Bank Competition and Strategic Adaptation to Climate Change

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Abstract

How do strategic interactions between financial institutions influence adaptation behavior to emergent risks where regulatory oversight is limited? We join detailed bank supervisory data with high resolution climate data to identify adaptation behavior of banks to climate change. We exploit heterogeneous in bank learning about climate shocks following Hurricane Harvey to examine the influence of the adaptation choices of competitors. First, banks that learn about climate risks reduce lending to riskier markets while uninformed banks increase market share. Second, despite learning, informed banks are less likely to adapt when facing greater competitive pressures. Finally, banks are less likely to adapt in markets where competitors are also less likely to do so, suggesting strategic complementarities in adaptation behavior. More broadly, our paper sheds light on the role of competitive forces in how banks manage emergent risks. *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 emergent risks, such as climate change.[1] The effects of climate-related financial risks are of increasing relevance to policymakers.[2] Yet, regulatory oversight of climate risks and other emergent risks is inherently limited—regulators as well as financial institutions face similar challenges in not only the identification but also the management of those risks. Climate change makes the distribution of disaster risks—e.g., hurricanes and flooding—nonstationary, and the uncertainty of nonstationary processes renders learning about them difficult.[3] Consequently, financial institutions face a joint problem of identifying appropriate models to properly capture evolving risks and quantifying exposures to them. A fundamental issue underlying this problem is that data on rare disasters are limited precisely because these events are rare.

This paper provides evidence of coordination across banks in their adaptation behavior to climate change. While there are other studies that also examine how interactions between competing financial institutions affect risk taking activities, they primarily focus on margins where supervisors provide guidance on managing those risks.[4] In contrast, regulators lack appropriate supervisory tools for emergent risks. In the absence of formal regulatory guidance, some financial institutions may become informed about risks before others. For example, institutions exposed to rare natural disasters may have access to data regarding those risks that may be costly to acquire otherwise. Competitive pressures may lead some institutions to act strategically in their adaptation to these risks. On the one hand, banks that become informed about risks may choose to curtail activities in risky markets. Uninformed banks may decide to continue those activities, potentially creating fragilities by concentrating risks in those institutions. On the other hand, despite their informational advantages, informed banks may choose not to adapt if competitors do not. As such,

[1] Hong et al. (2020), Furukawa et al. (2020), and Giglio et al. (2021) provide excellent overviews.
[2] 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.
[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] 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.

there may be important interactions amongst financial institutions that affect their adaptation choices, potentially creating vulnerabilities in the credit markets. Even if dislocations arise only initially, they may still have destabilizing effects.

Subjective beliefs about climate change are important to observe for properly identifying a bank's strategic choices with regard to adaptation. Interpretation of choices based on bank outcomes alone is incomplete, as some outcomes are observationally consistent with both a deliberate strategy and a lack of awareness. For instance, if an econometrician observes a bank continuing to lend in areas with rising flood risks but lacks insight into the bank's internal risk models, it remains ambiguous whether this is due to ignorance or strategic considerations. A key limitation of existing studies is the paucity of data on climate beliefs of financial institutions. We address this issue by using confidential bank regulatory data, allowing us to "under the hood" to directly identify individual bank beliefs from their internal risk models and track how their beliefs change in the face of climate shocks. We join the regulatory data with high resolution climate data in order to precisely pinpoint property-level exposures to natural disasters as well as future flood risk exposures in areas unaffected by those disasters. Specifically, our analysis focuses on the effects of bank loan portfolio exposures to Hurricane Harvey, one of the most expensive natural disasters in U.S. history (NOAA 2018).[5] We confirm that bank exposures to the hurricane is strongly correlated with bank learning about climate risks, allowing us to differentiate between banks that are informed and uninformed about climate risks for the main tests.

We construct tests that allow us to identify adaptation behavior, namely bank outcomes that can be linked to changes in beliefs. We find direct evidence of bank adaptation to climate change: informed banks, or banks with greater exposures to the hurricane, are more likely to internalize and subsequently reduce portfolio exposures to future flood risks. In contrast, we show that uninformed banks, or banks with lower exposures, respond by actually increasing their market share. We next perform further tests to better understand the competitive mechanisms underlying these results. First, we examine the effects of general competitive conditions across local markets. We show that local market competition has a dampening effect on adaptation behavior—the

[5] An important reason why we choose to focus on Hurricane Harvey is because of the prevalence of anthropogenic markers related to climate change associated with the event (Risser and Wehner 2017). This increased concerns in the scientific community about the validity of existing risk models due to the increasing relevance of climate change factors. These concerns were directly relevant to banks as well, given that many used the same model, and may have motivated some banks to invest in developing or expanding climate expertise.

reductions in risky lending disappear when local competitive pressures are higher. Second, we directly consider the effects of the adaptation behavior of competing banks. 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 adaptation behavior by financial institutions. Together, 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.

Overall, our findings have potentially important policy implications. For instance, much of the regulatory proposals and policy experiments currently being considered on climate risks have focused on the behavior of individual institutions, which are relevant for microprudential policies.[6] 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.

1.1 Related Literature

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 (2) the large extant literature on how competition affects outcomes in financial markets. Our findings are also relevant to the literature that studies investment under uncertainty.

1.1.1 Climate Finance

Our paper contributes to the literature that studies climate risks in financial markets. This is the first paper to consider the role of competitive dynamics in shaping how financial institutions adapt to climate risks. By offering perspectives from lenders—or credit suppliers—our paper enriches the extensive and evolving research on how climate risks, particularly flooding, impact household finance through the housing and mortgage markets (Bernstein et al. 2019; Baldauf et

[6] 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.

al. 2020; Murfin and Spiegel 2020; Bakkensen and Barrage 2022; Keys and Mulder 2022, Bakkensen, Wong, and Phan 2024).

Several papers also use regulatory data to examine the effects of climate-related financial risks on bank lending activities. Meisenzahl (2023) examines the relationship between county-level flood and wildfire risks on county-level bank activities related to residential and commercial property lending. He finds evidence that large U.S. banks have reallocated their loan portfolios away from counties with increased climate-related disaster risks in recent years, particularly following 2015. This study documents a related finding for HELOCs that is consistent with those patterns: on average, banks assign greater weights on climate risk factors in the internal risk models in the years following Hurricane Harvey, which directly feeds into lending decisions. An important difference is that we purposely exclude areas directly affected by the hurricane. Moreover, our analysis leverages granular loan-level that allows us to account for unobservable factors that are difficult to control for using aggregated data. Namely, we adopt an approach similar to Khwaja and Mian (2008) by employing high-dimensional fixed effects in our estimators to account for time-varying local demand and other supply shocks as well as other unobservable factors associated with the borrower.

