Physical Climate Risk Exposure and Bank Lending

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Abstract

Measuring systematic physical climate risk remains a central challenge in climate finance. We develop a framework that extracts latent factors from US county temperature anomalies, directly measuring systematic climate variation before it is reflected in disasters or financial markets. The estimated factors predict future disaster outcomes and are largely orthogonal to conventional asset-pricing and transition risk factors. Banks with greater exposure hold more capital and reduce small business lending by about 10%, particularly in more exposed counties and during elevated climate stress. The findings are consistent with a credit supply channel through which physical climate risk affects the real economy.

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1 Introduction

Physical climate risk is increasingly viewed as a threat to financial stability (TCFD, 2017; BCBS, 2022; ECB, 2022), but measuring banks' exposure to it remains empirically difficult. Realized disasters are imperfect proxies for systematic physical climate risk: their severity reflects local adaptation, insurance coverage, and public disaster response as much as the underlying shift in climate conditions (Hsiang, 2016).[1] Asset-price-based measures face a different problem: returns reflect physical climate fundamentals together with risk premia, investor preferences, liquidity, and other financial-market forces, making it difficult to isolate exposure arising from underlying physical conditions alone. What is needed is a measure, rooted in physical climate data, that summarizes systematic physical climate variation before it is reflected in disaster outcomes or financial markets.

The challenge, however, extends beyond distinguishing physical climate risk from realized disasters or asset prices. Physical climate conditions themselves contain both local variation, which is specific to individual locations, and variation that is shared across many locations simultaneously. While the former reflects local weather fluctuations, the latter captures climate dynamics that affect many regions at the same time. The economic relevance of these two components depends on the decision problem under consideration. For a geographically diversified financial intermediary, local climate fluctuations can, in principle, be diversified across borrowers, whereas climate variation shared across locations generates correlated credit exposures that survive geographic diversification. For a levered institution whose capital must absorb these correlated losses, this common component constitutes the economically relevant source of physical climate risk. Existing measures based on local climate conditions or realized disasters do not separate these two components, making it difficult to isolate the underlying source

[1] Measures based on realized disasters capture banks' responses after physical losses have occurred, while measures based on asset prices reflect risks that financial markets have already incorporated into valuations. Neither can isolate whether, or to what extent, banks adjust their exposures in anticipation of physical climate risk. Consequently, the extant banking literature (Cortés & Strahan, 2017; Koetter et al., 2020; Correa et al., 2022; Kruttli et al., 2025; Sastry, 2026, among others) cannot distinguish anticipatory risk management from responses to realized disasters.

of systematic physical climate risk. We measure this common component directly.

Because the systematic component of county-level temperature anomalies is not directly observable, we estimate latent factors from their covariance matrix, using anomalies defined as deviations of local temperatures from historical norms.[2] This follows a long tradition in asset pricing: since Ross (1976), latent factor models have recovered systematic sources of variation from covariance structures without identifying the factors ex ante, with economic content established by validating them against outcomes they should explain (Roll & Ross, 1980; Connor & Korajczyk, 1988; Bai & Ng, 2002; Kozak et al., 2018; Kelly et al., 2019; Giglio & Xiu, 2021). The resulting factors are distinct from transition risk measures based on carbon intensity or environmental ratings, which capture exposure to policy and technological change rather than physical conditions (Bolton & Kacperczyk, 2021; Pástor et al., 2021, 2022; Jung et al., 2025), and from location-specific physical measures tied to particular regions or asset classes (Acharya et al., 2022; Jung et al., 2024).

