Information on Hot Stuff: Do Lenders Pay Attention to Climate Risk?

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September 13, 2023

Abstract

This study shows that banks adapt to exacerbated climate risk pre-emptively by factoring market-level information into lending decisions. Geographically dispersed, multi-state, and larger banks reduce small farm lending by 2 to 3 percent more, relative to their counterparts, following a standard deviation increase in the frequency of abnormal hot temperature in a county. Banks do not reduce credit flows indiscriminately as they strategically shield markets with branch presence. Furthermore, within-bank analyses suggest significant rebalancing of farm loans across counties that differ in climate risk exposure.

Keywords: Small Farm Loans, Abnormal Temperature, Market-Level Information, Branch Network, Climate Adaptation.

JEL: G21, Q14, Q54

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1 Introduction

This paper shows that banks adapt to increased climate risk in a region by reducing the flow of credit. Climate change increases the likelihood of extreme temperatures exacerbating future climate-induced disasters (IPCC, 2001, 2012). The climate and topography vary by geography, and this feature induces variation in the occurrences of extreme temperatures and the severity of disasters across a bank's service regions. Therefore, it is important to study whether and how banks adapt their lending strategies to changing climatic conditions in their service regions.

The importance of financial flows in contributing to climate change is heavily debated. One perspective relates to banks' role in allocating resources and coordinating efforts to reduce emissions via curbing lending to *'brown'* firms, for instance. Another perspective relates to financial stability as banks' balance sheets are exposed to the adverse effects of climate change, such as more intense disasters and stranded assets of brown firms. This paper relates to the latter and contributes to the literature by showing a negative correlation between banks' willingness to lend and local anomalous climatic conditions. This correlation is robust to explanations based on banks responding to adverse effects of recent disaster realizations on affected borrowers by curtailing lending.

The setting we examine is the small agricultural farm lending in the contiguous US. The climate is an important input that decides the agriculture sector's viability and productivity in a region; thus, climate affects farm fundamentals in the *short* and *long* term. Moreover, land, and any structure fixed to it, is immovable. A farmer cannot mitigate climate risk by moving his piece of land to relatively safe regions. Also, banks are an important source of financing for small farms, which lack access to formal equity and debt markets. Therefore, lending to small farms is an ideal setting to uncover the linkages between credit flows and climate.

Our conjecture on banks' adaptations to climatic conditions in their borrowers' regions is premised on a simple assumption that banks worry about the impaired debt serviceability of borrowers due to impending natural disasters. This assumption builds on the idea espoused by the scientific community that abnormal temperatures exacerbate future climate-related disasters (IPCC, 2001). We begin our analysis by directly testing our underlying assumptions. First, we show that conditional on a disaster striking, the disaster intensities, measured by the inflation-adjusted per-capita dollar amounts of damages and by the presidential disaster declaration (PDD) events, are increasing in the frequency of abnormal hot temperature. Next, we show that the frequency of abnormal hot temperature deteriorates farm financials as the value of collateralizable assets (land and buildings and machinery) and income receipts correlate negatively with abnormal hot temperature occurrences. Together, these validation tests show that the frequency of abnormal hot temperature has *decision-relevant* content relating to disaster intensities and their adverse effects on borrowers' pledgeable collateral value and income streams.

There are two key challenges to identifying a clear supply effect of abnormal temperature occurrences on credit outcomes. First, abnormal temperature occurrences affect not only credit supply but also credit demand. For instance, a positive correlation between abnormal hot temperatures and impending disasters implies an increased need for adaptation, suggesting an increase in credit demand. Alternatively, a recent disaster realization may increase the exit rate of farms from agriculture, suggesting a decline in credit demand. Second, a change in abnormal hot temperature occurrences affects information asymmetries between farms and banks, which may affect the optimal matching between farms and banks. Thus, for one to interpret the association between abnormal hot temperature and credit in terms of credit supply, it is important to sufficiently control for credit demand and endogenous matching between farms and banks in a region.

In this study, our approach to identification relies on the interaction of bank characteristics with county-level abnormal temperature occurrences. The key intuition is that banks with access to a higher number of markets are less constrained to continue to lend to regions that experienced an increase in climate risk. In contrast, banks with access to a single or small number of markets are, ceteris paribus, constrained to continue lending operations in their service regions, regardless of changes in local climatic conditions.

We proceed by defining a bank's *geographic dispersion* as the number of counties with branch presence. Our econometric specification focuses on the *incremental effect* and compares whether a representative small farm from a county borrowing from two banks experiences a larger decline in lending from the bank with a relatively high geographic dispersion within a county-year.[1] Since the comparison is across banks for the same representative small farm from a county, the county-specific demand shocks are absorbed by the county-year fixed effects (Gilje et al., 2016; Cortés & Strahan, 2017). Moreover, the *county-year* fixed effects also absorb time-varying county-level heterogeneity, such as macroeconomic conditions and the amount of arable land, which may determine credit outcomes for small farms in a county. Additionally, we incorporate *bank-county* fixed effects to control for endogenous matching between small farms in a county and a bank.

We find that banks from the high geographic dispersion group, on average, originate a lower (2 percent) number of small farm loans in a county that experiences a standard deviation increase in the frequency of abnormal hot temperature in the previous period. This relative decline amounts to approximately 3.0 percent in loan volume extended to small farms. Given the sample mean loan volume of 1.3 million dollars by a bank to small farms in a county, this decline is equivalent to 40.9 thousand dollars. These results suggest that banks view a loan's default probability as relatively high in regions with increased climate risk such that they may not make a loan.

We also use bank size as a proxy for a bank's geographic dispersion, as large banks are more likely to operate in multiple regions. We continue to find the incremental effect of large banks on credit availability in a region to be negative, approximately -1.7 to -1.8 percent for the number of originations and -3.6 to -3.7 percent for the loan

[1] On average, a bank from high (low) geographic dispersion group operates in 345 (12) counties. This division of banks is based on the median value of banks' geographic dispersion.

volume. We also categorize banks into single- and multi-state banks based on whether a bank's branch network is confined to one or more contiguous US states. We find that banks operating in multiple states lend relatively less to small farms from counties that experience exacerbated climate risk.

A plausible confounding explanation of our baseline results is that banks curtail lending in response to adverse effects of disaster realizations, rather than that of abnormal temperature occurrences, on borrowers' fundamentals. In our baseline regression specification, the *county-year* fixed effects control for the direct effect of disaster occurrences in a county, but not the interaction effects. In an additional regression specification, we show that the baseline results are robust to the inclusion of the interaction effect of disaster occurrence and bank group based on geographic dispersion. In additional tests, we confirm the robustness of the baseline results based on counties that did not experience any major natural disaster in a current and past two periods. These results are hard to reconcile with an explanation that banks are simply reacting only to disaster realizations in the recent past.

An argument based on the presence of crop insurance undermines the baseline findings of this study. For instance, if a farm's production is insured, then it is not clear why a bank would reduce the flow of credit to a region. This argument is not as straightforward. Firstly, the ideal scenario is that a farm continues to service debt in line with the terms and conditions stipulated in a loan contract. Even if production is affected, estimating the production loss, making a claim, and receiving insurance benefits is a lengthy process. In the meantime, a farm is responsible for timely repayments for a loan contract. Moreover, a crop insurance contract is enacted only if a certain percentage of loss is realized. Still, we address this concern using insurance data sourced from the US Department of Agriculture. We show that the baseline effect documented in this study is robust to the potential effects of crop insurance.

After establishing our baseline results and their robustness, we document that the baseline decline in lending among counties that experience an increase in climate risk predominantly comes from counties outside a bank's branch network. The credit supply to such counties inside a bank's branch network remains unaffected. These results suggest that the bank-borrower relationships in counties inside a bank's branch network are of economic value to banks as they protect the extractable rents from those relationships. Overall, this finding aligns with prior literature suggesting the importance of bank-borrower proximity and highlights the importance and relevance of banks' branch networks.

Lastly, we focus on the within-bank analysis to understand what banks do with the loanable funds curtailed cautiously in response to the exacerbated climate risk. We argue that two conditions are necessary for local climate risk to influence loan portfolio rebalancing. First, banks must face some friction(s) in hedging climate risk. In our setting, these frictions stem from banks' limited access to adequate insurance coverage and a lack of a securitization market for small farm loans. Second, banks must have sufficient incentives and access to borrowers over whom they have a cost advantage relative to rival banks. While all banks have some exposure to climate risk, in our setting, only geographically dispersed banks can plausibly implement the rebalancing strategies by moving loanable funds among their service regions.

We find that geographically dispersed banks cut *proportion* of farm loans to counties experiencing exacerbated climate risk, suggesting redirection of curtailed loans to counties relatively unaffected by climate risk. We show that this decline is primarily concentrated in counties where a bank does not have a branch presence. This result highlights the role of branch networks in banks' adaptations to changing climatic conditions. We also test whether banks tackle climate risk by redirecting lending away from the farm sector but do not find support for such cross-sector rebalancing. These results suggest that changes in lending strategies are captured within banks' farm loan portfolios, resulting from the market-level climatic conditions informing banks' decisions about loan products to a relevant sector.

We acknowledge two data-driven caveats of this study. First, the small farms' lending data are observed only at the county-bank-year level. This feature hinders our ability to explore the small farm heterogeneity in a region.[2] Second, these data do not provide any information on loan pricing. Whether banks increase interest rates, in addition to a decline in loan volume documented in this study, due to an increase in abnormal temperature occurrences is an interesting avenue for future research.[3]

Our study makes several contributions to the literature. We contribute to the climate finance literature by presenting, to the best of our knowledge, the first evidence of the adverse impact of local climatic conditions on the *future* credit availability to small farms in a region. Ouazad & Kahn (2022) show that lenders are willing to make mortgage loans in hurricane-affected areas for amounts within conforming limits for securitization purposes. Nguyen et al. (2022) focus on the mortgage loan market and find that lenders view sea level rise as a long-term risk and that banks' perception of this risk is affected by the attention paid to and beliefs about climate change.[4] We complement these studies by focusing on *all* regions in which a bank has lending operations and showing that banks adapt their lending strategies *pre-emptively*, rather than *ex-post*, to avoid adverse effects that a natural disaster, if and when one strikes, may have on their loan portfolio. Moreover, these studies focus on the mortgage market because it is relatively larger, and loan contracts are of the longer term. Arguably, the agriculture sector offers the best setting to study interlinkages between climate change and credit outcomes. The short and long term viability of agriculture is critically dependent on climate, a reason for choosing small farms as the setting in this study.

[2]For instance, credit demand for a hog farm may differ from that of a corn farm. The abnormal temperature occurrences are likely to move the credit demand schedules of two farmers in the same direction. This co-movement in demand schedules of all farms in a given county is captured by the county-year fixed effects.

[3]Stiglitz & Weiss (1981) argue that increasing interest rates in an imperfect information scenario may increase adverse selection problems in banks' loan portfolios. Khwaja & Mian (2008) argue in the same vein as the authors find a statistically insignificant effect of liquidity shock on credit pricing.

[4]In the climate finance literature, some researchers study the implications for house prices from the perspective of sea level risk (Murfin & Spiegel, 2020; Baldauf et al., 2020; Giglio et al., 2021) and natural disasters (Gibson et al., 2017; Ortega & Taspinar, 2018; McCoy & Walsh, 2018; Eichholtz et al., 2019). Acharya et al. (2022) show that exposure to extreme heat stress is priced in (municipal and corporate) bond and equity markets. Studies, such as Brown et al. (2021) and Kacperczyk & Peydró (2021), focus on linkages between various aspects of the changing climatic conditions and the corporate loan outcomes.

We also contribute to the banking literature on capital reallocation by multi-market banks in response to natural shocks. Cortés (2023) finds that local lenders accounted for loan-market level residential real-estate overvaluation in their lending decisions, cutting lending more, even before the onslaught of the GFC, than non-local banks in such regions. This finding is consistent with lenders anticipating the bust based on the pre-GFC 'heating-up' of the residential real estate market. Gilje et al. (2016) study the propagation of a positive liquidity shock (liquidity windfall from natural gas and oil shale discoveries) and show that banks receiving funding windfalls expand lending only in markets with a branch presence. Cortés & Strahan (2017) study adverse liquidity shocks from natural disasters and find that banks, in response to higher demand for loans in some markets, cut lending predominantly in markets with no branch presence. These studies focus on changes in lending *ex-post* a natural disaster. We add texture to this literature by showing that geographically dispersed banks react to exacerbated climate risk, *ex-ante* natural disasters and changes in beliefs about climate change, by cutting lending the most where their comparative advantage is the least – in counties without branch presence. Our study extends this strand of literature by showing that abnormal temperature events that affect borrower fundamentals trigger loan portfolio rebalancing, suggesting that banks have a superior ability to collect and process information.