Correa et al. (2022) use regulatory data to examine how banks adjust pricing on commercial loans in response to natural disasters. They find evidence that loan spreads for borrowers with high exposures to hurricane-prone areas spike during climate-related natural disasters but find no effect for earthquakes. Interestingly, they find that the effects are short-lived and revert shortly after the events. Additionally, they document a corresponding spike in default probability levels. Their results are consistent with findings from the literature on learning from extreme events (Kousky 2010; Gallagher and Hartley 2017, Dessaint and Matray 2017, Alok et al. 2020, Ouazad 2022). Our results complement those studies in that we document longer-lived effects in the HELOC markets. In being able to look “under the hood” of banks’ decision making with the regulatory data on bank’s internal risk models, our paper provides new insights into how financial institutions update beliefs about future climate risks. We are able to detect a positive weight in bank internal risk models in the months following Hurricane Harvey but do not find a non-zero weight in prior periods. However, we show that the flood risk weights follow a concave pattern over time, increasing through four quarters following the event before stabilizing. In other words, while previous studies find that the effects of disasters on investors' choices tend to diminish gradually over time and consistent with the theory of salience bias, we find that the effects on banks are more persistent and grows stronger over time, suggesting that the effects are attributable to durable informational advantages related to exposures to the hurricane rather than salience. Importantly, another distinction between the analysis of this paper and that of prior studies is that we are able to identify heterogeneity in learning about climate risks, which we in turn relate to bank outcomes.

In documenting the strategic dimension of bank adaptation, our paper is related to Ouazad and Kahn (2022), who find evidence 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 (GSEs).[7] Blickle, Perry and Santos (2024) also find that nonbanks and local banks are likely to securitize mortgages to properties with high future flood risks but are outside of current official floodplain maps. Our study complements these studies by documenting the strategic dimension of bank adaptation to climate change in the HELOC markets. Here, banks have considerably more "skin in the game" compared to the first-lien mortgage market, primarily because they cannot readily sell these loans to the GSEs and so are more likely to retain those exposures. This provides our analysis with an advantage that mitigates potential selection issues associated with securitization.

1.1.2 Bank Competition

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.[8] This 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); and Whited et al. (2021); and Wang et al. (2022). Our analysis differs from these studies in several important ways. First, we are able to directly observe bank perceptions about risks, and study how they evolve over time. This allows us to distinguish between actions undertaken by banks to purposely increase risk and decisions made by a bank associated with risks unknown to the bank. We find evidence that banks actively

[7] Also see the discussions in Lacour-Little et al. (2021) and Ouazad and Kahn (2023). Also see Nguyen et al (2022).
[8] Berger et al. (2004) and Berger et al. (2017) provide excellent summaries of the earlier theoretical and empirical literature.

update their risk beliefs heterogeneously depending on their exposures to shocks associated with those risks. Namely, we show that bank learning is concentrated in banks with higher exposures to the hurricane; the effects are statistically and economically insignificant for banks with no exposure. These results suggest that banks collect data associated with these events and subsequently incorporate them into their internal risk models. As the effects do not revert in subsequent years, this form of soft information may represent a source of durable informational advantages for the affected banks.

Second, we consider a setting with limited regulatory oversight. The absence of formal supervisory guidance implies that banks are better able to take risks without significant regulatory interference. Despite this, we find evidence that banks still actively manage these risks under certain conditions. Our baseline specifications indicate that banks with higher hurricane exposures reduce lending in risky markets on average. Interestingly, these results also imply that banks with lower exposures increase their lending in response, though are unlikely to be aware of the associated risks. These results underscore the possibility of spillovers on other banks of risky activities in the absence of regulatory checks.

Third, our setting provides an ideal laboratory for studying the effects of competition on bank risk-taking. Again, limited oversight of emergent risks provides opportunities for regulatory leakage. We find evidence that competition conditions moderate bank adaptation responses despite learning. Banks with higher exposures to Hurricane Harvey 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 competitive markets. 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.

Finally, in analyzing a spillover in bank adaptation, our paper is also related to Di Maggio et al. (2019). That study provides 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. This paper considers a different setting. We study the effects of competitor exposures to the hurricane within the same local market. Our 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. The presence of spillovers are key in understanding whether there are potential inefficiencies in how banks manage emergent risks. The form of spillover that we document 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).

1.1.3 Investment Under Uncertainty

This study also informs the literature that examines investment under uncertainty. Doshi et al. (2018) examine the effects of price uncertainty on risk management policies of oil producing firms. Unlike this paper, their study focuses on transient uncertainty shocks and does not consider market structure. Our paper is more closely related to Guiso and Parigi (1999), Patnaik (2016) and Bulan et al. (2009). Using data on Italian manufacturing firms, Guiso and Parigi (1999) find evidence that uncertainty attenuates the responsiveness of investments to demand. When considering competition, they show that lower levels of competition increase the effects of uncertainty on investment. Patnaik (2006) finds consistent evidence. He exploits industry exposures to uncertainty related to weather changes associated with the El Niño Southern Oscillation cycle to estimate the uncertainty-investment relationship. He finds that higher uncertainty has a negative impact on investments, but primarily for firms in concentrated industries. Finally, Bulan et al. (2009) use Canadian data on listed condominium development firms. They find a negative relationship between stock returns volatility and investment behavior. Using local information on competing firms in proximity of each project, they find that competition reduces uncertainty-investment sensitivities. This paper differs in several important ways. First, we focus on risk management rather than only investment behavior. Second, our paper is able to estimate uncertainty-investment sensitivities within the same bank across investment projects with varying levels of risk. Given the granularity of the data, we are able to construct an empirical strategy that allows us to better account for omitted variables associated at both the bank- and project-levels.

1.2 Paper Organization

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

2. Data

2.1 Data Sources

We use confidential, bank supervisory data obtained from Schedule B.1 of the Federal Reserve Board's FR Y-14M from January 2014 through December 2019. The data are collected by regulators for the purpose of stress testing the largest U.S. bank holding companies. The data are reported monthly by large banks who hold or service domestic home equity loans and home equity lines of credit (HELOC), and include loan-level information on the respondent bank's HELOC portfolio.

