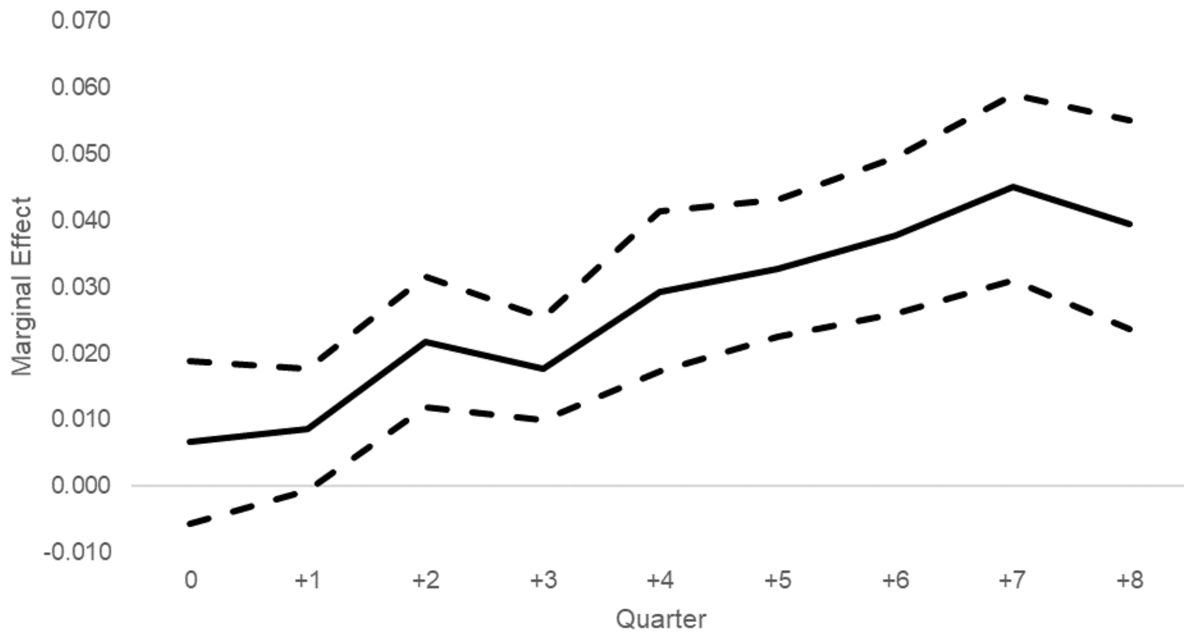

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Table 1

Variable Descriptions and Summary Statistics

The figure displays descriptions and summary statistics of household-month level variables that were used in this study. The table includes observation counts, sample means, standard deviations, and selected percentile values for the full sample of data that is used in the study.

Panel A: Variable Definitions

Variable Name	Variable Description
PD	Borrower's probability of default on the loan based on bank's internal risk model
FloodRisk	Risk of a property will be involved in a 1-in-100 year flood as of 2020
%SFHA	The fraction of properties in a ZIP code classified as being in a SFHA
BankExposure	The proportion of a bank's loan portfolio that is in the path of Hurricane Harvey
Delinquent	Non-current loan status
Drawdown	Dollar amount of line drawn down by borrower
Limit	Dollar amount of bank's commitment to the line

Panel B: Summary Statistics

Variable Name	N	Mean	Standard Deviation	25th Percentile	50th Percentile	75th Percentile
PD	176,566,141	0.045	0.185	0.000	0.002	0.007
FloodRisk	176,566,141	1.487	1.699	1.000	1.000	1.000
%SFHA	176,600,000	4.966	11.477	0.500	1.500	3.900
BankExposure	176,566,141	0.077	0.056	0.030	0.084	0.146
Delinquent	176,566,141	0.026	0.158	0.000	0.000	0.000
Drawdown	176,566,141	50,467	98,344	5,310	26,750	62,118
Limit	176,566,141	84,897	141,972	5,510	50,000	100,000

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Table 2

Flood Risk Distribution and Characteristics

The figure displays a table comparing distributional values of FEMA's percentage of households that fall in the agency's special flood hazard area by zip code, *%SFHA*, for *FloodRisk.* The table includes, for each value of *FloodRisk*, percentages of zip codes designated with this value as well as sample means, standard deviations and coefficients of variation of the corresponding *%SFHA* measures.