The reduction in lending, which we document in this study, has a few policy implications. For instance, the Federal Reserve Board is planning to conduct a pilot Climate Scenario Analysis (CSA) in 2023 to learn risk management practices, especially of large banks, to enhance better identification, measurement, monitoring, and management of climate-related financial risks. Our findings inform the policy debate on how regulators should view the potential effect of climate risk on banks' financial health and whether regulators should be forcing banks to adjust credit to limit investment in certain types of regions and entities therein. Further, a decline in access to credit can undermine various credit-dependent functions in a given region.[5] A key challenge for

[5]These functions are related to the entrepreneurial activity (Schumpeter & Opie, 1934; Banerjee et al., 2017), insurance (Udry, 1994), consumption smoothing (Gross & Souleles, 2002),

policymakers, therefore, is to strike a balance between improving financial stability in the face of climate-related financial risks and the welfare of people who continue to live in regions more exposed to climate risk due to various reasons, such as family and employment, and rely primarily on banks for their credit needs.

2 Data description

2.1 Temperature data

We source all temperature data from the National Oceanic and Atmospheric Administration (NOAA). The grid-level temperature data are from the Physical Sciences Laboratory (PSL) of NOAA and are constructed by Willmott & Matsuura (2001). This dataset provides a monthly time-series of the average temperature on a 0.5×0.5 degrees scale, which corresponds roughly to grids approximately 35 miles across at the equator. Using the shapefile from the US Census Bureau, we identify 4,398 grids for the contiguous US. Next, using representative longitudes and latitudes of all US counties, we calculate the distances between a county and grids, and match a county to the closest grid. This operation yields a stable matching of a county to a grid because the locations of counties and grids are fixed over time. The average distance between a county and its matched grid is 11.9 miles. The constructed dataset is a balanced panel and is robust to issues such as missing station data. This study uses the average monthly temperature data for 67 years (1951-2017).

2.2 Disaster damages data

We source county-level disaster data from the Spatial Hazard Events and Losses Database for the United States (SHELDUS). It covers natural hazards like thunderstorms, hurricanes, floods, wildfires, tornadoes, and perils such as flash floods and heavy rainfall, among others. SHELDUS provides information on the date of an event, the affected location (county and state), and the direct losses caused by the event, such as property and crop losses, injuries, and fatalities from 1960 onwards. We keep ob-

income (Karlan & Zinman, 2010), inequality (Solis, 2017), and total factor productivity (Krishnan et al., 2015).

servations where the reported hazard type is coastal, drought, flooding, hail, heat, hurricane, landslide, lightning, severe storm, tornado, wildfire, wind, winter weather, fog, and avalanche. We remove observations where the reported hazard type is an earthquake, volcano, tsunami, or seiche because scientists have not established a clear link between changes in long-term average temperatures and the occurrence of hazards that are primarily driven by changes in the Earth's interior. We aggregate the county-hazard-year level data to the county-year level. The used sample spans 21 years (1997-2017).

2.3 Farm lending and agriculture data

We use data made available to the Federal Financial Institutions Examination Council (FFIEC) under the Community Reinvestment Act (CRA). The Community Reinvestment Act intends to encourage depository institutions to help meet the credit needs of the communities in which they operate, consistent with safe and sound banking operations. We focus on the originations dataset that provides information on the aggregate amount and number of loans by a bank to small agricultural farms in a county. The CRA dataset is at the bank-county-year level. The sample period spans 21 years, starting in 1997. The bank-level financial data are from Reports of Condition and Income (Call Reports) of the FFIEC. To match the data reporting frequency of the CRA dataset, we merge the CRA dataset with the call reports data corresponding to the fourth quarter of a year. We follow Berger & Bouwman (2009) and Schüwer et al. (2018) and exclude banks that have no outstanding commercial or real estate loans or commercial and industrial loans or have zero or negative equity capital, or have assets less than 25 million dollars, or hold consumer loans in excess of 50 percent, or have capital ratios in excess of 40 percent. We also exclude banks with no outstanding agriculture loans. We source bank branch network data from the Summary of Deposits data. The sample period for call reports and summary of deposits data is from 1997 to 2017.

According to Key et al. (2019), in 2017:Q4, the FDIC-insured CRA-eligible banks accounted for more than 50 percent of agricultural loans. Also, among small farms, in

2017, 52 percent borrowed from commercial banks, whereas 44 percent of large farms borrowed from commercial banks. A 2016 Washington Post article criticized the Farm Credit System (FCS) for making only large loans (amounts greater than 1 million dollars) to entities unrelated to farming. In March 2016, the FCS Funding Corporation disclosed that, in 2015, 45.5 percent (equivalent to 107.3 billion dollars) of outstanding loans correspond to 4,458 borrowers (equivalent to less than a percent of its total of 527,462 borrowers).[6] This anecdotal evidence highlights the importance of commercial banks as financiers of small farms in the US.

The county-level agriculture data are from the Quick Stats Database of the United States Department of Agriculture National Agricultural Statistics Service (USDA-NASS). The Quick Stats Database provides the most comprehensive data on agricultural commodities and growing regions. We source county-level farm economic data from the quinquennial USDA census program. The census data provide information on farm economic and financial variables at the county level. We make use of data corresponding to the census years: 1997, 2002, 2007, 2012, and 2017.

2.4 Measuring local climatic conditions

We begin by conveying the intuition behind our approach to quantifying the decision-relevant information about climatic conditions in borrowers' regions. In Figure 1, the *previous* climate represents the *reference period* temperature distribution. The *current* climate represents the temperature distribution with an increase in mean or variance due to the non-stationarity of the temperature distribution. As shown in Figure 1-(a), an increase in the *mean only* leads to new record hot temperatures, leaving the range between the hottest and coldest temperatures unchanged. Figure 1-(b) shows that an increase in the *variance only* of the temperature distribution implies an increase in the probability of both hot and cold extremes and the absolute value of the extremes. Figure 1-(c) presents a scenario, which corresponds to an increase in the *mean* and *variance* of the temperature distribution. Such a change in the temperature distribution affects

[6] See the Washington Post article. Also, see an article from the American Banking Association for more details.

the frequency of abnormal hot and cold temperatures, with more frequent hot events with more abnormally high temperatures and fewer cold events. In this study, we focus on abnormally hot temperatures because, along the current climate trajectory, such temperatures are more likely in the future.

[Insert Figure 1 Here]

Our measure corresponds to the empirical likelihood of observing temperatures as abnormal as those we observe over a *fixed reference period*. In this study, we choose a fixed reference period of 30 years, in line with that of the Goddard Institute of Space Studies Surface Temperature Analysis (GISTEMP), starting in 1951. Choosing a fixed reference period makes temperature deviations from a fixed reference point *comparable* across periods. Over the reference period, we calculate county and month specific abnormal temperature threshold, denoted $\mathbb{T}^{99^{\text{th}}}_{cm,51-80}$, as follows:

$$\mathbb{T}^{99^{\text{th}}}_{cm,51-80} = P_{99}\big(\{\mathbb{T}_{cmt}\}^{1980}_{t=1951}\big) \qquad \forall \text{ c and } \forall \text{ m} \tag{1}$$

where P_{99} is an operator selecting the 99^{th} percentile of the quantity inside $(\cdot)$, and $\mathbb{T}_{cmt}$ represents the temperature for county *c* in month *m* of year *t*. From the year 1981 onwards, we generate a dichotomous variable, denoted $\mathbb{E}^{99}_{cmt}$ as follows:

$$\mathbb{E}^{99}_{cmt} = \begin{cases} 1 \text{ if } \mathbb{T}_{cmt} > \mathbb{T}^{99^{\text{th}}}_{cm,51-80} \\ 0 \text{ otherwise} \end{cases} \tag{2}$$

The construction of $\mathbb{E}^{99}_{cmt}$ accounts for geography and seasonalities as all calculations are county and month specific. Take Bullock County (Alabama) as an example for contextual purposes. In March 1997, the observed temperature ($\mathbb{T}_{cmt}$) is 63.0 degrees Fahrenheit. The reference abnormal hot ($\mathbb{T}^{99^{\text{th}}}_{cm,51-80}$) temperature for Bullock County for the month of March is 61.9 degrees Fahrenheit. In this case, the observed temperature exceeds the reference abnormal hot temperature, so $\mathbb{E}^{99}_{cmt}$ takes a value of 1. In June

1997, the observed temperature for Bullock County equals 74.3 degrees Fahrenheit, whereas $\mathbb{T}^{99^{\text{th}}}_{cm,51-80}$ equals 82.8 degrees Fahrenheit. For this month, $\mathbb{E}^{99}_{cmt}$ takes a value of 0. Thus, the reference abnormal hot temperature varying by county-month allows us to account for geography and seasonalities. In the last step, we construct the measure on local climatic conditions for county c in month m of year t as follows:

$$\text{Frequency of Abnormal Hot Temperature}_{cmt} = \text{MA}^{36}[\mathbb{E}^{99}_{cmt}], \quad \text{t} \geq 1981 \tag{3}$$

where $\text{MA}^{36}[\cdot]$ represents the past 36-month moving average (MA) observed in month m of year t.[7] Here, taking the moving average over 36 months implies that, for each county-month-year, we take the average over the same number of same months. Doing so allows us to control the effect of seasonalities further and ensures that estimated empirical frequency does not gravitate toward a particular month of a year.

It is likely that the change in the mean and variance of temperature distribution drive the occurrences of abnormal hot temperature. To identify the main driver (change in mean or change in variance of the temperature distribution) of shifts in the temperature distribution, we plot monthly time-series of cross-sectional averages of the *Probability of Abnormal Hot Temperature* and the *Probability of Abnormal Cold Temperature* in Figure 2.[8]

[Insert Figure 2 Here]

This figure presents visual evidence of a negative correlation (-54.3 percent) between the two series, suggesting that the change in the mean, not the variance, of temperature distribution is likely to be the primary driver of the frequency of abnormal hot temperature. This observation is consistent with the existing evidence on the association of extreme hot temperature occurrences and long-term average temperature.[9]

[7] For the rest of the study, we utilize this measure from 1997 onwards because our CRA sample period starts from 1997.

[8] *Frequency of Abnormal Cold Temperature* equals the past 36-month moving average of a dichotomous variable that equals 1 (0 otherwise) if the observed temperature for a county-month-year is below the county-month specific 1^{st} percentile observed over the reference period (1951-1980).

[9] See Mearns et al. (1984), Meehl et al. (2000), IPCC (2001, 2012), Meehl (2007), Christidis et

Thus, the pictorial evidence in Figure 2 lends support to the validity of our information measure.

2.5 Summary statistics

Table 1 presents the summary statistics of the key variables used in later sections of this study. In Panel A, the variables are observed at the county-time level. The frequency of abnormal hot temperature averages 4.2 percent and exhibits significant variation with a standard deviation of 4.4 percent. This county-year level measure corresponds to the average of twelve-monthly frequencies estimated over a calendar year. Property damages constitute a significant portion of the total damages, and about a quarter of the disaster occurrences coincide with a disaster declaration. The land value averages 3.9 thousand dollars per acre, and a representative farmer invests around 120.9 thousand dollars in farm machinery and registers approximately 19.8 thousand dollars of income receipts per operation. From an aggregate lending perspective, FDIC-insured banks originate approximately 62.0 new small farm loans totaling 4.8 million dollars on average.

[Insert Table 1 Here]

In Panel B, the data are at the bank-county-year level. An average bank in our sample originates approximately 17.0 new small farm loans in a county, amounting to 1.3 million dollars. The tier 1 capital ratio averages 11.1 percent and varies with a standard deviation of 2.8 percent. A bank earns an average return of 1.1 percent on its assets, and its non-performing loans average 0.3 percent on its assets.

In Panel C, the data are at the bank-year level. Weight$_{bt}$ equals $\frac{\sum_{c \in \mathbb{C}} \mathbb{L}_{cbt}}{\mathbb{L}_{bt}}$, where $\mathbb{C}$ represents the set of counties that experienced an increase in the frequency of abnormal hot temperature in the previous year, and $\mathbb{L}_{cbt}$ represents farm lending activity in county c by bank b in year t. On average, approximately 36.5 to 36.8 percent of new loans originate in such counties. It follows that approximately two-thirds of

al. (2013) and Seneviratne et al. (2014) among others.

farm loans originate in the other two of the three sets of counties (no change or a decrease in the frequency of abnormal hot temperature). Farm loans fetch a weight of approximately 6.2 percent in the aggregate loan portfolio of a representative bank. The equally-weighted bank-level frequency of abnormal hot temperature equals 4.3 percent, suggesting that in a given year, 4 out of 100 counties in which a bank has lending operations experience a temperature that exceeds the abnormal threshold.