One reason why our analysis focuses on the HELOC market is that it provides an excellent environment to study climate adaptation due to several institutional details. Like first-lien mortgage loans, HELOCs are collateralized by real estate assets, which are particularly exposed to future climate-related risks due to their durability and immobility. Unlike mortgages, HELOCs cannot be readily securitized and sold off the banks' balance sheets due to a relatively limited secondary market. Focusing on HELOCs helps us better identify the ways that banks may adapt to climate risks. HELOCs represent long-term investments that sit on bank balance sheets for quite some time, making it more likely for banks to be cognizant of associated risks. It also alleviates 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).[11]

This dataset features almost 180 million observations of 6.9 million households located across 2,962 counties. To be included in the analysis, we require the availability of certain fields, including those related to a bank's internal risk model, such as each loan's default probability.[12] The data provide unique loan identifiers allowing us to track the loan over time. Importantly, the data include the exact address of the underlying collateral. The data also includes information related to the loan, including loan terms and utilization, as well as borrower characteristics at origination.

Importantly, the reporting banks account for a majority share of the entire HELOC market, or approximately 59%. To assess the representativeness of the data to the complete market, we compare the loan coverage in the FR Y-14M data to a comprehensive sample based upon credit bureau data. **Figure 1** shows the geographic distribution of home equity line balances represented in the bank regulatory data, by county. The choropleth is formatted such that lower (higher) densities are shaded blue (orange). The figure indicates broad geographic coverage of the dataset. We next 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.

[Insert Figure 1]

[Insert Figure 2]

[11] 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.

[12] For further background, see Christensen (2007).

Detailed satellite imagery data that provides information on the path of Hurricane Harvey 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. Hurricane Harvey has been estimated to have caused approximately $125 billion in damages, making it one of the costliest natural disasters in U.S. history (NOAA 2018). One reason why the analysis focuses on Hurricane Harvey is the prevalence of anthropogenic markers related to climate change associated with the event (Risser and Wehner 2017). This uniquely signaled intensification of climate-related disasters (Trenberth et al 2018) and damage from inland flooding (Zhang et al 2018). In contrast, coastal flooding generally accounted for a bulk of damages for previous disasters. This spurred discussion in the scientific community on the appropriateness of existing models to project loss distributions due to disasters going forward. These discussions were also relevant to financial institutions, such as banks and insurers, as many of them relied on the same models.

Figure 3 displays a visualization of areas affected by Hurricane Harvey. Similar to 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. We use the data to identify properties associated with loans in the bank regulatory data that were crossed by the hurricane path.

[Insert Figure 3]

We also merge the regulatory data with data from the First Street Foundation in order to pinpoint each property's future flood risks. The First Street Foundation provides property-level flood future risk estimates, called the flood factor. The measure is defined on a scale from 1 to 10. It 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. The model 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). 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).

2.2 Data Description

Table 1 displays the summary statistics. The loan-level probability of default measure 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. Additionally, the flood risk measure from First Street Foundation also exhibits right skewness and is transformed similarly for the analysis.

[Insert Table 1]

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).

[Insert 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.

[Insert 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). Texas is excluded in our analysis for reasons discussed in the next section, 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.

[Insert Figure 5]

3. Empirical Design

An important identifying assumption underlying our main tests on competition relates to how banks learn about climate risks following a natural disaster. Specifically, we conjecture that banks with larger ex ante exposures to natural disasters are more likely to learn and therefore are better able to incorporate climate risks into their internal risk models. If so, we will be able to directly trace changes in bank beliefs about climate change based upon the exposures to bank outcomes. Importantly, this will allow us to examine how those responses are in turn conditioned by competitive factors.

3.1. Learning and Exposures to Natural Disaster

Our experimental setting focuses on bank learning about climate risks following a natural disaster. We argue that, while natural disasters are generally visible to all banks, 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.

Some banks may have better access to information about climate risks that would be otherwise costly to obtain relative to other banks due to exposures to natural disasters. Following a natural disaster, banks may be able to collect data on affected properties associated with their loan portfolios. On the one hand, 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. On the other hand, the severity of the damages due to the disaster may also 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. This form of soft information may provide banks with durable informational advantages that should correspond with meaningful changes in bank beliefs. As such, banks may be more likely to incorporate this information into their internal risk models.

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. In turn, 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 channels by which banks change their behavior following a natural disaster that are unrelated to changes in their risk 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. For example, Cortes and Strahan (2017) document declines in lending to markets connected to lenders exposed to natural disasters, driven mostly by smaller banks that are more likely to experience financial constraints. They find that the effects are concentrated in markets that are peripheral to a bank's core operations, but also find increased securitization activities as well as higher deposit yields in core markets. Their findings underscore the importance of differentiating bank outcomes that may not necessarily coincide with changes in bank risk perceptions. To contrast, our analysis focuses on a sample of the largest U.S. banks, mitigating potential effects related to this channel.

3.2. Bank Learning Tests

Identifying bank beliefs and learning is oftentimes inferred indirectly by examining changes in ex post behavior. However, there are cases where outcomes may not necessarily comport with belief changes, which may suggest alternative mechanisms at work, or where there is an absence of behavioral changes in spite of belief changes. Because our analysis focuses on assessing channels that modulate adaptation behavior, it is critical to observe both.

To overcome these challenges, our empirical strategy centers on extracting bank beliefs from their internal risk models that are directly used in lending decisions. This allows us to directly identify adaptation behavior: namely outcomes that can be directly tied to changes in beliefs. 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.

We take a reduced form approach in recovering weights related to climate factors from bank internal risk models. Typically, banks provide examiners extensive documentation on their internal risk models, which in some cases can be hundreds of pages long. We infer the model weights from the default probability estimates obtained through the regulatory data, which are directly derived from these models. Simply put, we regress the loan-level default probabilities on property-level climate risk measures; the resulting risk loading from the regression should correspond with the weight related to climate risks in the model.

One potential drawback with this approach is that the internal risk models may also include myriad covariates that are unobservable to the econometrician. These factors may include both time-varying credit demand as well as other supply factors. In order to address this issue, we employ high dimensional fixed effects estimators similar to Khwaja and Mian (2008). First, loan fixed effects allow us to restrict the model to time variation within the same household, which mitigates the influence of household and loan 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 enable 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.