FloodRisk Values	Frequency	$\%SFHA_z$ Mean	$\%SFHA_z$ Standard Deviation	$\%SFHA_z$ Coefficient of Variation
1	85.7%	3.1%	6.2%	2.00
2	2.6%	13.4%	15.2%	1.13
3	2.5%	11.5%	16.5%	1.43
4	2.4%	11.5%	19.4%	1.69
5	1.0%	17.2%	22.1%	1.28
6	2.9%	13.8%	21.4%	1.55
7	0.9%	13.3%	22.2%	1.67
8	0.3%	25.3%	27.5%	1.09
9	1.1%	34.8%	36.4%	1.05
10	0.7%	34.4%	36.7%	1.07

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Table 3

Baseline Regression Models

The figure displays a table of regression analysis where the dependent variable is the banks' estimates of probability of default (*PD*) for each borrower and the explanatory variables are interaction terms between *FloodRisk* and time dummies. The table entries show the coefficient estimates with standard errors in parentheses. The stars denote statistical significance level: ***, **, and * for significance at the 1%, 5%, and 10% levels respectively.

	(1)	(2)	(3)
Dependent Variable:	$PD_{i,g,b,t}$	$PD_{i,g,b,t}$	$PD_{i,g,b,t}$
$Post_t$	-0.001		
	(0.004)		
$Post_t$ x $FloodRisk_i$	0.011***	0.003***	
	(0.001)	(0.001)	
$Post_t$ (Q0) x $FloodRisk_i$			0.000
			(0.001)
$Post_t$ (Q1) x $FloodRisk_i$			0.001*
			(0.000)
$Post_t$ (Q2) x $FloodRisk_i$			0.002***
			(0.001)
$Post_t$ (Q3) x $FloodRisk_i$			0.003***
			(0.001)
$Post_t$ (Q4) x $FloodRisk_i$			0.004***
			(0.001)
$Post_t$ (Q5) x $FloodRisk_i$			0.004***
			(0.001)
$Post_t$ (Q6) x $FloodRisk_i$			0.004***
			(0.001)
$Post_t$ (Q7) x $FloodRisk_i$			0.004***
			(0.001)
$Post_t$ (Q8) x $FloodRisk_i$			0.004***
			(0.001)

Table 3 (cont.)

HH FEs	YES	YES	YES
Bank x Date FEs	NO	YES	YES
County x Date FEs	NO	YES	YES
N	176,300,388	176,297,415	176,297,430
R^2	86.3%	86.4%	85.9%

[Return to Text]

Table 4

Bank Exposures to Hurricane Harvey

The figure displays a table of regression analysis where the dependent variable is the banks' estimates of probability of default (*PD*) for each borrower and the explanatory variables are interaction terms between *FloodRisk*, *BankExposure* and time dummies. The table entries show the coefficient estimates with standard errors in parentheses. The stars denote statistical significance level: ***, **, and * for significance at the 1%, 5%, and 10% levels respectively.

	(1)	(2)
Dependent Variable:	$PD_{i,g,b,t}$	$PD_{i,g,b,t}$
$Post_t$	-0.010*	
	(0.006)	
$Post_t$ x $FloodRisk_i$	0.007***	-0.002*
	(0.001)	(0.001)
$Post_t$ x $BankExposure_b$	138.018**	
	(66.912)	
$Post_t$ x $BankExposure_b$ x $FloodRisk_i$	41.851***	57.618***
	(10.860)	(9.225)
HH FEs	YES	YES
Bank x Date FEs	NO	YES
County x Date FEs	NO	YES
N	176,300,388	176,297,415
R^2	86.3%	86.4%

[Return to Text]

Table 5

Utilization

The figure displays a table of regression analysis where the dependent variable of each column are transformations of the banks' reported values of *ΔDrawDown* and *ΔLimit,* and the explanatory variables are interaction terms between *FloodRisk*, *BankExposure* and time dummies for each borrower-month. The table entries show the coefficient estimates with standard errors in parentheses. The stars denote statistical significance level: ***, **, and * for significance at the 1%, 5%, and 10% levels respectively.