3 Methods and results

We report regression models for three sets of analyses. The *first* part uses county-year level data and relates to validating the frequency of abnormal hot temperature as a measure of information about the local climatic conditions. The *second* set of analyses employs county-bank-year level data to identify a supply channel driving changes in credit outcomes for small farms in a region due to abnormal hot temperature occurrences in the recent past. The *last* set of analysis corresponds to within bank analysis to provide further corroborating evidence on the possible rebalancing of a bank's farm loan portfolio among regions.

3.1 Validation

3.1.1 Disaster intensities

According to IPCC (2001, 2012), an increase in the mean of temperature distribution increases the likelihood of abnormal temperatures that *exacerbate* intensities of natural disasters. Climate science (IPCC, 2001) frequently relates climate change to the intensities of disasters rather than their occurrences. Given intensity is observed upon a disaster striking, our specification tests how disaster intensities correlate with the frequency of abnormal hot temperature, and takes the following form:

$$\begin{aligned}\text{Disaster Intensity}_{ct} = &\beta_1 \times \text{Frequency of Abnormal Hot Temperature}_{ct-1} + \text{County}_c \\ &+ \text{Year}_t + \text{u}_{ct}.\end{aligned} \tag{4}$$

In equation (4), the dependent variable is one of the proxies for disaster intensity. The first two proxies are the logarithm of per-capita total and property damages inflation-adjusted to the 2016 level. If a disaster is intense, the state governors can ask the US president to declare a disaster and offer assistance. The *'intensity'* of a disaster is a key determinant of presidential disaster declaration (PDD) and a disaster's subsequent and potentially adverse effects on a region's economic quantities. Therefore, we use another dependent variable PDD_{ct}, which equals 1 (0 otherwise) if, for a county-year, the reported total damages in the presidential disaster declaration database within SHELDUS are positive.

The independent variable is *lagged* county-year level frequency of abnormal hot temperature.[10] We include year fixed effects to control for any year-specific events and county fixed effects to account for different average levels of damages due to economic, geographic, or institutional differences between counties. We cluster the standard errors at the county level.

[Insert Table 2 Here]

In columns (1) and (2) of Table 2, the economic size of the coefficients suggests that conditional on a disaster striking, a standard deviation increase in the frequency of abnormal hot temperature leads to an increase of 6.5 and 6.0 percent increase in total and property damages, respectively. In column (3), the coefficient suggests an increase of 2.0 percent with a standard deviation increase in the frequency of abnormal hot temperature in the previous period. This increase is equivalent to 7.7 percent of the mean probability of a presidential disaster declaration (26.2 percent).

In Table OA.1, we show that the results in this section are robust to measuring the frequency of abnormal hot temperature using alternative percentiles to determine reference abnormal hot temperature and to correcting standard errors for spatial correlation. The results in this section lend support to using the frequency of abnormal hot temperatures as a valid measure of the climatic conditions in a county.

[10]The disaster damages in the annual SHELDUS data are measured over a year. We match county-year level SHELDUS data with the county-year level frequency of abnormal hot temperature corresponding to the average of twelve-monthly frequencies of abnormal hot temperature estimated over a calendar year.

3.1.2 Farm financials

There is anecdotal evidence that banks are concerned about the effects of the changing climatic conditions on their borrowers' debt serviceabilities. For instance, consider the following excerpt from the 10-K filings of Regions Financial Group for the year 2016:

"While we maintain insurance coverings for many of these weather-related events ⋯ there is no insurance against ⋯ resulting adverse impact on our borrowers to timely repay their loans and the value of collateral held by us. The severity and impact of future ⋯ weather-related events ⋯ may be exacerbated by climate change."

This excerpt mentions two of the five C's of credit: *capacity* and *collateral*.[11] The *capacity* refers to the borrower's financial capability. In our context, a farmer's future income receipts are an important factor in the credit analysis to evaluate whether the farmer has the capability to make the repayments over the loan term. Despite costs associated with it, *collateral* is widely used in (secured) lending.[12] From a bank's perspective, collateral reduces risk (Berger et al., 2016; Greenbaum et al., 2019), signals quality (Bester, 1985; Besanko & Thakor, 1987a,b), and reduces moral hazard problems that may stem in the form of asset substitution (Smith Jr & Warner, 1979), under-investment (Myers, 1977; Stulz & Johnson, 1985; Cerqueiro et al., 2016), and inadequate effort supply (Greenbaum et al., 2019). In our setting, a farmer may provide collateral in the form of land and buildings, farm machinery and equipment that he intends to use to produce farm output. Moreover, these assets are important items on a farmer's balance sheet.

We test the assumption that climatic conditions in a borrower's region and debt

[11] The other three C's are: *capital, character, and conditions*. These experience-based 'heuristics' are useful in determining a borrower's creditworthiness (Greenbaum et al., 2019).

[12] Greenbaum et al. (2019) argue that borrowers can undertake actions that may undermine collateral value; thus, collateral monitoring is required. The bank partly bears these costs. Additionally, there are liquidity costs associated with the acquisition and sale of collateral *ex-post* the default by a borrower.

serviceability are correlated using the following regression model:

$$\begin{aligned}\Delta\text{Farm Outcome}_{cp} =& \gamma_1 \times \Delta\text{Frequency of Abnormal Hot Temperature}_{cp-1} \\ &+ \text{County}_c + \text{Census Year}_p + \epsilon_{cp}.\end{aligned} \tag{5}$$

In equation (5), ΔFarm Outcome$_{cp}$ equals log growth in land value per acre, and machinery value and income receipts per operation for county c over census years p and *p-1*. The independent variable equals the frequency of abnormal hot temperature differenced over census years *p-1* and *p-2*. Due to the quinquennial nature of USDA's census program, the results in this section relate the impact of the frequency of abnormal hot temperature on financial outcomes of farms in the medium-term (5 years).[13] We include year fixed effects to control for events common to all counties in a year. The county fixed effects in the differenced data absorb a substantial amount of county-specific heterogeneity. Our results in this section remain qualitatively similar if we use *levels*, rather than *changes*, data in estimating equation (5). Table 3 presents results based on the specification in equation (5).

[Insert Table 3 Here]

We find that the value of pledgeable collateral (Bergman et al., 2020) and the debt capacity of farms is negatively correlated with the frequency of abnormal hot temperature in the medium term. A standard deviation increase in the frequency of abnormal hot temperature suggests a decline of 2.8 and 1.5 percent in land value per acre and machinery value per operation, and income receipts per operation, respectively. This decline is equivalent to 109.3 dollars in average land value per acre, 3,396.8 dollars in average machinery value per operation, and 300.9 dollars in income receipts per operation. This association between the frequency of abnormal hot temperature and pledgeable collateral is robust to alternative percentiles used to determine abnormal

[13]Our approach in equation (5) is similar to that of Burke & Emerick (2016), who, using data differenced over 10-years, show long-term effects of climate change on crop yields.

hot temperatures (Panels A and B of Table OA.2) and spatial clustering of standard errors (Panels C of Table OA.2).

To bolster confidence in the frequency of abnormal hot temperature capturing the relevant information, we propose a canonical measure of local climate beliefs and test how it correlates with hot temperature occurrences in the recent past, and furnish the results in Tables A.1, which also provides details of the underlying intuition and the empirical approach to measuring climate beliefs. In line with the findings of Kaufmann et al. (2017), we show that beliefs about changing climatic conditions strengthen after the realization of abnormally hot temperatures.

Overall, results in this section establish the relevance of the frequency of abnormal hot temperature for banks lending to borrowers from the agriculture sector whose yields (Schauberger et al., 2017; Siebert et al., 2017; Vogel et al., 2019), and productivity (Ortiz-Bobea et al., 2021) are affected by climatic conditions. As a sophisticated investor, a bank may tread carefully in its lending decisions given the correlation between climatic conditions and impending disasters' intensities in the short-term and a borrower's *capacity* and *collateral* in the medium term.

3.2 Within county-year analysis

3.2.1 Identification and baseline results

In section 3.1, our results suggest that the frequency of abnormal temperature correlates positively with disaster intensities in the subsequent periods and negatively with farm financials in the medium term. Given asymmetries in the frequency of abnormal hot temperature across regions due to heterogeneity in geographical topography, a bank may reduce the flow of credit to regions that become more vulnerable to climate-related adversities. In this section, we delve into understanding whether and how the frequency of abnormal hot temperature interacts with lending outcomes for small farms.[14]

[14]According to Hsiang (2016), climate change affects various economic outcomes via two mechanisms. The first mechanism, *the direct effect*, relates to realizations of extreme climate events that may affect agents directly. The second mechanism, *the beliefs effect*, relates to agents updating their beliefs about climate change as a phenomenon and taking steps to adapt to a

As *'geography'* is an important concept in climate-related studies, a bank's branch network is a reliable source of information on its geographical presence in our setting. Moreover, branch presence implies that a bank has the expertise to serve that market. It also implies that a bank can form informative bank-farm relationships over time because it learns about its borrower and local market, lessening the private information gap between the borrower (Greenbaum et al., 2019) and the bank and mitigating moral hazard issues in its loan portfolio (Bhattacharya & Thakor, 1993; Boot & Thakor, 1994; Freixas & Rochet, 2008; Ioannidou & Ongena, 2010). We argue that *geographic dispersion*, defined as the number of counties in which a bank has at least one branch, of branch network is a relevant proxy for the flexibility with which a bank can flow credit among its service regions.

A bank with branches in multiple regions is less constrained to continue to lend to counties that experience deterioration in climatic conditions. Thus, the intuition underlying our identification approach is that if *high* geographic dispersion banks reduce credit availability to a given region more than *low* geographic dispersion banks, this effect is more likely to be supply-driven. The following model captures this intuition:

$$\begin{aligned}\Delta\text{Lending Outcome}_{cbt} =& \beta_1 \mathbb{1}^{\text{High Geographic Dispersion}}_{bt-1} \times \Delta\text{Frequency of Abnormal Hot Temperature}_{ct-1} \\ &+ \Gamma'\Delta\text{Controls}_{bt-1} + \text{Bank}_b \times \text{County}_c + \text{County}_c \times \text{Year}_t + \upsilon_{cbt}.\end{aligned} \tag{6}$$

In equation (6), ΔLending Outcome$_{cbt}$ represents log growth in the number and amount of loans extended by a bank to small farms in a county-year. The dichotomous variable, $\mathbb{1}^{\text{High Geographic Dispersion}}_{bt-1}$, equals 1 (0 otherwise) if a bank belongs to the high geographic dispersion group of banks. The division of banks into high and low groups is based on the median value of geographic dispersion. An average bank in the *High (Low) Geographic Dispersion* group has branches in 345 (12) counties. Thus, banks with higher geographic dispersion have relatively high flexibility in adjusting credit flows among regions.

new climate with a higher average temperature. In this study, we are *agnostic* between the two mechanisms and link changing climatic conditions directly to the regional lending outcomes.

In line with the Khwaja & Mian (2008) approach, the first-differenced dependent and independent variables are transformed within *'*$County_c \times Year_t$*'*. This transformation corresponds to testing whether a representative small farm from a county borrowing from two banks experiences a larger decline in lending from the bank with a relatively high geographic dispersion. Since the comparison is across banks for the same representative small farm from a county, the county-specific demand shocks and other observed and unobserved county-level heterogeneity are absorbed by the county-year fixed effects (Gilje et al., 2016; Cortés & Strahan, 2017).[15] Apart from absorbing county-specific credit demand shocks, the *'*$County_c \times Year_t$*'* fixed effects are also useful in controlling the direct effect of extreme disasters that may deteriorate farm financials, causing banks to curtail lending in that region. The *'*$Bank_b \times County_c$*'* fixed effects control for unobserved heterogeneity shared by small farms in a county, and unobserved heterogeneity at the bank level. These fixed effects also control for any time-invariant relationship shared by small farms in a county with a bank and endogenous matching of small farms within a county and banks. Due to the county-year level measurement of the key independent variable, we cluster the standard errors at the county level.