A key identifying assumption we make in the analysis relates to differentiating banks that learn from banks that do not, or banks that are informed and uninformed with respect to climate risks, respectively. Namely, we assume that bank exposures to Hurricane Harvey correspond with learning about climate risks. We start the analysis by directly testing this assumption. Specifically, we recover weights from internal bank risk models related to climate risk factors and measure how they change in response to the hurricane, and how the changes in those weights differ based upon the loan portfolio exposures across banks. 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 (i.e., Texas).

In order to test this assumption, we consider several tests. We start with 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 loan fixed effects to mitigate these concerns, we also provide tests in the next section that inform to what extent this identifying assumption holds.

For loan 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.

3.3. Market Share Tests

We next describe the main tests that focus on adaptation behavior. Those tests examine the change in the competitive positions of treated and untreated banks in the aftermath of Hurricane Harvey outside of the affected areas. Specifically, we focus on changes in banks' market shares for each local market. Critically, we focus on the differential responses for loans that have higher and lower climate risks within a particular market. An implication of adaptation is that informed banks, or banks with hurricane exposures, should decrease market shares in riskier markets following the hurricane. 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 is a triple-difference estimator where the dependent variable is the change in local market share from July 2017 to December 2019. The data is aggregated to the levels 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 the end of 2019, (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.

4. Bank Learning Results

This section presents the results from the tests that examine bank learning about climate risks following Hurricane Havey. We find evidence in support for our key identifying assumption that bank exposures to the hurricane is strongly associated with bank learning about climate risks.

4.1. Flood Risk and Internal Bank Models

We start with simple tests based on univariate regression models where the dependent variable is the loan-level default probability, i.e., PD, and the explanatory variable is the property-level 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 given a one-standard deviation increase in $FloodRisk$ relative to its sample mean. For example, for the +8-quarter subsample, the marginal effect is 1.3%. In comparison, the sample mean is 4.5%.

[Insert 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 appear to 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. There are several explanations that can potentially explain these patterns. First, there was considerable discussion in the scientific community following Hurricane Harvey on the failures of existing climate models to predict the large losses associated with the event. This may have motivated some banks to invest in developing their own expertise to better understand climate risks. Second, technological advances during this period may have 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 multivariate regression model specifications, which address various endogeneity issues described in the previous section. The results are displayed in **Table 3**.

[Insert Table 3]

We present the results iteratively including additional factors in each specification to help assess their importance. Column (1) only include loan 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. 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.

4.2. Heterogenous Bank Learning

We next examine heterogeneity in how internal bank risk models are updated in response to bank exposures to Hurricane Harvey. The tests will assess to what degree exposures to the hurricane provide informational advantages to banks with respect to climate risks.

To examine the role of bank exposures to the natural disaster, we augment the baseline specification with the exposure measure, or $BankExposure$, as described earlier. **Table 4** displays the results. Column (1) only includes loan 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.

[Insert Table 4]

We next consider the extent to which the results are due to 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.

[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.

[Insert Figure 7]

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 mean of 4.5%. These results support the interpretation that the effects are related to informational advantages of the affected banks.

[Insert Figure 8]

4.3. Robustness Checks

We next consider several robustness checks in order to dig deeper into the results and evaluate 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 all banks before the event—the FEMA Special Flood Hazard Area (SFHA) classifications. **Table Al** 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 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, and New York. **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**).

4.4. Bank-level Lending Tests

We next analyze bank adaptation by checking if the effect of learning corresponds with changes in drawdown behavior and credit line provisioning on existing loans. 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.

[Insert 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.

5. Bank Adaptation Behavior

This section presents the results from tests on bank 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. As such, we use loan portfolio exposures to Hurricane Harvey as in instrument to help us differentiate informed versus uninformed banks with respect to climate risks. In response to the risks, informed banks may choose to adapt to these risks; that is, they may pull out of or decrease exposures to riskier segments of the market. This may be particularly true for junior lien property loans, as insurance payout are less likely to cover losses due to lower seniority in the absolute priority rule.

Table 6 displays evidence on the market share tests. The dependent variable is the change in the natural log of one plus the market share from July 2017 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.

[Insert 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 due to the hurricane.

Overall, these results provide direct evidence of bank adaptation to climate change. The results also suggest that uninformed banks respond by actually increasing their lending activities in riskier markets. This suggests a potential source of vulnerability, as it implies that risks will be concentrated in these institutions, which have 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 are more likely to 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. These results are also consistent with strategic substitutability in risky lending, as uninformed banks appear to take on loans that informed banks choose to pass on.

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.

[Insert 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.

6. Competitive Mechanisms

In this section, we examine mechanisms underlying the adaptation results related to competitive dynamics.

We start by examining the effects of general competitive conditions across local markets. We use a setup that is similar to that of Table 6, though the specifications are augmented by the local market Herfindahl–Hirschman index (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.

[Insert Table 8]

Across the specifications, the results indicate that the main effects are primarily isolate to concentrated markets. In other words, 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.

These results suggest that, despite their informational advantages, informed banks choose not to adapt when they face higher competitive pressures in local markets. One reason why they may do so is because banks may be more willing to take losses in issuing riskier loans if they are able to recoup these losses in other business lines through product bundling (DeYoung and Rice, 2004).

Next, we investigate whether there is a potential spillover in banks' climate adaptation strategies. 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 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.

[Insert 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 is statistically significant.

These results provide evidence of coordination in bank adaptation behavior. Namely, the results are consistent with strategic complementarities in adaptation behavior. These dynamics 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. This may be particularly true if the bank is more concerned about preserving their market shares (Di Maggio et al 2019).

7. Conclusion

Joining confidential, bank supervisory data with high resolution climate data, we provide evidence of coordination in bank adaption behavior to climate change. We provide direct evidence of bank adaptation that links changes in lending behavior with changes in beliefs about climate risks in the aftermath of Hurricane Harvey. However, we find that banks are less likely to adapt when facing greater competitive pressures in local markets. Moreover, we document a spillover in adaptation behavior, namely evidence of strategic complementarities in adaptation: a bank is less likely to adapt when competitors are unlikely 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.

Our findings highlight the interdependence of adaptation outcomes among banks for climate change, and potentially other emergent risks: 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.

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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.