Any factor decomposition of correlated series recovers dominant common variation by construction, so the economic interpretation of the recovered factors must be established through external validation. County factor loadings measure the extent to which local temperature anomalies co-move with each common factor and exhibit pronounced geographic structure, providing a spatial representation of systematic physical climate risk. We therefore validate the economic interpretation of the recovered factors using four complementary exercises. The factors predict subsequent disaster incidence and damages, whereas the residual component of temperature anomalies does not; their loadings align closely with climate geography constructed solely from latitude and longitude; the decomposition remains stable across expanding estimation windows; and the recovered factors the factors are nearly identical to those recovered from AR(1)-GARCH(1,1) and AR(1)-Trend innovations, so are robust to alternative specifications that remove persistence, conditional heteroskedasticity, and deterministic warming

[2] Temperature anomalies are the standard metric used by climate scientists to track warming (IPCC, 2021). We measure them at the US county level using high-resolution gridded data from the University of East Anglia's Climate Research Unit (CRU).

trends. Together, these validation exercises support interpreting the recovered factors as measures of systematic physical climate risk.

Our factors are estimated from temperature anomalies, so it is useful to clarify why we interpret them as measures of physical climate risk. Temperature is a fundamental state variable of the climate system and influences many of the physical processes underlying climate-related hazards. Atmospheric moisture capacity rises with temperature, sea level responds to thermal expansion and ice melt, and sea surface temperature affects the energy available to tropical storms (IPCC, 2001, 2012; Meehl et al., 2000). The empirical counterpart of this argument is the validation itself: although the factors are estimated exclusively from temperature anomalies, they predict subsequent disaster incidence and damages across a set of hazards whose dynamics are plausibly influenced by temperature, such as tropical storms, hurricanes, floods, and heavy rainfall. Hazards whose incidence is largely unrelated to temperature remain outside the scope of our measure.

The factor model yields common temperature factors that summarize systematic climate variation over time and county-specific factor loadings that measure each county's exposure to those common climate dynamics. The first factor explains approximately 60% of the systematic variation in temperature anomalies and closely tracks the cross-sectional average temperature anomaly, making it a parsimonious summary of aggregate climate variation, consistent with the literature's emphasis on the leading latent factor as the dominant source of common variation (Baker & Wurgler, 2006). The close relationship between the leading factor and the cross-sectional average temperature anomaly is economically informative: it anchors an otherwise unlabeled statistical factor to aggregate warming and cooling, while the associated county loadings provide the cross-sectional heterogeneity that distinguishes exposure across locations. In contrast, the cross-sectional mean weights all counties equally and therefore, by construction, lacks cross-sectional variation in exposure. The factor loadings recover this cross-sectional heterogeneity, which we use in the analysis presented in Section 4.4.

Banks provide a natural setting for studying systematic physical climate risk because their geographically diversified lending portfolios make common climate variation difficult to diversify away, while their central role in financial intermediation allows such shocks to propagate throughout the financial system. To measure exposures, we construct factor-mimicking portfolios and estimate bank climate betas from equity returns, following standard practice for non-traded factors (Huberman et al., 1987; Lamont, 2001; Pástor & Stambaugh, 2003, among others). Our framework therefore separates the identification of systematic temperature variation from its mapping into institutional exposure. The factors and county loadings use no financial data and so cannot be shaped by risk premia, investor preferences, liquidity, or market microstructure. Equity returns are used only in the second stage to estimate banks' exposure to factor-mimicking portfolios constructed from the temperature factors.

Combining the estimated betas with the systemic capital shortfall framework of Jung et al. (2025) implies aggregate expected capital shortfalls exceeding $980 billion under the adopted stress scenario, equivalent to approximately 17% of the market capitalization of listed US banks in December 2022. This is a conditional stress-test calculation rather than a forecast, and expected shortfalls are larger when banks are simultaneously under financial stress because adverse climate events require more capital to absorb when bank balance sheets are weaker. Our objective is not to establish that systematic physical climate risk is priced in the cross-section of equity returns. We find no evidence that the temperature factors command a risk premium. The economic content of our measure derives from banks' exposure to systematic physical climate risk and the resulting implications for intermediary behavior.