[Insert Table 4 Here]

Overall, the results in Table 4 suggest that banks that operate in multiple markets reduce the number of originations and loan volume relatively more in the period following an increase in the frequency of abnormal hot temperature in a region.[16] The economic significance of the coefficients in columns (1) and (2) suggests a decline of approximately 2.0 percent in the number of small farm loan originations by banks from *high geographic dispersion* group with a standard deviation increase in the frequency of abnormal hot temperature in the previous period. The results in columns (3) and (4)

[15]Given our data constraints and the result in column (3) of Table 2 of Degryse et al. (2019), the county-year fixed effects, or equivalently county-industry-year fixed effects in our setting as we focus on only one industry, would fare reasonably well as a control for the credit demand.

[16]The direct effect of lagged frequency of abnormal hot temperature is perfectly collinear with the county-year fixed effects.

suggest that the loan volume by banks from *high geographic dispersion* group is 3.1 and 3.0 percent lower. Based on the mean loan volume of 1,348.1 thousand dollars, the implied decline is equivalent to 41.7 and 40.9 thousand dollars in columns (3) and (4), respectively.

Our baseline model in equation (6) assumes that the frequency of abnormal hot temperature does not interact with other bank characteristics. We relax this assumption by augmenting equation (6) with the interactions of bank characteristics and the frequency of abnormal hot temperature and present results in Table A.2. We find that our baseline results remain qualitatively and quantitatively similar. We also construct two dichotomous variables that signify a decline in small farm lending (number and volume of loans).[17] The first (second) equals 1 if growth in the number of originations (loan volume) from a bank to a county-year is negative and equals 0 otherwise. We use these two dichotomous variables as the dependent variables and present results in Table A.3. We continue to find that the probability of a decline in lending increases following an increase in the frequency of abnormal hot temperature.

One may argue that insurance is a useful tool to mitigate risks due to changes in local climatic conditions. For instance, Cornaggia (2013) shows that insurance and agriculture productivity correlate positively. There are many impediments due to which insurance markets, at best, can offer partial insulation against various adverse effects of climate-related factors. From a bank's perspective, the incompleteness of insurance markets (Froot, 2001) reveals itself in the lack of insurance contracts for declining borrowers' debt serviceabilities and collateral value due to climate-related risks. Monast (2020) also notes that only 15 percent of all (large and small) US farms participate in crop insurance, suggesting that a vast majority of the US agricultural production is left unprotected by crop insurance and vulnerable to short- and long-term climate-related risks.[18] While the county-year fixed effects control for time-varying county-level het-

[17] These variables are less prone to issues such as lack of lending in a prior year or the presence of potential outliers.

[18] Monast (2020) notes other impediments due to which crop insurance may not offer complete protection against climate-related risks as crop insurance typically provides a maximum cover of 85 percent. Additionally, crop insurance, in aggregate, covers only one-quarter of farm

erogeneity, we test the robustness of results in this section to the interaction effect of insurance prevalence and abnormal hot temperature occurrences in a county. The results in Table A.4 suggest that the findings of this section are robust and align with our intuition that insurance contracts offer partial insulation against crop losses due to natural disasters.

The negative correlation between credit availability and frequency of abnormal hot temperature for geographically dispersed banks should be stronger for counties that experience similar consecutive changes in the frequency of abnormal temperature, signifying persistence and intensity in the treatment. In Table OA.3, we test and confirm this conjecture by dividing counties into groups based on whether a county experiences an increase or not in the frequency of abnormal hot temperature in year *t-1* and *t-2*.[19] We find that for geographically dispersed banks, the decline is largest for counties that experience an increase in the frequency of abnormal hot temperature in the previous two periods. Furthermore, in Table OA.4, we find that our baseline results are robust to clustering standard errors along alternative dimensions, namely i) bank, ii) county and bank, iii) county, bank and year, and iv) spatial. Overall, our baseline results indicate that banks incorporate market-level information into their lending decisions, and banks' willingness to lend is declining in climate risk.[20]

production in the US. In a different context, Oh et al. (2022) study the role state-level regulation of homeowners insurance plays in inducing frictions that may lead to inefficient risk pricing in a given region.

[19] In this setting, the reference group includes counties that do not experience an increase in the frequency of abnormal hot temperatures in year *t-1* and *t-2*. The second group includes counties that experience an increase in the frequency of abnormal hot temperature in either year *t-1 or t-2*. The last group includes counties that experience an increase in the frequency of abnormal hot temperature in both years *t-1 and t-2*.

[20] Due to data-driven restrictions, we are unable to assess the effects of small farm type heterogeneity. For instance, it is plausible that corn and hog farmers have different credit demand schedules. Note that impending physical disasters and movements toward extreme climatic conditions are likely to have similar effects on credit demand schedules for corn and hog farmers. Therefore, their demand schedules are likely to co-move in the same direction due to changes in the local climatic conditions. In our specification, this co-movement is captured by the county-year fixed effects.

3.2.2 Alternative explanation: Recent disasters affecting borrowers' fundamentals?

Our baseline evidence thus far suggests that the abnormal hot temperature occurrences are associated negatively with the number of originations and loan volume in the subsequent period. Arguably, recent natural disaster realizations may deteriorate borrower fundamentals, due to which banks may curtail credit in affected regions. Such an argument may confound our preferred interpretation, despite controlling for the direct effects of natural disasters in equation (6) via county-year fixed effects. We address this plausible confounding explanation in Table 5.

Insert Table 5 Here

In panel A, we re-run the baseline specification, presented in equation (6), augmented with the interactions of contemporaneous and lagged disaster intensity measures with the bank group variable.[21] Doing so allows us to isolate the independent effect of abnormal hot temperature occurrences on subsequent lending while controlling for the potential adverse effects of (contemporaneous and lagged) disasters on loan outcomes. In Panel B, we restrict our analysis only to counties that did not experience any intense disaster in a current and past two years. In both panels of Table 5, the results suggest that alternative explanations based on recent adverse weather-driven changes in bank lending are unlikely to confound our baseline results.

3.2.3 Robustness of baseline results

3.2.3.1 Size-based evidence

In this section, we focus on *bank size*, a characteristic that correlates positively with geographic dispersion. In our setting, bank size is an interesting bank characteristic to explore because size affects a bank's ability to lend to informationally opaque borrow-

[21] In unreported results, we find similar results when we augment equation (6) with interactions of the bank group variable and contemporaneous and lagged continuous disaster intensity measures based on inflation-adjusted and per capita disaster damages.

ers.[22] Given a majority of the small-medium enterprise (SME) lending is relationship lending (Petersen & Rajan, 1994, 1995; Degryse, Kim, & Ongena, 2009), and that small banks are superior in channeling funds to SMEs (Berger et al., 2005), and that large banks engage relatively more in transactional lending (Cole, 1998; Cole et al., 2004), one may expect the *incremental effect* of an increase in the frequency of abnormal hot temperature to be negative for large banks. In Panel A of Table 6, the dichotomous variable $\mathbb{1}_{bt-1}^{\text{Large Bank Size Group}}$ equals 1 (0 otherwise) if the logarithm of a bank's total assets is above the median value. The logarithm of bank size averages 18.5 and 14.1 for the *large* and *small* bank size group, respectively. The rest of the variables are defined the same way as in equation (6).

Overall, in Panel A of Table 6, we find that the large banks exhibit a higher tendency to tighten credit availability following an increase in the frequency of abnormal hot temperature in a region. The economic significance of the coefficients in the first two columns suggests that large banks, on average, originate a 1.7 to 1.8 percent lower number of small farm loans in a county year following a standard deviation increase in the frequency of abnormal hot temperature. The results in columns (3) and (4) suggest that large banks, on average, lend 48.9 to 49.3 thousand dollars less than small banks, with a standard deviation increase in the frequency of abnormal hot temperatures in the previous period. Overall, the results in this section suggest that the negative correlation between abnormal hot temperature occurrences and subsequent credit availability in a region is stronger for the sub-sample corresponding to relatively large-sized banks.

[Insert Table 6 Here]

3.2.3.2 Alternative definition of a market

In our baseline results, we define a market as a county. While the sample of banks with all their branches in a single county is tiny, the sample of banks whose branch network

[22]See Berger & Udell (1995); Berger et al. (1998); Strahan & Weston (1998); Berger et al. (1999, 2005); Degryse, Laeven, & Ongena (2009) among others.

is confined to a single state is sizeable. This feature provides us with a decent-sized comparable group, and allows us to present results under an alternative specification in Panel B of Table 6. The dichotomous variable $\mathbb{1}_{bt-1}^{\text{Multi-State Bank}}$ equals 1 (0 otherwise) if a bank's complete branch network spans more than one US state. On average, the branch network of a multi-state bank in our sample spans 13 states. On the contrary, the branch network of a single-state bank, by definition, is confined to a single state.

The results in Panel B of Table 6 echo our baseline results. Banks with higher geographic dispersion are relatively more likely to reduce credit supply to regions that experience an increase in abnormal hot temperature occurrences in the previous period. In columns (1) and (2), the coefficients imply a relative reduction of 2.4 percent in the number of small farm loan originations. In columns (3) and (4), the relative reduction in loan volume ranges between 2.8 and 2.9 percent, equivalent to 38.0 and 39.1 thousand dollars, respectively.

3.2.4 Role of bank branch network: Core versus non-core markets

In this section, we test how variation in credit supply depends on market characteristics. For these tests, we follow Cortés & Strahan (2017), and define *(non-)core market* as a county where a bank lent in the prior year to small farms (without) with a branch presence.[23] Table 7 presents an analysis in which we separate our sample into core and non-core markets.

[Insert Table 7 Here]

In Panel A, for non-core markets, we find that the coefficient of interest equals -0.8 and -1.2 in columns (1) and (3), respectively. In contrast, for core markets, the coefficients of interest lack statistical significance. Together, the results in Panel A suggest that the baseline decline we document in Table 4 is primarily driven by the reduction in lending in non-core markets. The results are qualitatively similar in Panels B and C of Table 7, where we form bank groups based on size and whether a bank operates in one

[23] Gilje et al. (2016) define local and non-local markets as counties with and without branch presence. In a similar approach, Cortés (2023) defines a bank as local to a county if it has at least one branch in that county.

or more states, respectively. These results suggest that banks protect the rents that they are able to extract from their bank-borrower relationships in counties where they have a physical presence. Hence, these results align with prior literature that emphasizes the importance of bank-borrower proximity.

3.3 Within bank analysis

Our results so far indicate that geographically dispersed banks lend relatively less to small farms in counties that experience an increase in the frequency of abnormal hot temperature in the previous period. What does a bank that cuts lending volume to such counties do with the loanable funds curtailed cautiously? Our baseline results, thus, beg the question of whether banks rebalance their farm loan portfolios given the changing abnormal temperature occurrences across their service regions. In this section, we test the presence of rebalancing *within* a bank loan portfolio.

3.3.1 Rebalancing within and across sectors

A bank, reacting to year-to-year variations in the frequency of abnormal hot temperature, may rebalance its farm loan portfolio between counties that experience an increase in the frequency of abnormal hot temperature and those that do not. To test this conjecture, we employ the following *within* bank specification:

$$\begin{aligned}\Delta\text{Weight}^{\mathbb{C}}_{bt} =& \beta_1 \mathbb{1}^{\text{High Geographic Dispersion}}_{bt-1} \times \Delta\text{Frequency of Abnormal Hot Temperature}_{bt-1} \\ &+ \beta_2 \mathbb{1}^{\text{High Geographic Dispersion}}_{bt-1} + \beta_3 \Delta\text{Frequency of Abnormal Hot Temperature}_{bt-1} \\ &+ \Gamma' \Delta\text{Controls}_{bt-1} + \text{Bank}_b + \text{Year}_t + \upsilon_{bt}.\end{aligned} \tag{7}$$

In equation (7), the dependent variable is the change in county's share of new originations (based on number and volume of loans) *within* a bank, denoted by $Weight^{\mathbb{C}}_{bt}$, which equals $\frac{\sum_{c\in\mathbb{C}} \mathbb{L}_{cbt}}{\mathbb{L}_{bt}}$, where $\mathbb{C}$ represents the set of counties that experienced an increase in the frequency of abnormal hot temperature in the previous year, and $\mathbb{L}_{cbt}$ represents lending activity in county c by bank b in year t. The lending activity is based on either the number of originations or the loan volume. *Frequency of Abnormal Hot Temperature*$_{bt-1}$ equals $\frac{1}{|\mathbb{B}_{bt-1}|} \sum_{c\in\mathbb{B}_{bt-1}}$ Frequency of Abnormal Hot Temperature$_{ct-1}$, where $|\mathbb{B}_{bt-1}|$ represents the number of counties in which a bank operates in a given year. The idea here is to construct a measure that reflects the aggregated changes in the climate risk exposure of the focal bank across its service regions that differ in terms of climate risk.[24] The coefficient of interest is β_1, which captures the *incremental effect* of a change in aggregate bank-level frequency of abnormal hot temperature for a geographically dispersed bank. Since the dependent variable is expressed as *weight*, a natural interpretation of a negative (positive) β_1 is an increase (decrease) in the *weight* to other counties that do not experience an increase in the frequency of abnormal hot temperature in the previous period.