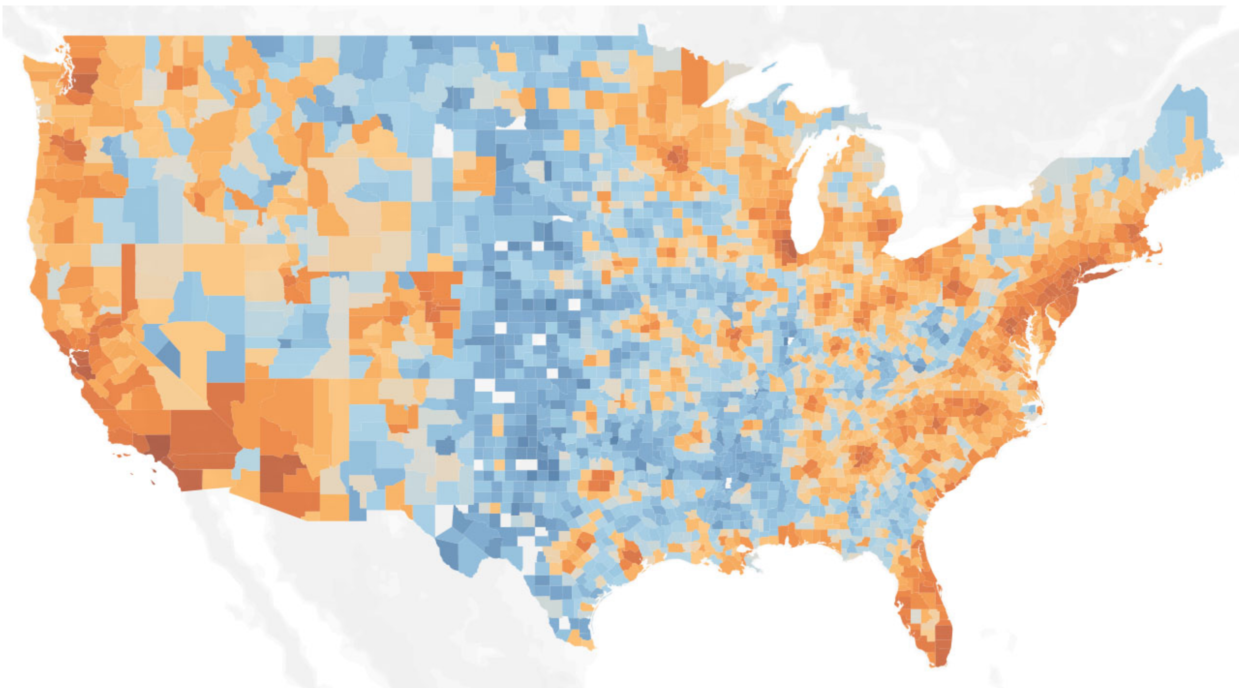

Figure 2

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.