Because the leading temperature factor explains approximately 60% of the systematic variation in temperature anomalies and closely tracks aggregate temperature anomalies, we refer to the corresponding bank beta as the *physical climate risk beta*. Banks with greater deposit-weighted and equally weighted county loadings for the leading temperature factor exhibit higher estimated physical climate risk betas. Banks with a higher physical climate risk beta hold more capital, originate fewer loans relative to assets, and rely less on deposit funding, consistent with a more conservative approach to balance sheet management. These adjustments do not coincide with lower profitability or higher non-performing loan ratios, suggesting that banks respond proactively rather than in reaction to realized losses. This interpretation is reinforced by the timing of our measure. Physical climate risk betas are estimated from rolling windows of historical equity returns, whereas balance sheet outcomes are measured subsequently. A backward-looking exposure measure is economically relevant only insofar as it is informative about future exposure: losses already incurred are sunk, and value-maximizing banks do not hold precautionary capital against them. Together, these findings suggest that banks incorporate systematic physical climate risk into financial decisions well before it becomes evident in realized disasters or bank performance.

The balance sheet evidence suggests that banks actively manage systematic physical climate risk. A natural question is: do these adjustments extend to credit supply? If so, lending should adjust along two margins. First, greater exposure to systematic physical climate risk increases the vulnerability of a bank's balance sheet, leading to a reduction in credit supply. Second, if banks actively manage exposure to the underlying climate factor, these lending reductions should be concentrated in counties whose temperature anomalies co-vary more strongly with that factor. Because counties with higher loadings on the leading temperature factor are more exposed to systematic climate variation, reducing lending to these counties lowers a bank's overall exposure to physical climate risk. We find support for both predictions.

We find that an increase in banks' physical climate risk is associated with economically meaningful reductions in small business lending. A one-unit increase in the physical climate risk beta reduces the number of loan originations by approximately 10 percent and loan volume by about 5 percent, corresponding to roughly five fewer loans and $145,000 less lending annually for the average bank-county pair. The contraction in lending is not uniform across counties. Instead, banks disproportionately reduce lending in counties with greater exposure to the first temperature factor, indicating that credit is reallocated away from regions with greater exposure to systematic physical climate risk. This geographic reallocation is unrelated to whether a county is part of the bank's branch network, suggesting that relationship lending does not insulate borrowers from a reduction in credit supply associated with physical climate risk. Moreover, lending responses become more pronounced when the underlying temperature factor experiences large realizations, consistent with banks tightening credit supply during periods of elevated systematic climate stress, when demand for reconstruction financing would be expected to increase, providing additional evidence that the response reflects tighter credit supply rather than weaker demand. Finally, the results remain robust after allowing banks to respond differentially to contemporaneous and lagged natural disasters, indicating that the estimated effects reflect exposure to physical climate risk rather than heterogeneous responses to realized disaster events.

This paper makes three contributions. First, we develop a measure of systematic physical climate risk using physical climate data. Existing climate finance research has focused predominantly on transition risk arising from climate policy, technological change, and carbon repricing (Bolton & Kacperczyk, 2021; Pástor et al., 2021; Jourde & Moreau, 2024; Jung et al., 2025). Empirical evidence on physical climate risk remains comparatively limited and typically relies on realized disasters or asset-level exposures to those disasters (Cortés & Strahan, 2017; Koetter et al., 2020; Nguyen et al., 2022; Sastry et al., 2024; Kruttli et al., 2025; Sastry, 2026). Our approach complements this literature by moving closer to the underlying physical source of climate risk that gives rise to both realized disaster outcomes and financial-market assessments of climate risk. Methodologically, our approach builds on a long tradition of recovering latent systematic factors whose economic interpretation established through their ability to explain economically meaningful outcomes rather than through *a priori* labels (Ross, 1976; Connor & Korajczyk, 1988; Stock & Watson, 2002; Ludvigson & Ng, 2007, 2009; Kozak et al., 2018; Kelly et al., 2019; Lettau & Pelger, 2020; Giglio & Xiu, 2021). We extend this framework to estimate systematic factors extracted directly from temperature anomalies rather than financial asset prices. Consequently, the factors are identified independently of investor sentiment, liquidity conditions, and market microstructure.