In columns (1)-(2) of Panel A of Table 8, the results suggest that within the farm loan portfolio, geographically dispersed banks decrease the aggregate share of lending activity more for counties that experience an increase in the frequency of abnormal hot temperature in the previous year. A geographically dispersed bank weighs such counties between 10.5 and 12.1 percent less, relative to the mean value of 36.5 and 36.8 percent based on loan volume and number of originations, respectively, in their farm loan portfolio in the year following a standard deviation increase in the bank-level frequency of abnormal temperature.

In columns (3)-(4) and (5)-(6) of Panel A of Table 8, we divide counties that experienced an increase in the frequency of abnormal hot temperature in the previous year into core and non-core markets, respectively. The results in columns (3)-(6) of Panel A suggest the decline in weight noted in the first two columns is driven by banks protecting lending in their core markets by reducing lending to non-core markets. Observing these findings in the bank-year level panel bolsters further confidence in results presented in Table 7, and corroborate with extant literature that suggests the importance

[24]This aggregation leads to loss of information as the bank-level frequency of abnormal hot temperature *conceals* the identities of counties that experience an increase, a decrease, or no change in their county-level counterpart. Nevertheless, an increase, on average, in the bank-level frequency of abnormal hot temperature indicates that the bank-level representative small farm borrower is from one of the counties that experience an increase in the frequency of abnormal hot temperature.

of branch networks and bank-borrower relationships.

[Insert Table 8 Here]

An alternative to a bank rebalancing among regions within its farm loan portfolio is that a bank may choose to reallocate credit away from the farm sector. We test for this alternative way of rebalancing credit by using the specification in equation (7) with changes in the ratio of the farm loans to total loans as the dependent variable and present results in Panel B of Table 8. The lack of statistical and economic significance of coefficients in columns (1) and (2) suggests a lack of differential effect for banks with higher geographic dispersion on their exposure to the farm sector.

In a set of unreported tests, we find that the findings of this section remain qualitatively similar when using loan volume-weighted, rather than equally-weighted, bank-level frequency of abnormal hot temperature. Overall, the *within bank* results corroborate the evidence presented in the previous section that, given the scope, banks' willingness to lend in a region declines with an increased frequency of abnormal temperature. These results suggest that the change in banks' lending strategies is captured within their farm loan portfolios, resulting from the market-level local climatic conditions informing banks' decisions about the loan product that caters to the needs of a sector that ends up bearing the brunt of long-term changes in the weather.

4 Conclusion

A key takeaway of this study is that banks, as sophisticated investors, understand the intricacies of the local climatic conditions and their effect on borrowers. We show that banks *adapt* to increased climate risk in a region by reducing credit supply to borrowers in that region. Banks do not reduce credit flows indiscriminately as they shield their core markets strategically: cutting lending predominantly in counties outside their branch networks. These results highlight the vital role played by branch networks in financial integration. Relatedly, we also show that banks tend to rebalance their farm loan portfolios by diverting credit from counties that experienced an increase in climate risk in the previous period to those that did not.

These findings constitute insights for a relatively under-explored segment of financial intermediation – lending to small farms. These findings directly speak to the current policy debate surrounding financial stability due to banks' climate risk exposure. Credit not flowing to the at-risk, geographically constrained economic agents suggests that banks' adaptations that improve banks' solvency and financial stability have welfare costs for those unable to mitigate climate risk by moving to relatively safe regions.

Our findings have implications for the relevant literature that finds minor or no impact on the financial sector in general and the banks in particular. Overlooking banks' ability to pre-empt the suffering of significant loan losses by adapting lending strategies, by either curtailing lending or rebalancing loan portfolios, *ex-ante* natural disaster occurrences, it may seem that banks are resilient to the adverse effects of extreme weather-related disasters. This 'resiliency' may embolden the notion that banks are not prone to the risks posed by short and long term changes in climate.

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Table 1: **Summary statistics**
This table presents summary statistics of the relevant variables used in the analysis. The sample period is from 1997 to 2017.

	N	Mean	SD	p25	p50	p75
Panel A: Within county analysis						
Frequency of abnormal hot temperature (in %)	64,806	4.17864	4.35774	1.15741	2.77778	5.55556
Ln(total damages)	47,914	1.739	2.688	-0.105	1.597	3.467
Ln(property damages)	47,914	1.415	2.614	-0.238	1.421	3.113
PDD (1 = Yes, 0 = No)	47,914	0.262	0.440	0.000	0.000	1.000
Land value per acre (in ’000s)	9,085	3.949	7.784	1.909	2.930	4.542
Machinery value per operation (in ’000s)	9,084	120.850	89.793	60.034	87.832	153.190
Income receipts per operation (in ’000s)	8,912	19.788	18.446	9.037	14.738	24.544
Number of originations	45,887	62.373	89.561	9.000	29.000	78.000
Loan volume (in ’000s)	45,887	4,759.387	7,299.812	600.000	2,116.000	5,880.000
Panel B: Within county-year analysis						
Number of originations	129,630	16.931	36.727	2.000	5.000	15.000
Loan volume (in ’000s)	129,630	1,348.124	2,871.346	101.000	412.000	1,277.000
Frequency of abnormal hot temperature (in %)	129,630	4.265	4.028	1.620	3.009	5.556
Capital ratio (in %)	129,630	11.131	2.753	9.452	10.648	12.424
Ln(bank size)	129,630	16.418	2.628	14.205	15.967	18.756
Profitability (in %)	129,630	1.094	0.648	0.886	1.175	1.380
NPL-to-assets (in %)	129,630	0.349	0.535	0.023	0.109	0.403
Panel C: Within bank analysis						
Weight - Number of originations	7,858	0.368	0.384	0.005	0.198	0.769
Weight - Loan volume	7,858	0.365	0.385	0.003	0.190	0.766
Proportion of farm loans	7,858	0.062	0.088	0.008	0.028	0.079
Frequency of abnormal hot temperature - Equally weighted (in %)	7,858	4.330	2.943	2.263	3.988	5.798
Capital ratio (in %)	7,858	12.145	3.218	9.896	11.376	13.602
Ln(bank size)	7,858	14.246	1.563	13.154	13.944	14.926
Profitability (in %)	7,858	1.064	0.717	0.837	1.127	1.410
NPL-to-assets (in %)	7,858	0.126	0.253	0.005	0.043	0.139

Table 2: **Abnormal hot temperature and disaster intensities**
This table presents the validation results for the frequency of abnormal hot temperature. In column (1), the dependent variable is the logarithm of inflation-adjusted-per-capita *total* damages due to all disaster types in a county-year. In column (2), the dependent variable is the logarithm of inflation-adjusted-per-capita *property* damages due to all disaster types in a county-year. In column (3), the dependent variable is *PDD*, which is a dichotomous variable that equals 1 if, for a county-year, the reported total damages in the presidential disaster declaration database within SHELDUS are positive and equals 0 otherwise. The independent variable is *lagged* frequency of abnormal hot temperature in a county-year. The sample period is from 1997 to 2017. The standard errors are clustered by county, and t-statistics are presented in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)
	Dependent variable:		
	Ln(total damages)	Ln(property damages)	PDD (1 = Yes, 0 = No)
Frequency of abnormal hot temperature	1.497***	1.373***	0.462***
	(3.715)	(3.179)	(6.469)
N	47,914	47,914	47,914
R^2	0.312	0.256	0.141
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 3: **Abnormal hot temperature and farm financials**
This table presents results from tests relating the value of pledgeable collateral, debt serviceability, and the frequency of abnormal hot temperature in the previous census year. The dependent variable is log growth in land value per acre, machinery value per operation, and farm income receipts per operation in columns (1), (2), and (3), respectively. The independent variable is *lagged* frequency of abnormal hot temperature differenced over two census years. The sample corresponds to five USDA census years: 1997, 2002, 2007, 2012, and 2017. The standard errors are clustered at the county level, and t-statistics are presented in parentheses. Significance levels: * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01.

	(1)	(2)	(3)
	Dependent variable:		
	Land value growth	Machinery value growth	Income receipts growth
Change in frequency of abnormal hot temperature	-0.635***	-0.645***	-0.349**
	(-8.176)	(-8.854)	(-2.149)
N	9,085	9,084	8,912
R^2	0.423	0.288	0.188
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 4: **Abnormal hot temperature and credit outcomes – Baseline**

This table presents results linking credit outcomes at the county-bank-year level and the frequency of abnormal hot temperature in the previous year. In columns (1)-(2), the dependent variable is the growth in the number of small farm loan originations by a bank to small farms in a county-year. In columns (3)-(4), the dependent variable is growth in the total loan amount extended by a bank to small farms in a county-year. *Geographic dispersion* of a bank is defined as the number of counties in which a bank has at least one branch. The *high geographic dispersion bank* is a dichotomous variable that equals 1 (0 otherwise) if a bank's geographic dispersion is above the median value. The independent variable is *lagged* and differenced frequency of abnormal hot temperature. The lagged control variables are the change in *capital ratio* that equals tier 1 capital as a fraction of total assets, the change in the logarithm of *bank size* measured by the total assets of a bank, the change in *profitability* that equals the return on assets, and the change in *NPL-to-assets* that equals non-performing loans as a fraction of total assets of a bank. The sample period is from 1997 to 2017. The standard errors are clustered by county, and t-statistics are presented in parentheses. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

	(1)	(2)	(3)	(4)
	Dependent variable: Growth in (·)			
	Number of originations		Loan volume	
High geographic dispersion bank × Change in frequency of abnormal hot temperature	-0.476**	-0.479**	-0.768***	-0.753**
	(-2.383)	(-2.394)	(-2.612)	(-2.558)
High geographic dispersion bank	-0.018	-0.011	-0.028	-0.022
	(-0.971)	(-0.576)	(-0.985)	(-0.770)
Change in capital ratio		0.006**		0.007
		(2.085)		(1.613)
Change in ln(bank size)		0.127***		0.135***
		(5.471)		(3.723)
Change in profitability		0.006		-0.005
		(0.884)		(-0.550)
Change in NPL-to-assets		1.644		3.767*
		(1.303)		(1.909)
N	129,630	129,630	129,630	129,630
R^2	0.376	0.376	0.374	0.375
Bank×County FE	Yes	Yes	Yes	Yes
County×Year FE	Yes	Yes	Yes	Yes

Table 5: **Frequency of abnormal hot temperature, contemporaneous and lagged disaster realizations, and credit outcomes**

This table presents results linking credit outcomes at the county-bank-year level and the frequency of abnormal hot temperature in the previous year. In columns (1)-(2), the dependent variable is the growth in the number of small farm loan originations by a bank to small farms in a county-year. In columns (3)-(4), the dependent variable is growth in the total loan amount extended by a bank to small farms in a county-year. *Geographic dispersion* of a bank is defined as the number of counties in which a bank has at least one branch. The *high geographic dispersion bank* is a dichotomous variable that equals 1 (0 otherwise) if a bank's geographic dispersion is above the median value. The independent variable is *lagged* and differenced frequency of abnormal hot temperature. *PDD* is a dichotomous variable that equals 1 if, for a county-year, the reported total damages in the presidential disaster declaration database within SHELDUS are positive and equals 0 otherwise. In Panel B, the analysis corresponds to a sample of counties for which there were *no* major disasters (PDD events) in recent years (*t*, *t-1*, and *t-2*). The lagged control variables are the change in *capital ratio* that equals tier 1 capital as a fraction of total assets, the change in the logarithm of *bank size* measured by the total assets of a bank, the change in *profitability* that equals the return on assets, and the change in *NPL-to-assets* that equals non-performing loans as a fraction of total assets of a bank. The sample period is from 1997 to 2017. The standard errors are clustered by county, and t-statistics are presented in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)
	Dependent Variable: Growth in (.)			
	Number of originations		Loan volume	
Panel A: Ruling out confounding effects of recent disaster realizations				
High geographic dispersion Bank×Change in frequency of abnormal hot temperatures	-0.475**	-0.477**	-0.752**	-0.738**
	(-2.376)	(-2.384)	(-2.551)	(-2.501)
High geographic dispersion Bank×PDD_t	-0.004	-0.006	0.019	0.016
	(-0.316)	(-0.402)	(0.845)	(0.740)
High geographic dispersion Bank×PDD_{t-1}	-0.006	-0.005	0.038*	0.037*
	(-0.436)	(-0.403)	(1.779)	(1.730)
High geographic dispersion Bank×PDD_{t-2}	-0.020	-0.019	-0.039*	-0.039*
	(-1.412)	(-1.368)	(-1.790)	(-1.776)
R^2	0.376	0.376	0.374	0.375
N	129,630	129,630	129,630	129,630
Panel B: Subsample analysis – Counties with no recent disaster realizations				
High geographic dispersion Bank×Change in frequency of abnormal hot temperatures	-0.577**	-0.558*	-0.779*	-0.756*
	(-2.007)	(-1.939)	(-1.782)	(-1.729)
R^2	0.413	0.414	0.409	0.409
N	70,289	70,289	70,289	70,289
Bank controls	No	Yes	No	Yes
Bank×County FE	Yes	Yes	Yes	Yes
County×Year FE	Yes	Yes	Yes	Yes