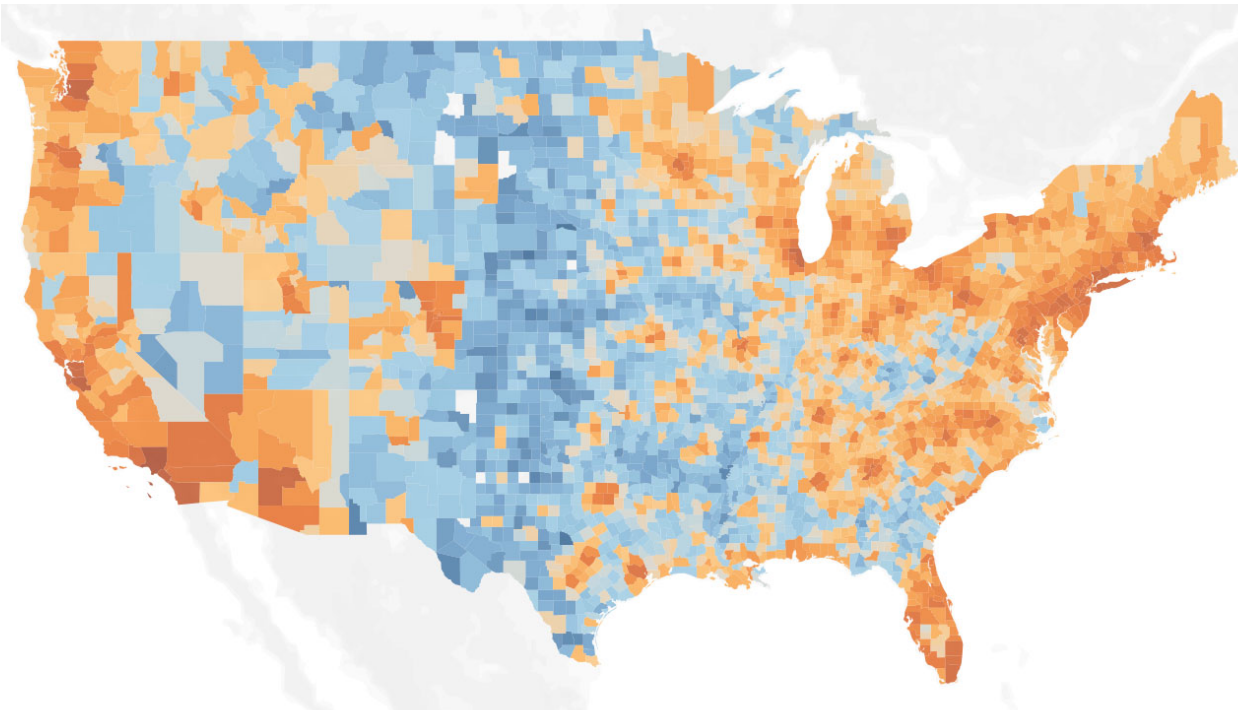

Figure 3

Areas Affected by Hurricane Harvey

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

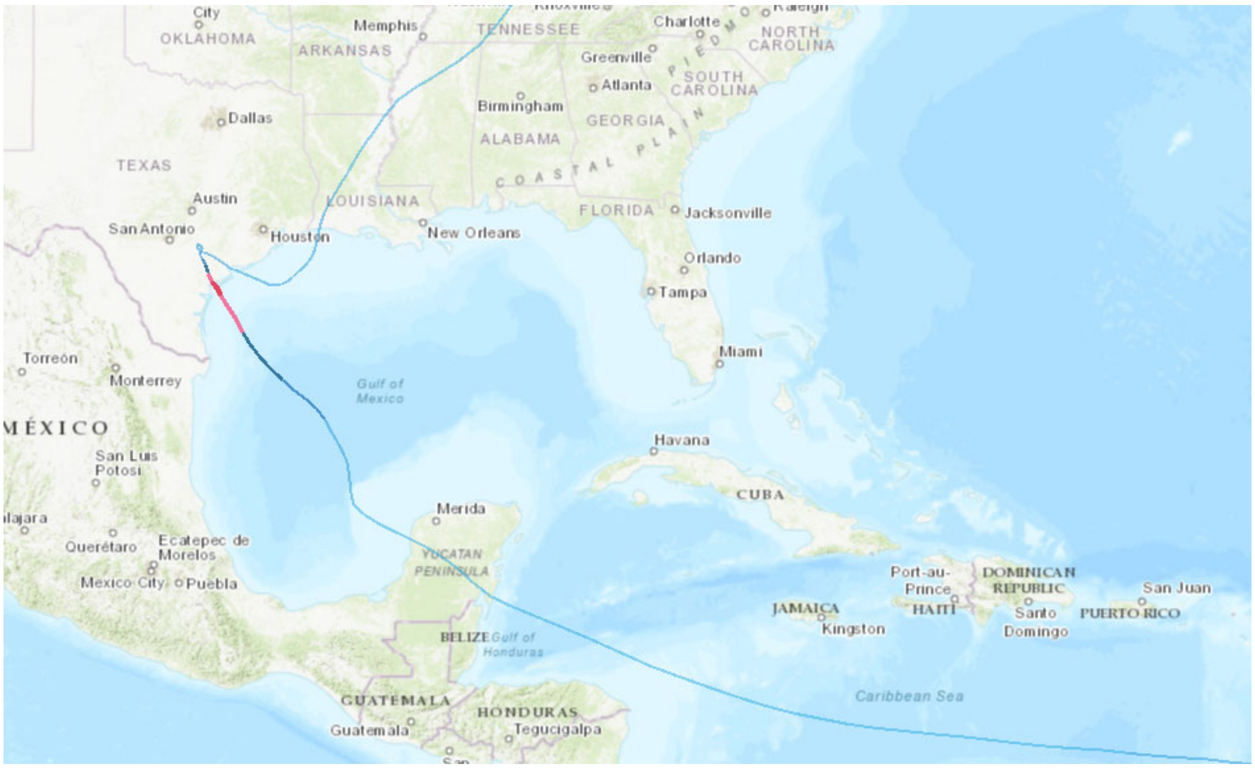

Figure 4

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.

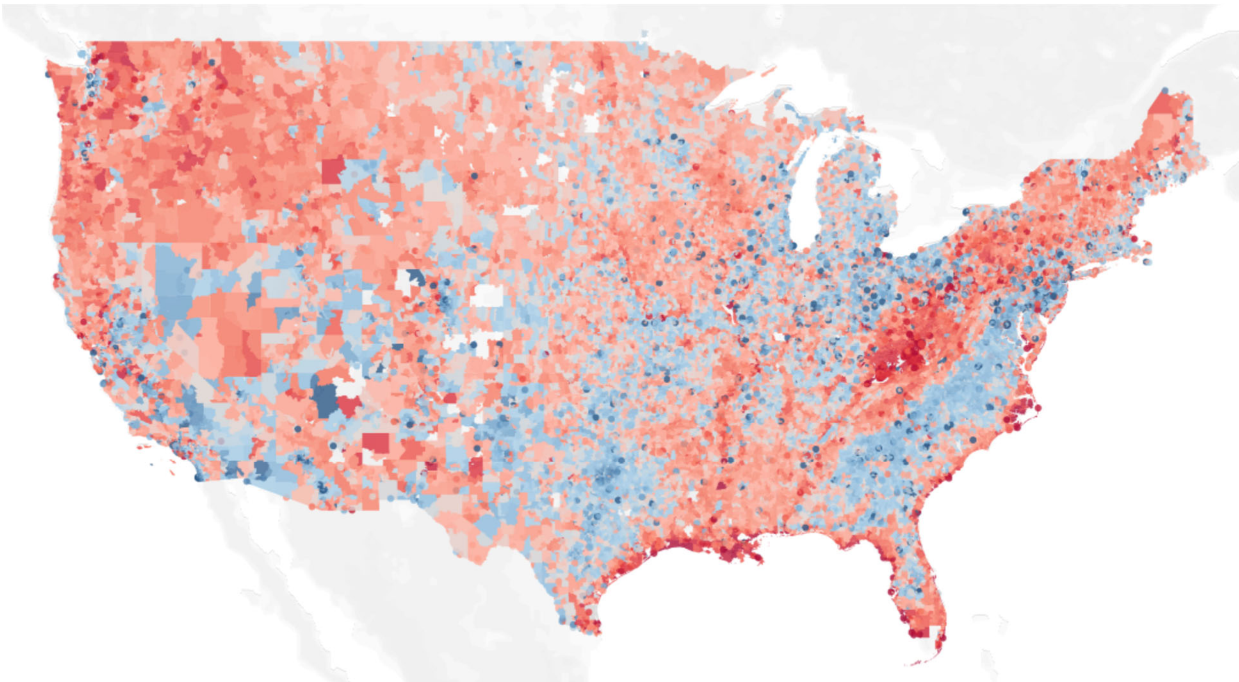

Figure 5

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.