	(1)	(2)
Dependent Variable:	$\Delta DrawDown_{i,g,b,t}$	$\Delta TotalLimit_{i,g,b,t}$
$Post_t$ x $FloodRisk_i$	0.000***	0.000
	(0.000)	(0.000)
$Post_t$ x $BankExposure_b$ x $FloodRisk_i$	-0.170***	-0.434***
	-(0.002)	-(0.097)
HH FEs	YES	YES
Bank x Date FEs	YES	YES
County x Date FEs	YES	YES
N	165,852,880	149,641,041
R^2	5.2%	6.6%

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Table 6

Bank Adaptation

The figure displays a table of regression analysis where the dependent variable is the change in market share of a bank in a particular county. Column (1), (2) and (3) display the results based upon the subsamples associated with a FSF Flood Factor score within the bottom, middle and top tercile, respectively. Columns (4) and (5) display the results for the full sample. *MediumFloodRisk* and *HighFloodRisk* are indicators that are 1 when the *FloodRisk* value of a home falls in the middle and top tercile, and 0 otherwise, respectively. The table entries show the coefficient estimates with standard errors in parentheses. The stars denote statistical significance level: ***, **, and * for significance at the 1%, 5%, and 10% levels respectively.

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	$\Delta MarketShare_{i,j,c}$				
$BankExposure_i$	-32.639***	-42.924***	-51.576***	-33.680***	
	(2.761)	(2.939)	(3.552)	(2.772)	
$MediumFloodRisk_{j,c}$				0.000***	0.000***
				(0.000)	(0.000)
$HighFloodRisk_{j,c}$				0.000	0.000
				(0.000)	(0.000)
$BankExposure_i \times MiddleFloodRisk_{j,c}$				-8.616***	-6.598**
				(3.280)	(3.262)
$BankExposure_i \times HighFloodRisk_{j,c}$				-17.686***	-12.379***
				(3.985)	(3.961)
County FEs	YES	YES	YES	YES	YES
Bank FEs	NO	NO	NO	NO	YES
N	29,951	36,138	31,664	97,756	97,756
R^2	3.21%	3.06%	3.05%	2.04%	15.15%

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Table 7

Market Share

The figure displays a table of regression analysis where the dependent variable is the change in market share of a bank in a particular county. *MediumFloodRisk* and *HighFloodRisk* are indicators that are 1 when the *FloodRisk* value of a home falls in the middle and top tercile, and 0 otherwise, respectively. The table entries show the coefficient estimates with standard errors in parentheses. The stars denote statistical significance level: ***, **, and * for significance at the 1%, 5%, and 10% levels respectively.

	(1)	(2)	(3)
MarketShare^{2014} Subsample:	Low	High	All
Dependent Variable:	ΔMarketShare$_{i,j,c}$		
MediumFloodRisk$_{j,c}$	0.000	0.002***	0.000***
	(0.000)	(0.000)	(0.000)
HighFloodRisk$_{j,c}$	0.000*	-0.001	0.000
	(0.000)	(0.001)	(0.000)
BankExposure$_i$ × MediumFloodRisk$_{j,c}$	0.637	-17.539*	-3.582
	(1.344)	(9.787)	(4.103)
BankExposure$_i$ × HighFloodRisk$_{j,c}$	-1.938*	-34.591***	-11.178**
	(1.114)	(11.859)	(4.816)
MediumFloodRisk$_{j,c}$ × MarketShare$^{2014}_{i,j}$			-0.017***
			(0.003)
HighFloodRisk$_{j,c}$ × MarketShare$^{2014}_{i,j}$			-0.027***
			(0.004)
BankExposure$_i$ × MarketShare$^{2014}_{i,j}$			-857.487***
			(74.299)
BankExposure$_i$ × MediumFloodRisk$_{j,c}$ × MarketShare$^{2014}_{i,j}$			-115.967
			(73.703)
BankExposure$_i$ × HighFloodRisk$_{j,c}$ × MarketShare$^{2014}_{i,j}$			-190.068**
			(79.551)

Table 7 (cont.)

County FEs	YES	YES	YES
Bank FEs	YES	YES	YES
N	48,807	48,865	97,756
R^2	16.89%	27.55%	18.69%

[Return to Text]

Table 8

Market Concentration

The figure displays a table of regression analysis where the dependent variable is the change in market share of a bank in a particular county. *MediumFloodRisk* and *HighFloodRisk* are indicators that are 1 when the *FloodRisk* value of a home falls in the middle and top tercile, and 0 otherwise, respectively. *HHI* is the home equity loan HHI for in the county. The table entries show the coefficient estimates with standard errors in parentheses. The stars denote statistical significance level: ***, **, and * for significance at the 1%, 5%, and 10% levels respectively.