Second, we develop a measure of systematic physical climate risk at the bank level and connect it to systemic financial vulnerability. Existing studies show that location-specific climate exposure affects expected returns and firm performance (Acharya et al., 2022; Addoum et al., 2023). Our approach complements this literature by isolating the component of physical climate variation that is common across regions and therefore cannot be diversified geographically. We then combine the resulting bank climate betas with the CRISK framework of Jung et al. (2025), which builds on the SRISK framework of Acharya et al. (2012) and Brownlees & Engle (2017), to quantify systemic physical climate risk in the US banking sector. More broadly, our approach relates to studies that use equity return sensitivities to recover latent institutional characteristics such as diversification, merger effects, and efficiency (Vennet, 1996, 2002; Baele et al., 2007), and extends this idea to measuring physical climate risk.

Third, we contribute to the literature on climate risk and bank lending. Existing studies examine how realized disasters, such as hurricanes, floods, wildfires, and extreme heat, affect bank lending and credit supply (Cortés & Strahan, 2017; Koetter et al., 2020; Blickle et al., 2022; Correa et al., 2022; Rajan & Ramcharan, 2023; Abedifar et al., 2024). Our analysis complements this literature by examining whether banks' ex ante exposure to systematic physical climate risk shapes credit allocation even outside disaster episodes. We show that banks with greater climate exposure systematically reduce lending to counties that are more exposed to the same latent climate factors, with these effects becoming stronger following realized climate shocks. Our findings also help reconcile the limited balance sheet effects documented by Blickle et al. (2022). Although more climate exposed banks do not experience lower profitability or higher non-performing loan ratios, they adjust ex ante by holding more capital and reallocating credit away from climate exposed regions, suggesting that limited realized losses partly reflect precautionary balance sheet adjustment before disasters occur.

2 Data description

2.1 Temperature Data

We source monthly mean temperature data from the Climatic Research Unit (CRU) at the University of East Anglia. The dataset has a 0.5°× 0.5°latitude-longitude resolution. These dimensions are equivalent to approximately 55 kilometers at the equator. We match county centroids to the nearest CRU grid cell. This approach ensures unique time-consistent matching as the locations of counties and grids do not vary over time. Following the NASA Goddard Institute for Space Studies (GISS) methodology, we estimate county-month temperature anomalies relative to the 1951–1980 reference period. Expressing temperatures as anomalies removes persistent geographic differences in climate and isolates deviations from local historical norms, allowing systematic variation across counties to be compared on a common scale. The sample spans 1951-2022. The longer temperature sample is used to estimate latent climate factors, whereas subsequent analyses use shorter samples dictated by the availability of disaster, banking, and lending data.

2.2 Disaster Damages Data

We use county-level natural disaster data from the Spatial Hazard Events and Losses Database for the US (SHELDUS). The database records weather-related hazards, including thunderstorms, hurricanes, floods, wildfires, and tornadoes, along with event dates, affected locations, and direct damages (property and crop losses, injuries, and fatalities) beginning in 1960. Our analysis focuses on weather-related hazards, including coastal storms, droughts, floods, hail, heatwaves, hurricanes, landslides, lightning, severe storms, tornadoes, wildfires, wind events, winter weather, fog, and avalanches. Geological hazards, such as earthquakes, volcanoes, tsunamis, and seiches, are excluded because they are unrelated to temperature anomalies. We construct a county-month panel spanning 1981–2022 by aggregating individual hazard records at the county-hazard-month level. All damage variables are adjusted to 2022 dollars and scaled by county population to provide comparable, per-capita measures of disaster intensity. This structure yields a consistent panel of disaster occurrence and severity over time.