Table 6: **Abnormal hot temperature and credit outcomes – Robustness**
This table presents results linking credit outcomes at the county-bank-year level and the frequency of abnormal hot temperature in the previous year using bank size as a proxy for a bank's geographic dispersion. In columns (1)-(2), the dependent variable is the growth in the number of small farm loan originations by a bank to small farms in a county-year. In columns (3)-(4), the dependent variable is growth in the total loan amount extended by a bank to small farms in a county-year. In Panel A, the *large bank size group* is a dichotomous variable that equals 1 (0 otherwise) if the logarithm of bank size measured by the total assets of a bank is above the median value. In Panel B, the *multi-state bank* is a dichotomous variable that equals 1 (0 otherwise) if a bank has a branch presence in more than one US state. The independent variable is *lagged* and differenced frequency of abnormal hot temperature. The lagged control variables are the change in *capital ratio* that equals tier 1 capital as a fraction of total assets, the change in the logarithm of *bank size* measured by the total assets of a bank, the change in *profitability* that equals the return on assets, and the change in *NPL-to-assets* that equals non-performing loans as a fraction of total assets of a bank. The sample period is from 1997 to 2017. The standard errors are clustered by county, and t-statistics are presented in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)
	Dependent variable: Growth in (·)			
	Number of originations		Loan volume	
Panel A: Size-based evidence				
Large bank size group × Change in frequency of abnormal hot temperature	-0.432**	-0.441**	-0.911***	-0.903***
	(-2.178)	(-2.222)	(-3.032)	(-3.004)
N	130,178	130,178	130,178	130,178
R^2	0.375	0.376	0.374	0.374
Panel B: Alternative definition of a market				
Multi-state bank × Change in frequency of abnormal hot temperature	-0.600***	-0.600***	-0.721**	-0.701**
	(-2.604)	(-2.601)	(-2.067)	(-2.011)
N	129,575	129,575	129,575	129,575
R^2	0.375	0.376	0.374	0.374
Bank Controls	No	Yes	No	Yes
Bank×County FE	Yes	Yes	Yes	Yes
County×Year FE	Yes	Yes	Yes	Yes

Table 7: **Abnormal hot temperature and credit outcomes – Core versus non-core markets**
This table presents a sub-sample analysis linking credit outcomes at the county-bank-year level and the frequency of abnormal hot temperature in the previous year. In odd-numbered columns, the sample corresponds to *non-core markets*, defined as counties outside a bank's branch network. In even-numbered columns, the sample corresponds to *core markets*, defined as counties in which a bank has at least one branch. In columns (1)-(2), the dependent variable is the growth in the number of small farm loan originations by a bank to small farms in a county-year. In columns (3)-(4), the dependent variable is growth in the total loan amount extended by a bank to small farms in a county-year. Panel A presents results based on *geographic dispersion* of a bank is defined as the number of counties in which a bank has at least one branch. The *high geographic dispersion bank* is a dichotomous variable that equals 1 (0 otherwise) if a bank's geographic dispersion is above the median value. Panel B presents bank-size-based results. The *large bank size group* is a dichotomous variable that equals 1 (0 otherwise) if the logarithm of bank size measured by the total assets of a bank is above the median value. In Panel C, *multi-state bank* is a dichotomous variable that equals 1 (0 otherwise) if a bank has a branch presence in more than one US state. The independent variable is *lagged* and differenced frequency of abnormal hot temperature. The lagged control variables are the change in *capital ratio* that equals tier 1 capital as a fraction of total assets, the change in the logarithm of *bank size* measured by the total assets of a bank, the change in *profitability* that equals the return on assets, and the change in *NPL-to-assets* that equals non-performing loans as a fraction of total assets of a bank. The sample period is from 1997 to 2017. The standard errors are clustered by county, and t-statistics are presented in parentheses. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

	(1)	(2)	(3)	(4)
	Non-core market	Core market	Non-core market	Core market
	Dependent variable: Growth in (.)			
	Number of originations		Loan volume	
Panel A				
High geographic dispersion bank × Change in frequency of abnormal hot temperature	-0.810**	-0.299	-1.250**	-0.347
	(-2.058)	(-1.035)	(-2.054)	(-0.844)
N	61,326	68,304	61,326	68,304
R^2	0.463	0.426	0.460	0.419
Panel B				
Large bank size group × Change in frequency of abnormal hot temperature	-0.869**	-0.467	-1.421**	-0.818*
	(-2.217)	(-1.587)	(-2.327)	(-1.887)
N	61,872	68,306	61,872	68,306
R^2	0.463	0.426	0.460	0.419
Panel C				
Multi-state bank × Change in frequency of abnormal hot temperature	-1.226***	-0.217	-1.182*	-0.439
	(-2.709)	(-0.643)	(-1.719)	(-0.883)
N	61,275	68,300	61,275	68,300
R^2	0.463	0.426	0.460	0.419
Bank controls	Yes	Yes	Yes	Yes
Bank×County FE	Yes	Yes	Yes	Yes
County×Year FE	Yes	Yes	Yes	Yes

Table 8: ***Within* bank analysis – Rebalancing**

The table presents results on the possible rebalancing of farm loan portfolios and the frequency of abnormal hot temperature in the previous period. In Panel A, the dependent variable, *weight* equals $\frac{\sum_{c \in \mathbb{C}} \mathbb{L}_{cbt}}{\mathbb{L}_{bt}}$, where $\mathbb{C}$ represents the set of counties that experienced an increased in the frequency of abnormal hot temperature in the previous year, and $\mathbb{L}_{cbt}$ represents farm lending activity in county c by bank b in year t. In columns (1)-(2), (3)-(4) and (5)-(6), *weight* all, non-core, and core markets (counties), respectively, which are constituents of $\mathbb{C}$. A *(non-)core market* is defined as a county in a bank (does not) does have a physical branch. In panel A1 (A2), the lending activity is based on the number of originations (loan volume). In Panel B, the dependent variable is the change in the proportion of farm loans relative to total loans. Here, the independent variable is *lagged* changes in *bank level frequency of abnormal hot temperature*, which equals the (equally-weighted) average frequency of abnormal hot temperature across all counties in which a bank has farm loan operations. *Geographic dispersion* of a bank is defined as the number of counties in which a bank has at least one branch. The *high geographic dispersion bank* is a dichotomous variable that equals 1 (0 otherwise) if a bank's geographic dispersion is above the median value. The lagged control variables are the change in *capital ratio* that equals tier 1 capital as a fraction of total assets, the change in the logarithm of *bank size* measured by the total assets of a bank, the change in *profitability* that equals the return on assets, and the change in *NPL-to-assets* that equals non-performing loans as a fraction of total assets of a bank. The sample period is from 1997 to 2017. The standard errors are clustered by bank, and t-statistics are presented in parentheses. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

Panel A: Cross-country reallocation

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: Change in a county's share of new originations *within* a bank					
	All		Non-core market		Core market	
Panel A1: Weight based on number of originations						
High geographic dispersion bank x Change in bank level frequency of abnormal hot temperature	-1.520**	-1.516**	-0.731***	-0.731***	-0.789	-0.785
	(-2.223)	(-2.221)	(-4.191)	(-4.184)	(-1.277)	(-1.273)
R^2	0.389	0.389	0.157	0.157	0.355	0.355
Panel A2: Weight based on loan volume						
High geographic dispersion bank x Change in bank level frequency of abnormal hot temperature	-1.306*	-1.300*	-0.846***	-0.845***	-0.460	-0.454
	(-1.899)	(-1.894)	(-4.240)	(-4.234)	(-0.756)	(-0.749)
R^2	0.373	0.373	0.144	0.144	0.335	0.335
N	7,858	7,858	7,858	7,858	7,858	7,858
Bank Controls	No	Yes	No	Yes	No	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Cross-sector reallocation

	(1)	(2)
	Dependent variable: Change in proportion of farm loans	
High geographic dispersion bank x Change in bank level frequency of abnormal hot temperature	0.014	0.014
	(1.304)	(1.344)
R^2	0.200	0.202
N	7,858	7,858
Bank controls	No	Yes
Bank FE	Yes	Yes
Year FE	Yes	Yes

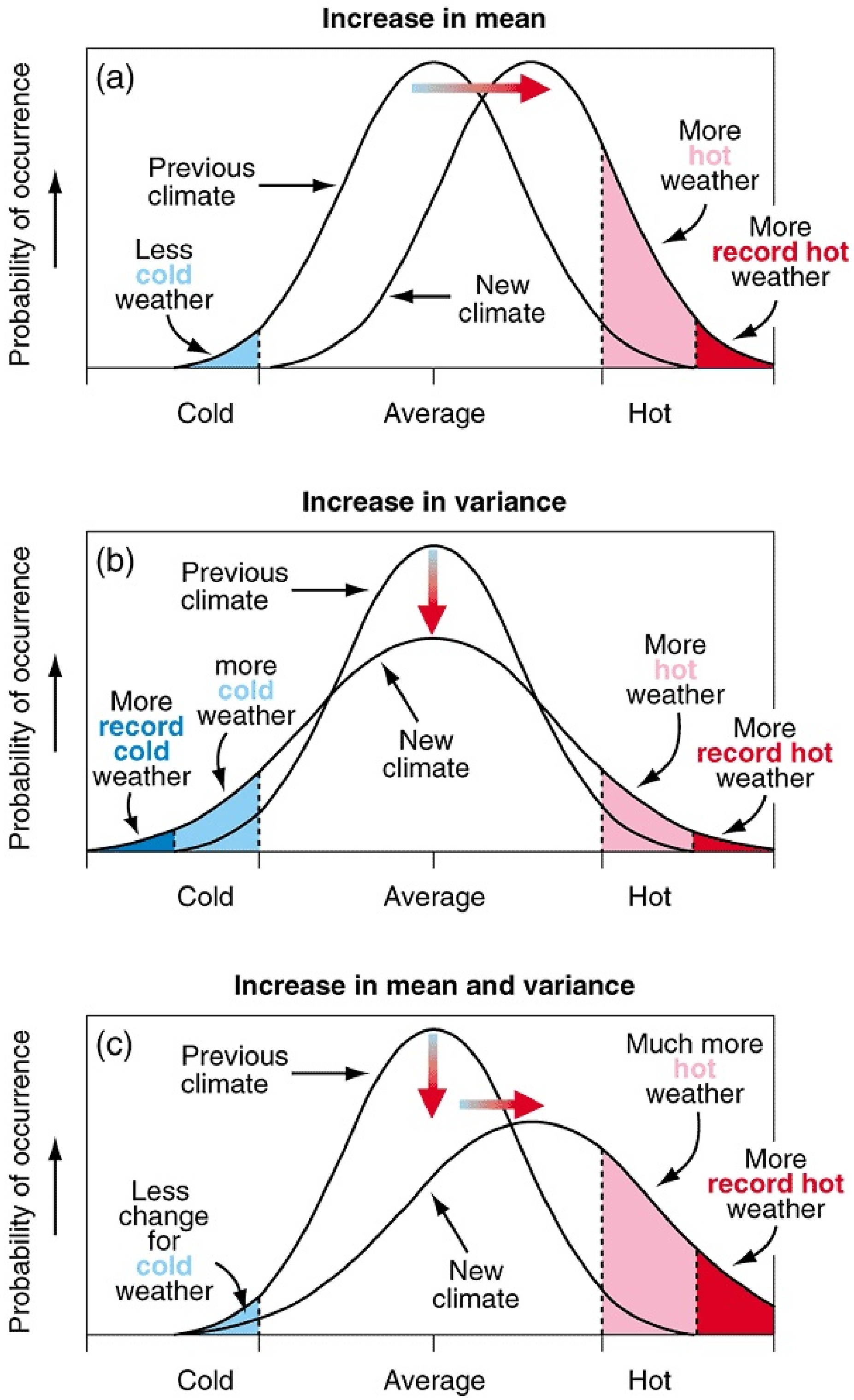

Figure 1: The figure depicts the effect of a change in (a) mean, (b) variance, and (c) mean and variance of temperature distribution on the probability of abnormal hot and cold temperatures. (Source: Folland et al. (2001)).