	(1)	(2)	(3)
HHI Subsample:	Low	High	All
Dependent Variable:	$\Delta MarketShare_{i,j,c}$		
$MidRisk_{j,c}$	0.000**	0.001**	0.001***
	(0.000)	(0.000)	(0.000)
$HighRisk_{j,c}$	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
$BankExposure_i \times MidRisk_{j,c}$	2.064	-11.343	-4.990
	(2.082)	(6.961)	(3.697)
$BankExposure_i \times HighRisk_{j,c}$	1.048	-18.594**	-11.847***
	(2.572)	(8.113)	(4.423)
$MidRisk_{j,c} \times HHI_j$			0.021*
			(0.011)
$HighRisk_{j,c} \times HHI_j$			0.024**
			(0.012)
$BankExposure_i \times HHI_j$			-781.351***
			(149.198)
$BankExposure_i \times MidRisk_{j,c} \times HHI_j$			-203.475
			(191.783)
$BankExposure_i \times HighRisk_{j,c} \times HHI_j$			-451.903**
			(222.549)

Table 8 (cont)

County FEs	YES	YES	YES
Bank FEs	YES	YES	YES
N	48,867	48,889	97,756
R^2	17.51%	16.29%	15.50%

[Return to Text]

Table 9

Peer Exposure

The figure displays a table of regression analysis where the dependent variable is the change in market share of a bank in a particular county. *MediumFloodRisk* and *HighFloodRisk* are indicators that are 1 when the *FloodRisk* value of a home falls in the middle and top tercile, and 0 otherwise, respectively. *PeerExposure* is the fraction of competing banks in the local market with *BankExposure* above the sample mean. The table entries show the coefficient estimates with standard errors in parentheses. The stars denote statistical significance level: ***, **, and * for significance at the 1%, 5%, and 10% levels respectively.

	(1)	(2)	(3)
PeerExposure Subsample:	Low	High	All
Dependent Variable:	ΔMarketShare$_{i,j,c}$		
MidRisk$_{j,c}$	0.000	0.001**	0.000***
	(0.000)	(0.000)	(0.000)
HighRisk$_{j,c}$	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
BankExposure$_i$ × MidRisk$_{j,c}$	0.423	-9.967	-3.070
	(2.357)	(6.454)	(3.428)
BankExposure$_i$ × HighRisk$_{j,c}$	-1.509	-18.019**	-9.529**
	(3.009)	(7.898)	(4.312)
MidRisk$_{j,c}$ × PeerExposure$_{i,j}$			0.032***
			(0.004)
HighRisk$_{j,c}$ × PeerExposure$_{i,j}$			0.030***
			(0.005)
BankExposure$_i$ × PeerExposure$_{i,j}$			-88.730**
			(39.507)
BankExposure$_i$ × MidRisk$_{j,c}$ × PeerExposure$_{i,j}$			-99.145**
			(47.664)
BankExposure$_i$ × HighRisk$_{j,c}$ × PeerExposure$_{i,j}$			-128.634**
			(59.700)

Table 9 (cont.)

County FEs	YES	YES	YES
Bank FEs	YES	YES	YES
N	49,256	48,463	97,748
R^2	19.61%	18.84%	15.39%

[Return to Text]

Table A1

Alternative Flood Risk Measure

The figure displays a table of regression analysis where the dependent variable is the banks' estimates of PD for each borrower and the explanatory variables are interaction terms between *%SFHA*, *BankExposure* and time dummies. The table entries show the coefficient estimates with standard errors in parentheses. The stars denote statistical significance level: ***, **, and * for significance at the 1%, 5%, and 10% levels respectively.