2.3 Financial and Lending Data

We source stock return data from the Center for Research in Security Prices (CRSP) via Wharton Research Data Services (WRDS), the standard source for US equity prices, returns, and market indices. These data are used to construct the factor-mimicking portfolios and estimate bank climate betas. To link publicly traded bank stocks to regulatory filings and lending activity, we use the CRSP–FRB link dataset provided by the Federal Reserve Bank of New York. Factor returns and 48 industry portfolios are obtained from Kenneth French's data library for benchmarking and validation exercises.

We compile quarterly bank balance sheet information from Call Reports to measure capitalization, funding structure, profitability, and other bank characteristics. Deposit funding and geographic branch networks are obtained from the Summary of Deposits dataset, with deposits aggregated to the bank-county-year level and branch counts recorded at the county level. Finally, we measure small business lending using the Community Reinvestment Act (CRA) originations dataset, which records the number and volume of loans originated by each bank in each county from 1997 to 2022. The CRA data are matched to year-end Call Report balance sheet information to relate banks' lending decisions to their financial characteristics.

3 Measuring Physical Climate Risk Exposure

3.1 Constructing Temperature Anomaly Factors

Physical climate risk reflects spatial variation in environmental conditions, with temperature deviations increasing the likelihood and severity of climate-related disasters (IPCC, 2001, 2012; Meehl et al., 2000). We exploit temperature anomalies to isolate departures from typical local climate, capturing the physical mechanisms that influence both climate outcomes and adaptation behavior. By construction, temperature anomalies strip out predictable seasonal cycles and persistent geographic differences, enabling us to examine economically meaningful variation in local climate that is comparable across regions.

We define the temperature anomaly for county c in month m and year y as

$$\Delta\mathbb{T}_{cmy} = \mathbb{T}_{cmy} - \bar{\mathbb{T}}_{cm}, \quad y \geq 1981, \tag{1}$$

where $\mathbb{T}_{cmy}$ denotes the observed temperature and $\bar{\mathbb{T}}_{cm}$ is the historical average temperature for county c in month m, computed over the 1951–1980 reference period. This normalization accounts for both *seasonality* and *geographic heterogeneity* by benchmarking each observation relative to the long-term local climate for a given county and month. As a result, $\Delta\mathbb{T}_{cmy}$ captures deviations from expected local conditions rather than absolute temperature levels.

Figure 1 presents summary statistics on temperature and temperature anomalies. Figure 1b displays the spatial distribution of average temperatures and temperature anomalies for the 42-year period starting in January 1981. The data reveal a pronounced geographic gradient in average temperatures, with higher values at lower latitudes and lower values at higher latitudes. In contrast, temperature anomalies do not follow a systematic pattern by latitude, indicating that deviations from historical norms are not monotone in latitude and longitude.

[Insert Figures 1 Here]

The left panel of Figure 1b shows the distribution of average temperatures for the periods 1951–1980, 1984–2000, and 2001–2022. The distribution shifts rightward over time, indicating both an increase in mean temperatures and a higher frequency of extreme heat events. The right panel reports the distribution of temperature anomalies for 1984–2000 and 2001–2022. The mean anomaly increases from 0.3 degrees Celsius in the earlier period (range: –0.2 to 1) to 0.8 degrees Celsius in the later period (range: 0.4 to 1.4), representing a 2.6-fold rise. These patterns indicate that several regions are nearing the 1.5 degrees Celsius threshold established in the Paris Agreement, and that unusually high temperature anomalies have become more prevalent over time.