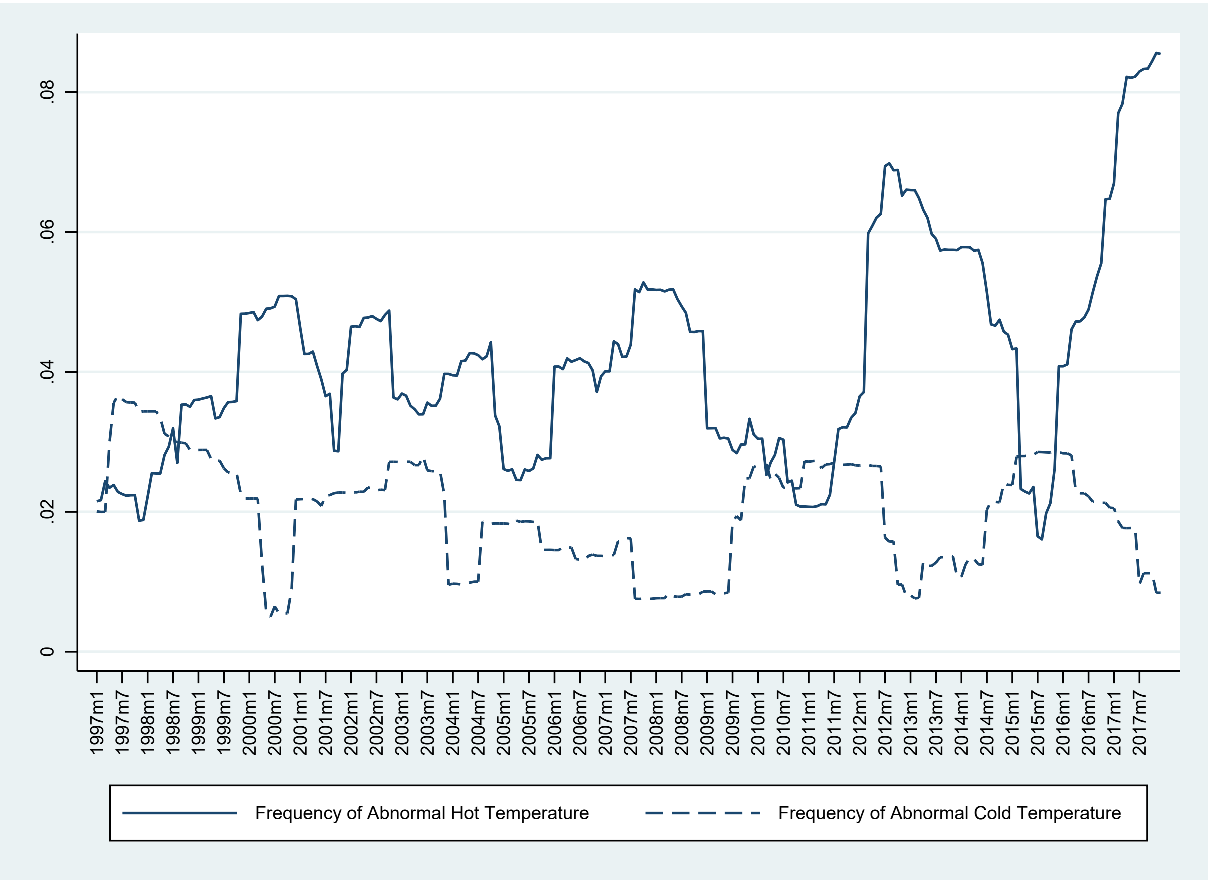

Figure 2: The figure presents a time-series plot of cross-sectional means of *Frequency of Abnormal Hot Temperature* (solid line) and *Frequency of Abnormal Cold Temperature* (dashed line). Here, *Frequency of Abnormal Hot (Cold) Temperature* equals the past 36-month moving average of a dichotomous variable that equals 1 (0 otherwise) if the observed temperature for a county-month-year is above (below) the county-month specific 99^{th} (1^{st}) percentile observed over the reference period (1951-1980). The sample period is 1997:M1-2017:M12.

Appendix

Information on Hot Stuff: Do Lenders Pay Attention to Climate Risk?

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Table A.1: **Frequency of abnormal hot temperature and climate change beliefs**
The table presents additional results validating the *frequency of abnormal hot temperature* proposed in this study. Specifically, we test the association of *lagged* frequency of abnormal hot temperature with the beliefs about climate change in a region. In this table, *climate beliefs* equals the total acres in a county devoted to soybean crop as a fraction of total acres devoted to soybean and corn crop in county c in year t. The data to construct climate beliefs are from the USDA-NASS annual survey program. The sample period is from 1997 to 2017. The standard errors are clustered by county, and t-statistics are presented in parentheses. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

	(1)
	Dependent variable: Climate beliefs
Frequency of abnormal hot temperatures	0.057*
	(1.862)
N	22,024
R^2	0.893
County FE	Yes
Year FE	Yes

Rationale and discussion: Climate change may prompt agents to update their beliefs about the changing climatic conditions. This update is reflected in their decisions, regardless of weather realizations in a region. Analyzing agents' beliefs (or adaptations) is challenging because beliefs are unobservable (Hsiang, 2016). Note that the climate has a profound effect on the agricultural practices of farmers whose beliefs about changing climate are likely to be reflected in their crop portfolios; see Kelly et al. (2005) and Burke & Emerick (2016). For instance, a farmer may adapt to a new climate with a higher average temperature by substituting a more heat-sensitive crop with a less heat-sensitive crop. Since land is immovable, a representative farmer's adaptations correspond to his location.
Moreover, temperature plays a vital role from a crop's yield perspective. Hatfield et al. (2008) list optimal temperatures for various field crops grown in the US. The optimal temperature for corn yield (18-22 degrees Celsius) is lower than that for soybean (22-24 degrees Celsius). Besides, the failure temperature, at which yield drops to zero, for corn is 35 degrees Celsius compared with 39 degrees Celsius for soybean. Schlenker & Roberts (2009) find that soybean (corn) yield starts to decline after the temperature exceeds the threshold of 30 (29) degrees Celsius. These thresholds imply that soybean has higher heat tolerance relative to corn from a yield perspective. Also, the growing season of the two crops differs across states but shows significant overlap within a state, see USDA (1997). It follows that, in a given year, a farmer can use a given plot of land to grow either corn or soybean, but not both. If a farmer believes the average temperature to be higher in the future, then the number of acres allocated to soybean, relative to those allocated to corn, would increase over time.
Building on these insights, we construct a proxy for beliefs about climate change as follows:

$$\text{Climate Beliefs}_{ct} = \frac{\text{Acres Planted}_{ct,\text{Soybean}}}{\text{Acres Planted}_{ct,\text{Soybean}} + \text{Acres Planted}_{ct,\text{Corn}}}$$

where Acres $\text{Planted}_{ct,\text{Soybean}}$ equals the aggregate number of acres planted for soybean in county c in year t. Acres $\text{Planted}_{ct,\text{Corn}}$ is defined analogously for corn. Climate Beliefs_{ct} averages 49.2 percent with a standard deviation of 19.2 percent. The dataset is an unbalanced county-year panel made up of 1,816 counties from 31 US contiguous states covered over 21 year period, starting in 1997. The average temporal coverage of a county is approximately 13 years.
In line with our expectations, *climate beliefs* correlate positively with the frequency of abnormal hot temperature, implying a meaningful relationship between the two variables. Note that a representative farmer growing both crops signals that soil type and quality are suitable for soybean and corn. We include county fixed effects in the regression specification to control for any time-invariant county-specific factors such as soil type. These results, thus, further lend support to the frequency of abnormal hot temperature that captures the relevant aspects of market-level information on abnormal hot temperature occurrences.

Table A.2: **Abnormal hot temperature and credit outcomes – Robustness I**

This table presents the robustness of our baseline results to interactions of bank characteristics and the change in the frequency of abnormal hot temperature. In column (1), the dependent variable is the growth in the number of small farm loan originations by a bank to small farms in a county-year. In column (2), the dependent variable is growth in the total loan amount extended by a bank to small farms in a county-year. *Geographic dispersion* of a bank is defined as the number of counties in which a bank has at least one branch. The *high geographic dispersion bank* is a dichotomous variable that equals 1 (0 otherwise) if a bank's geographic dispersion is above the median value. The independent variable is *lagged* and differenced frequency of abnormal hot temperature. The lagged control variables are the change in *capital ratio* that equals tier 1 capital as a fraction of total assets, the change in the logarithm of *bank size* measured by the total assets of a bank, the change in *profitability* that equals the return on assets, and the change in *NPL-to-assets* that equals non-performing loans as a fraction of total assets of a bank. The sample period is from 1997 to 2017. The standard errors are clustered by county, and t-statistics are presented in parentheses. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

	(1)	(2)
	Dependent Variable: Growth in (·)	
	Number of originations	Loan volume
High geographic dispersion bank×Change in frequency of abnormal hot temperatures	-0.479**	-0.777***
	(-2.381)	(-2.612)
N	129,630	129,630
R^2	0.376	0.375
Bank controls	Yes	Yes
Bank controls×Change in frequency of abnormal hot temperatures	Yes	Yes
Bank×County FE	Yes	Yes
County×Year FE	Yes	Yes

Table A.3: **Abnormal hot temperature and credit outcomes – Robustness II**
This table presents robustness of our baseline findings linking credit outcomes at the county-bank-year level and the frequency of abnormal hot temperature in the previous year. In columns (1)-(3), the dependent variable equals 1 (0 otherwise) if the growth in the number of small farm loan originations by a bank to small farms in a county-year is negative. In columns (4)-(6), the dependent variable equals 1 (0 otherwise) if the growth in loan volume by a bank to small farms in a county-year is negative. *Geographic dispersion* of a bank is defined as the number of counties in which a bank has at least one branch. The *high geographic dispersion bank* is a dichotomous variable that equals 1 (0 otherwise) if a bank's geographic dispersion is above the median value. The independent variable is *lagged* and differenced frequency of abnormal hot temperature. The lagged control variables are the change in *capital ratio* that equals tier 1 capital as a fraction of total assets, the change in the logarithm of *bank size* measured by the total assets of a bank, the change in *profitability* that equals the return on assets, and the change in *NPL-to-assets* that equals non-performing loans as a fraction of total assets of a bank. The sample period is from 1997 to 2017. The standard errors are clustered by county, and t-statistics are presented in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Decline in (·) (1 = Yes, 0 = No)					
	Number of originations			Loan volume		
High geographic dispersion bank×Change in frequency of abnormal hot temperature	0.296*	0.312**	0.327**	0.375**	0.381**	0.392***
	(1.960)	(2.062)	(2.145)	(2.508)	(2.546)	(2.599)
N	129,630	129,630	129,630	129,630	129,630	129,630
R^2	0.420	0.420	0.420	0.399	0.399	0.399
Bank controls	No	Yes	Yes	No	Yes	Yes
Bank controls×Change in frequency of abnormal hot temperature	No	No	Yes	No	No	Yes
Bank×County FE	Yes	Yes	Yes	Yes	Yes	Yes
County×Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A.4: **Frequency of abnormal hot temperature, crop insurance, and credit outcomes**
This table presents results linking credit outcomes at the county-bank-year level and the frequency of abnormal hot temperature in the previous year. In columns (1)-(2), the dependent variable is the growth in the number of small farm loan originations by a bank to small farms in a county-year. In columns (3)-(4), the dependent variable is growth in the total loan amount extended by a bank to small farms in a county-year. *Geographic dispersion* of a bank is defined as the number of counties in which a bank has at least one branch. The *high geographic dispersion bank* is a dichotomous variable that equals 1 (0 otherwise) if a bank's geographic dispersion is above the median value. The independent variable is *lagged* and differenced frequency of abnormal hot temperature. *Proportion of policies paying premium* equals the fraction of policies sold that are paying a premium in the previous year, and *proportion of policies indemnified* is defined analogously. The crop insurance data are from the Risk Management Agency (RMA) of the USDA. The lagged control variables are the change in *capital ratio* that equals tier 1 capital as a fraction of total assets, the change in the logarithm of *bank size* measured by the total assets of a bank, the change in *profitability* that equals the return on assets, and the change in *NPL-to-assets* that equals non-performing loans as a fraction of total assets of a bank. The sample period is from 1997 to 2017. The standard errors are clustered by county, and t-statistics are presented in parentheses. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