	(1)	(2)	(3)
Dependent Variable:	$PD_{i,g,b,t}$	$PD_{i,g,b,t}$	$PD_{i,g,b,t}$
$Post_t$	0.012***		
	(0.004)		
$Post_t$ x $\%SFHA_g$	0.010***	0.002***	-0.002**
	(0.001)	(0.000)	(0.001)
$Post_t$ x $BankExposure_b$ x $\%SFHA_g$			42.670***
			(9.388)
HH FEs	YES	YES	YES
Bank x Date FEs	NO	YES	YES
County x Date FEs	NO	YES	YES
N	176,559,372	176,559,372	176,559,372
R^2	85.8%	86.0%	86.0%

[Return to Text]

Table A2

Flood Risk versus SFHAs

The figure displays a table of regression analysis where the dependent variable is the banks' estimates of PD for each borrower and the explanatory variables are interaction terms between *FloodRisk*, *BankExposure* and time dummies. The regressions are performed on subsamples based on whether the observation is below and above the sample median for *%SFHA*. The table entries show the coefficient estimates with standard errors in parentheses. The stars denote statistical significance level: ***, **, and * for significance at the 1%, 5%, and 10% levels respectively.

	(1)	(2)	(3)	(4)
Dependent Variable:	$PD_{i,g,b,t}$	$PD_{i,g,b,t}$	$PD_{i,g,b,t}$	$PD_{i,g,b,t}$
$Post_t$ x $FloodRisk_i$	0.0213***	0.003***	0.0142***	-0.004**
	(0.002)	(0.001)	(0.003)	(0.002)
$Post_t$ x $BankExposure_b$			219.133***	-46.01
			(55.803)	(67.141)
$Post_t$ x $BankExposure_b$ x $FloodRisk_i$			61.648**	90.640***
			(29.449)	(21.794)
HH FEs	YES	YES	YES	YES
Bank x Date FEs	NO	YES	NO	YES
County x Date FEs	NO	YES	NO	YES
N	176,564,108	176,564,108	176,564,108	176,564,108
R^2	85.8%	86.0%	85.8%	86.0%

[Return to Text]

Table A3

Probability of Default Estimates with Selected States Dropped

The figure displays a table of regression analysis where the dependent variable is the banks' estimates of PD for each borrower and the explanatory variables are interaction terms between *FloodRisk*, *BankExposure* and time dummies. Across the columns, the results are displayed based upon which state associated with the loan is dropped from the estimation. The table entries show the coefficient estimates with standard errors in parentheses. The stars denote statistical significance level: ***, **, and * for significance at the 1%, 5%, and 10% levels respectively.

	(1)	(2)	(3)	(4)	(5)
Dropped State:	California	Florida	Louisiana	New York	Texas
$Post_t$ x $FloodRisk_i$	-0.001	-0.000	-0.002**	-0.002**	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$Post_t$ x $BankExposure_b$ x $FloodRisk_i$	72.186***	37.729	60.327***	59.026***	57.577***
	(10.207)	(6.838)	(10.211)	(9.577)	(9.221)
HH FEs	YES	YES	YES	YES	YES
Bank x Date FEs	YES	YES	YES	YES	YES
County x Date FEs	YES	YES	YES	YES	YES
N	140,511,455	160,583,231	175,361,475	163,645,476	176,512,296
R^2	85.6%	86.0%	86.0%	86.0%	86.0%

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Table A4

Flood Risk Dummy Specification

The figure displays a table of regression analysis where the dependent variable is the banks' estimates of PD for each borrower and the explanatory variables are interaction terms between *FloodRisk*, *BankExposure* and time dummies. In this specification, *FloodRisk* is a dummy based upon FSF Flood Factor scores of five or higher. The table entries show the coefficient estimates with standard errors in parentheses. The stars denote statistical significance level: ***, **, and * for significance at the 1%, 5%, and 10% levels respectively.

	(1)	(2)	(3)	(4)
Dependent Variable:	$PD_{i,g,b,t}$	$PD_{i,g,b,t}$	$PD_{i,g,b,t}$	$PD_{i,g,b,t}$
$Post_t$ x $FloodRisk_i$	0.011***	0.003***	0.009***	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
$Post_t$ x $BankExposure_b$			131.694*	-18.405
			(78.887)	(53.803)
$Post_t$ x $BankExposure_b$ x $FloodRisk_i$			22.156*	32.332***
			(12.4718)	(10.241)
HH FEs	YES	YES	YES	YES
Bank x Date FEs	NO	YES	NO	YES
County x Date FEs	NO	YES	NO	YES
N	124,734,380	124,734,380	124,734,380	124,734,380
R^2	85.7%	85.9%	85.7%	85.9%

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