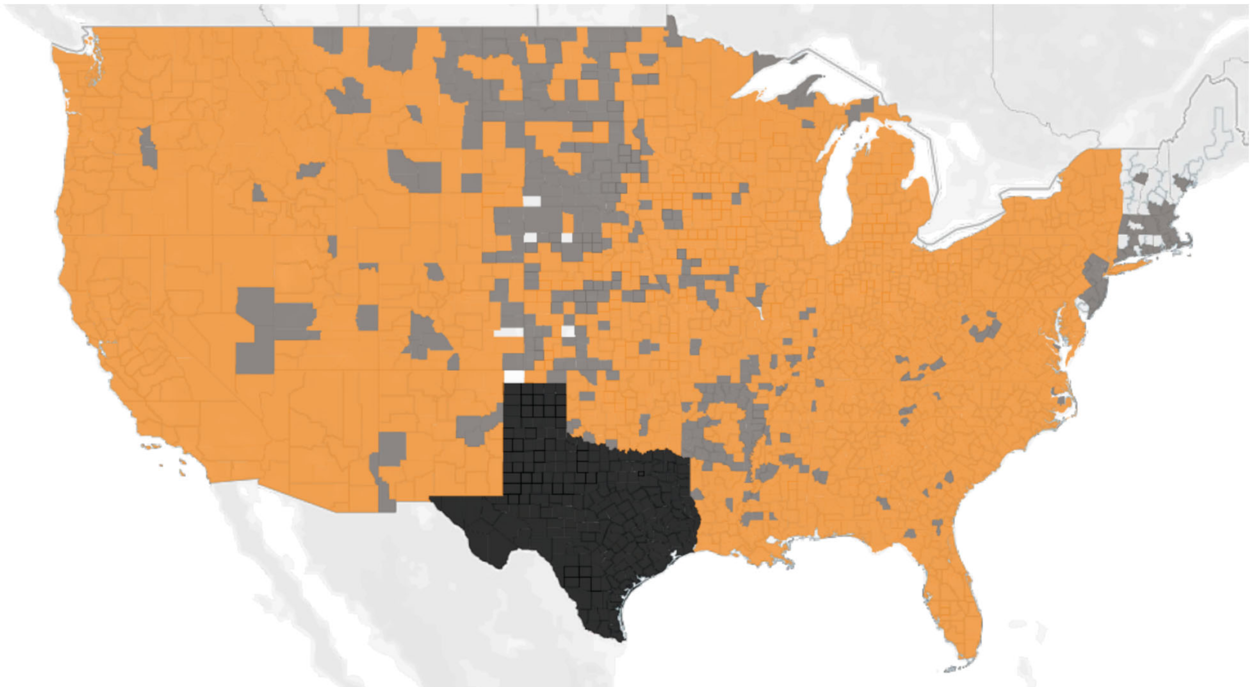

Figure 6

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.

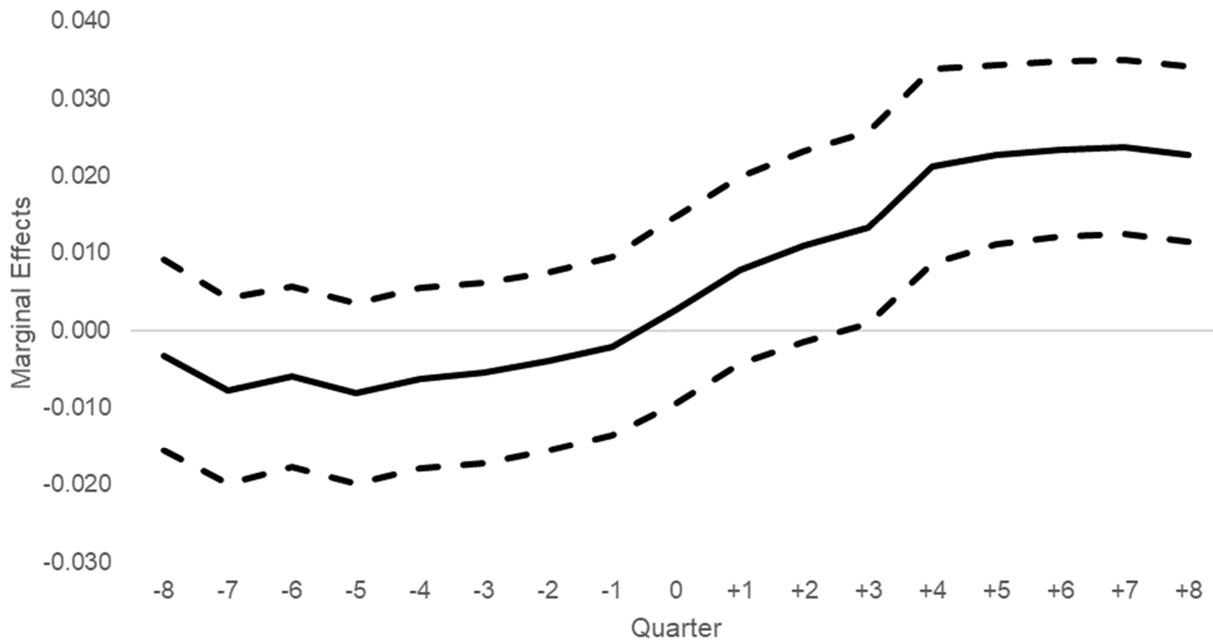

Figure 7

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.