We model temperature anomalies as a linear factor structure that captures systematic co-movement across counties:

$$\Delta \mathbb{T}_{ct} = \sum_{k=1}^{K} \lambda_{ck} f_{kt} + \epsilon_{ct}, \tag{2}$$

where f_{kt} denotes the realization of factor k at time t, λ_{ck} is the loading of county c on factor k, and ϵ_{ct} is an idiosyncratic component. These latent factors summarize the common variation in temperature anomalies across counties, while the factor loadings measure the extent to which temperature anomalies in each county co-move with these common climate factors. In this respect, the loadings play a role analogous to factor betas in empirical asset pricing: they measure the sensitivity of a county's temperature anomalies to latent systematic climate factors rather than the level of temperature experienced by that county. We estimate the latent factors using factor analysis (Connor & Korajczyk, 1988), which recovers common variation from the covariance structure of high-dimensional data, for 3,108 US counties over the period January 1981 to December 2022.

Consistent with the empirical asset pricing literature, latent factors are interpreted through the covariance structure they summarize rather than through predetermined economic labels (Roll & Ross, 1980; Chamberlain & Rothschild, 1983; Connor & Korajczyk, 1988; Lehmann & Modest, 1988; Bai & Ng, 2002; Onatski, 2010; Kozak et al., 2018). Their economic content is therefore established through external validation rather than imposed *a priori*. Our setting permits robust validation because the estimated factors can be evaluated against physical outcomes, including subsequent disaster incidence, disaster damage, and the geographic distribution of county loadings.[3] Note that a factor

[3]Section 5 demonstrates that the estimated factor structure is robust to alternative representations of temperature dynamics, including location-based temperature anomaly factors, AR(1)-GARCH innovations, AR(1)-Trend residuals, and projected warming measures. Across all specifications, the estimated factor scores exhibit near one-for-one relationships with the baseline estimates, indicating that the extracted covariance structure is not driven by a particular specification of the underlying temperature process.

loading measures the extent to which a county's temperature anomalies co-vary with the common temperature factors. Consequently, counties with large factor loadings are not necessarily those experiencing the greatest warming or the largest temperature anomalies, but rather those whose temperature anomalies are more strongly associated with the systematic component of climate variation. This interpretation follows from the objective of factor analysis, which is to recover the dominant covariance structure underlying temperature anomalies rather than differences in their levels or long-term trends.

[Insert Table 1 and Figure 2 Here]

Table 1 presents summary statistics for the first four latent factors extracted from standardized county-level temperature anomalies using factor analysis, while Figure 2 and Figure A.1 display the corresponding factor loadings across counties and time series of scores, respectively. Panel A of Table 1 indicates that these four factors together explain 88.9% of the total variation in temperature anomalies, with the first factor accounting for 59.8% . This concentration of explanatory power suggests that a limited set of common factors captures most of the large scale climate variation in the contiguous US. The spatial patterns in factor loadings, shown in Figure 2, reveal pronounced geographic heterogeneity, as counties in different regions load differently on each factor. The geographic patterns are consistent with atmospheric and climatic processes, including maritime influences, subtropical air masses, and El Niño–Southern Oscillation dynamics (Wallace & Hobbs, 2006; Trenberth et al., 2007). The observed heterogeneity in factor exposures across counties provides a foundation for measuring systematic differences in physical climate risk. Building on this, we use the estimated factors and county-level loadings to construct bank-level exposure measures that link local climate dynamics to the geographic distribution of banks' operations and their equity returns.

We assess the stability of the factor structure over time by re-estimating the factors for each terminal year from 2001 to 2022, using an expanding window that starts in

January 1981. For each window, we track the share of cross-county variation explained by the leading factors. We find that the variance explained by each factor remains stable across estimation periods, as shown in Figure A.2. This pattern suggests that the co-movement in temperature anomalies across US counties is not driven by a particular sub-sample and that the estimated covariance structure is stable over time, supporting its use as the basis for measuring systematic climate exposure throughout the sample period.