	(1)	(2)	(3)	(4)
	Dependent variable: Growth in (·)			
	Number of originations		Loan volume	
High geographic dispersion bank × Change in frequency of abnormal hot temperature	-0.448**	-0.463**	-0.672**	-0.689**
	(-2.193)	(-2.265)	(-2.240)	(-2.294)
High geographic dispersion bank × Change in proportion of policies paying premium	-0.063		0.097	
	(-0.788)		(0.761)	
High geographic dispersion bank × Change in proportion of policies indemnified		0.027		0.053
		(0.861)		(1.007)
N	120,498	120,498	120,498	120,498
R^2	0.372	0.372	0.370	0.370
Bank Controls	Yes	Yes	Yes	Yes
Bank×County FE	Yes	Yes	Yes	Yes
County×Year FE	Yes	Yes	Yes	Yes

Table A.5: **Abnormal hot temperature and county level credit outcomes**
This table presents coefficient estimates from a specification relating the county level credit outcomes and the frequency of abnormal hot temperature in the previous period. In columns (1)-(2), the dependent variable is the logarithm of the number of loan originations in a given year. In columns (3)-(4), the dependent variable is the logarithm of the total loan amount extended by all banks to small farms in a county-year. The independent variable is *lagged* frequency of abnormal hot temperature in a county-year. The sample period is from 1997 to 2017. The standard errors are clustered by county, and t-statistics are presented in parentheses. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

	(1)	(2)	(3)	(4)
	Dependent variable:			
	Ln(Number of originations)		Ln(Loan volume)	
Frequency of abnormal hot temperature	-1.125**	-0.253	-1.362**	-0.646***
	(-2.223)	(-1.433)	(-2.202)	(-2.717)
N	45,887	45,887	45,887	45,887
R^2	0.355	0.852	0.310	0.815
State×Year FE	Yes	Yes	Yes	Yes
County FE	No	Yes	No	Yes

Rationale and discussion: Our baseline results suggest that geographically dispersed banks pull capital out of regions with exacerbated climate risk. It is plausible that the geographically non-dispersed banks in such regions extend credit to borrowers denied credit by their geographically dispersed counterparts. Such action may leave the aggregate credit origination in a region unaffected. In this table, we test this conjecture using county-level data.
Lending Outcome$_{ct}$ equals the logarithm of either total *number* of loan originations or total *amount* of loans from all banks to small farms in county c in year t in columns (1)-(2) and (3)-(4), respectively. $State_{c \in s} \times Year_t$ control for the time-varying state-level heterogeneity, such as local macroeconomic conditions, affecting counties' credit outcomes, and $County_c$ control for time-invariant heterogeneity present among counties.
Overall, the results in Table A.5 point towards a reduction in credit availability in the period following an increase in the frequency of abnormal hot temperature. In column (1), the economic size of the coefficient (-1.1) suggests a reduction of 4.9 percent in the aggregate number of loan originations with a standard deviation increase in the frequency of abnormal hot temperature. Based on an average of 62.0 loans in a county-year, this decline is equivalent to three fewer loans. In columns (3) and (4), the results imply a reduction of 282.5 and 134.0 thousand dollars, equivalent to 5.9 and 2.8 percent, in mean loan volume (4,759.4 thousand dollars) due to a standard deviation increase in the frequency of abnormal hot temperature in the previous period. Combined with the baseline results, these results suggest that abnormal hot temperature occurrences indeed result in an overall reduced flow of credit to small farms in a county. Since our analysis is confined to FDIC-insured institutions, we are unable to directly test whether other non-FDIC-insured institutions fill the lending gap. We leave such an analysis for future research. This decline in lending predominantly accrues from geographically dispersed banks in counties outside their branch network.

Online Appendix

Information on Hot Stuff: Do Lenders Pay Attention to Climate Risk?

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Table OA.1: **Abnormal hot temperature and disaster intensities: Robustness**

This table presents the validation results for the frequency of abnormal hot temperature. In column (1), the dependent variable is the logarithm of inflation-adjusted-per-capita *total* damages due to all disaster types in a county-year. In column (2), the dependent variable is the logarithm of inflation-adjusted-per-capita *property* damages due to all disaster types in a county-year. In column (3), the dependent variable is *PDD*, which is a dichotomous variable that equals 1 if, for a county-year, the reported total damages in the presidential disaster declaration database within SHELDUS are positive and equals 0 otherwise. The independent variable is *lagged* frequency of abnormal hot temperature in a county-year. The sample period is from 1997 to 2017. The standard errors are clustered by county in Panel A and B, spatially clustered for a radius of 100 kilometers in Panel C, and t-statistics are presented in parentheses. Significance levels: * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01.

	(1)	(2)	(3)
	Dependent variable:		
	Ln(total damages)	Ln(property damages)	PDD (1 = Yes, 0 = No)
Panel A: 90^{th} percentile as reference abnormal hot temperature			
Frequency of Abnormal Hot Temperatures	0.749***	0.715***	0.079**
	(3.531)	(3.244)	(2.121)
R^2	0.312	0.255	0.141
Panel A: 95^{th} percentile as reference abnormal hot temperature			
Frequency of Abnormal Hot Temperatures	0.648**	0.753**	0.130***
	(2.274)	(2.487)	(2.703)
R^2	0.312	0.255	0.141
Panel C: Spatially clustered SEs			
Frequency of Abnormal Hot Temperatures	1.497**	1.373**	0.462***
	(2.267)	(2.096)	(3.706)
R^2	0.312	0.256	0.141
N	47,914	47,914	47,914
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table OA.2: **Abnormal hot temperature and farm financials – Robustness**
This table presents results from tests relating the value of pledgeable collateral, debt serviceability, and the frequency of abnormal hot temperature in the previous census year. The dependent variable is log growth in land value per acre, machinery value per operation, and farm income receipts per operation in columns (1), (2), and (3), respectively. The independent variable is *lagged* frequency of abnormal hot temperature differenced over two census years. The sample corresponds to five USDA census years: 1997, 2002, 2007, 2012, and 2017. The standard errors are clustered by county in Panel A and B, spatially clustered for a radius of 100 kilometers in Panel C, and t-statistics are presented in parentheses. Significance levels: * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01.

	(1)	(2)	(3)
	Dependent Variable:		
	Land Value Growth	Machinery Value Growth	Income Receipts Growth
Panel A: 90^{th} percentile as reference abnormal hot temperature			
Change in Frequency of Abnormal Hot Temperatures	-0.160***	-0.277***	-0.254***
	(-4.207)	(-7.345)	(-2.893)
R^2	0.416	0.283	0.188
Panel B: 95^{th} percentile as reference abnormal hot temperature			
Change in Frequency of Abnormal Hot Temperatures	-0.312***	-0.467***	-0.180
	(-6.231)	(-9.299)	(-1.568)
R^2	0.419	0.288	0.188
Panel C: Spatially clustered SEs			
Change in Frequency of Abnormal Hot Temperatures	-0.635***	-0.645***	-0.349
	(-5.671)	(-6.975)	(-1.445)
R^2	0.423	0.288	0.188
N	9,085	9,084	8,912
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table OA.3: **Abnormal hot temperature and credit outcomes: County groups**
This table presents results linking credit outcomes at the county-bank-year level and the frequency of abnormal hot temperature in the previous year. In columns (1)-(2), the dependent variable is the growth in the number of small farm loan originations by a bank to small farms in a county-year. In columns (3)-(4), the dependent variable is growth in the total loan amount extended by a bank to small farms in a county-year. *Geographic dispersion* of a bank is defined as the number of counties in which a bank has at least one branch. The *high geographic dispersion bank* is a dichotomous variable that equals 1 (0 otherwise) if a bank's geographic dispersion is above the median value. We divide counties into three groups. The reference group (*County group 1*) includes counties that do not experience an increase in the frequency of abnormal hot temperatures in year *t-1* and *t-2*. *County group 2* includes counties that experience an increase in the frequency of abnormal hot temperature in either year *t-1 or t-2*. *County group 3* includes counties that experience an increase in the frequency of abnormal hot temperature in both years *t-1 and t-2*. The lagged control variables are the change in *capital ratio* that equals tier 1 capital as a fraction of total assets, the change in the logarithm of *bank size* measured by the total assets of a bank, the change in *profitability* that equals the return on assets, and the change in *NPL-to-assets* that equals non-performing loans as a fraction of total assets of a bank. The sample period is from 1997 to 2017. The standard errors are clustered by county, and t-statistics are presented in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)
	Dependent variable: Growth in (·)			
	Number of originations		Loan volume	
High geographic dispersion bank x County group 2	-0.017	-0.016	-0.034*	-0.034*
	(-1.268)	(-1.210)	(-1.676)	(-1.654)
High geographic dispersion bank x County group 3	-0.049***	-0.048***	-0.074***	-0.074***
	(-2.901)	(-2.855)	(-2.825)	(-2.842)
High geographic dispersion bank	0.003	0.009	0.009	0.014
	(0.123)	(0.408)	(0.287)	(0.434)
N	129,630	129,630	129,630	129,630
R^2	0.376	0.376	0.375	0.375
Controls	Yes	Yes	Yes	Yes
Bank×County FE	Yes	Yes	Yes	Yes
County×Year FE	Yes	Yes	Yes	Yes

Table OA.4: **Abnormal hot temperature and credit outcomes: Alternative clustering scenarios**

The table presents the robustness of baseline results, linking credit outcomes at the county-bank-year level and the frequency of abnormal hot temperature in the previous year to clustering standard errors along alternative dimensions. In Panel A, the dependent variable is the growth in the number of small farm loan originations by a bank to small farms in a county-year. In Panel B, the dependent variable is growth in the total loan amount extended by a bank to small farms in a county-year. *Geographic Dispersion* of a bank is defined as the number of counties in which a bank has at least one branch. The *High Geographic Dispersion Bank* is a dichotomous variable that equals 1 (0 otherwise) if a bank's geographic dispersion is above the median value. The independent variable is *lagged* and differenced frequency of abnormal hot temperature. The lagged control variables are the change in '*Capital Ratio*' that equals tier 1 capital as a fraction of total assets, the change in the logarithm of bank size measured by the total assets of a bank, the change in '*Profitability*' that equals the return on assets, and the change in '*NPL-to-Assets*' that equals non-performing loans as a fraction of total assets of a bank. The sample period is from 1997 to 2017. The standard errors are clustered by bank in columns (1) and (2), double clustered by county and bank in columns (3) and (4), triple clustered by county, bank and year in columns (5) and (6) and spatially clustered for the 100-kilometer radius in columns (7) and (8), and t-statistics are presented in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Dependent variable - Growth in number of originations								
High geographic dispersion bank x Change in frequency of abnormal hot temperatures	-0.476**	-0.479**	-0.476**	-0.479**	-0.476*	-0.479*	-0.476**	-0.479**
	(-2.081)	(-2.067)	(-2.150)	(-2.141)	(-1.944)	(-1.938)	(-2.246)	(-2.257)
R^2	0.376	0.376	0.376	0.376	0.376	0.376	0.376	0.376
Panel B: Dependent variable - Growth in loan volume								
High geographic dispersion bank x Change in frequency of abnormal hot temperatures	-0.768**	-0.753**	-0.768**	-0.753**	-0.768***	-0.753***	-0.768**	-0.753**
	(-2.086)	(-2.102)	(-2.254)	(-2.259)	(-2.961)	(-2.962)	(-2.490)	(-2.440)
R^2	0.374	0.375	0.374	0.375	0.374	0.375	0.376	0.376
N	129,630	129,630	129,630	129,630	129,630	129,630	129,630	129,630
Bank Controls	No	Yes	No	Yes	No	Yes	No	Yes
Bank×County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered by	Bank		County and Bank		County, Bank, and Year		Spatial	