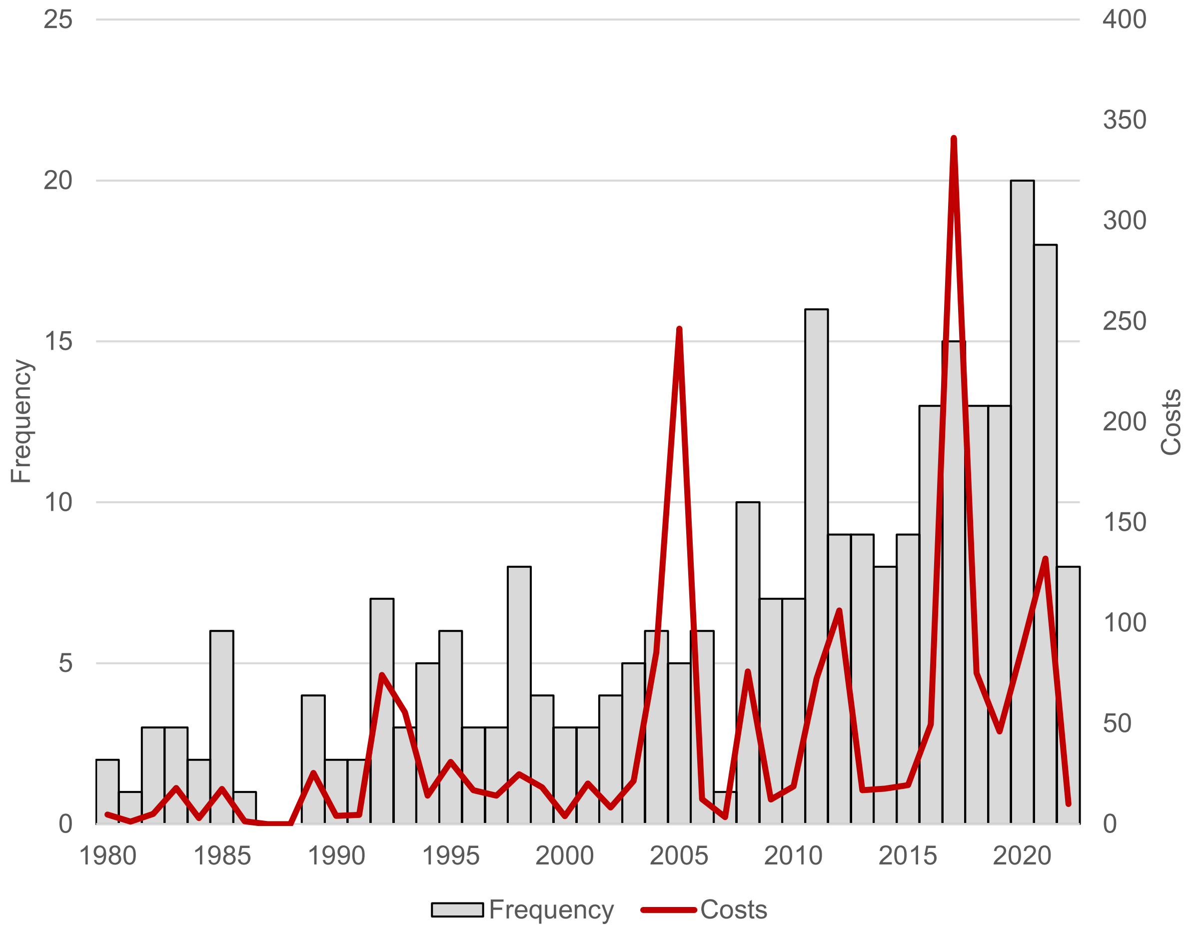

Figure 8

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.

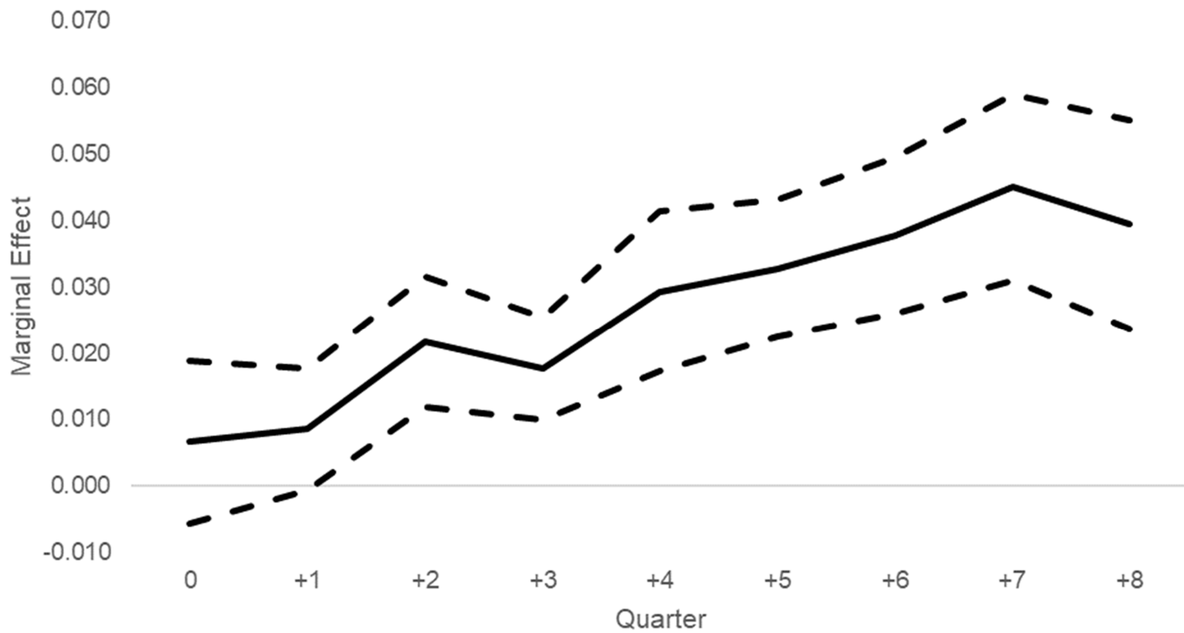

Table 1

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 Devication	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

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

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.)

Loan 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%

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)
Loan 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%

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)
Loan 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%

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)
$BankExposure_i$ × $MiddleFloodRisk_{j,c}$				-8.616***	-6.598**
				(3.280)	(3.262)
$BankExposure_i$ × $HighFloodRisk_{j,c}$				-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%

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 and risk bucket from July 2017 to December 2019. *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:		$\Delta MarketShare_{i,j,c}$	
$MediumFloodRisk_{j,c}$	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)
$BankExposure_i \times MediumFloodRisk_{j,c}$	0.637	-17.539*	-3.582
	(1.344)	(9.787)	(4.103)
$BankExposure_i \times HighFloodRisk_{j,c}$	-1.938*	-34.591***	-11.178**
	(1.114)	(11.859)	(4.816)
$MediumFloodRisk_{j,c} \times MarketShare^{2014}_{i,j}$			-0.017***
			(0.003)
$HighFloodRisk_{j,c} \times MarketShare^{2014}_{i,j}$			-0.027***
			(0.004)
$BankExposure_i \times MarketShare^{2014}_{i,j}$			-857.487***
			(74.299)
$BankExposure_i \times MediumFloodRisk_{j,c} \times MarketShare^{2014}_{i,j}$			-115.967
			(73.703)
$BankExposure_i \times HighFloodRisk_{j,c} \times MarketShare^{2014}_{i,j}$			-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%

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 and risk bucket from July 2017 to December 2019. *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%

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 and risk bucket from July 2017 to December 2019. *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:		$\Delta MarketShare_{i,j,c}$	
$MidRisk_{j,c}$	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)
$BankExposure_i \times MidRisk_{j,c}$	0.423	-9.967	-3.070
	(2.357)	(6.454)	(3.428)
$BankExposure_i \times HighRisk_{j,c}$	-1.509	-18.019**	-9.529**
	(3.009)	(7.898)	(4.312)
$MidRisk_{j,c} \times PeerExposure_{i,j}$			0.032***
			(0.004)
$HighRisk_{j,c} \times PeerExposure_{i,j}$			0.030***
			(0.005)
$BankExposure_i \times PeerExposure_{i,j}$			-88.730**
			(39.507)
$BankExposure_i \times MidRisk_{j,c} \times PeerExposure_{i,j}$			-99.145**
			(47.664)
$BankExposure_i \times HighRisk_{j,c} \times PeerExposure_{i,j}$			-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%

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)
Loan 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%