An alternative interpretation is that the estimated factor loadings simply rank counties by their projected warming rather than measuring exposure to systematic climate variation. We evaluate this possibility by comparing county factor loadings with projected warming under the four Shared Socioeconomic Pathway (SSP) scenarios. For each county and scenario, projected warming is measured as the change in the average temperature anomaly between 2023–2042 and 2081–2100, using twenty-year averages to abstract from short-run weather fluctuations. Panel A of Table A.1 shows that projected warming explains less than 6% of the cross-sectional variation in the dominant factor loading across all four SSP scenarios. Explanatory power is similarly limited for the remaining factors, with the largest R^2 reaching only about 18%. These findings suggest that the estimated factor loadings reflect systematic temperature variation that cannot be explained solely by differences in projected warming across counties.

3.2 Validating Temperature Anomaly Factors

In this section, we evaluate the economic content of the estimated factors through external validation exercises using data that were not used in their estimation. We examine whether the estimated factors and counties' loadings predict subsequent disaster outcomes and whether the factors represent a distinct source of systematic variation in financial markets beyond conventional asset pricing and transition risk factors.

3.2.1 Validation Using Subsequent Disaster Outcomes

If the estimated factors summarize the systematic component of temperature anomalies associated with physical climate risk, counties with greater exposure to those factors should experience a higher probability and severity of subsequent disaster events, consistent with evidence that anomalous temperatures increase the frequency and intensity of many climate-related extremes (IPCC, 2001, 2012). We relate county-level disaster incidence and damages to the interaction between factor realizations and county-specific loadings, $\hat{\lambda}_{ck}\hat{f}_{kt}$, which measures each county's exposure to the common component of temperature anomalies. To isolate local variation unrelated to these common factors, we additionally control for the residual temperature anomaly, $\hat{\epsilon}_{ct} = \Delta\mathbb{T}_{ct} - \sum_{k=1}^{4}\hat{\lambda}_{ck}\hat{f}_{kt}$. We employ the following regression specification:

$$Y_{ct} = \sum_{k=1}^{4}\beta_k(\hat{\lambda}_{ck} \times \hat{f}_{kt-1}) + \beta_\epsilon\hat{\epsilon}_{ct-1} + \gamma_c + \gamma_t + u_{ct}. \tag{3}$$

In equation (3), Y_{ct} is the disaster occurrence or the disaster intensity conditional on occurrence. The time fixed effects (γ_t) absorb all aggregate shocks common across counties, including factor realizations themselves and seasonal variation; the county fixed effects (γ_c) absorb time-invariant geographic and institutional heterogeneity, including each county's average exposure to disasters. This design addresses the concern that counties experiencing greater warming over the sample period may also have experienced more disasters, such that factors with loadings concentrated in those counties would mechanically predict disaster outcomes. The fixed effects absorb this cross-sectional association, so β_k is identified from within-county covariation between aggregate factor realizations and subsequent local disaster outcomes.

[Insert Table 2 Here]

Table 2 presents the results. The first two factors, which account for 77% of the variation in temperature anomalies across US counties, are associated with disaster outcomes. Counties with higher exposures to these factors experience both a greater probability of disaster and significantly larger damages on the intensive margin. The effects are economically meaningful: for a county with a Factor 1 loading of 0.7, a one-standard-deviation increase in Factor 1 raises the probability of disaster by 0.22 percentage points, the probability of a major disaster by 0.94 percentage points, and increases crop, property, and total damages by 18.6% , 5.1% , and 4.6% , respectively. These findings indicate that the dominant temperature anomaly factors contain economically meaningful information about subsequent physical climate outcomes. By contrast, the residual component of temperature anomalies is negatively associated with disaster outcomes, suggesting that local idiosyncratic fluctuations do not capture the same risk as common factors.

The factors are estimated exclusively from temperature data, without reference to disaster outcomes; these results provide external validation of the extracted factors.[4] Together, the evidence indicates that the latent factors summarize systematic variation in temperature anomalies that is informative about subsequent physical climate outcomes.

3.2.2 Validation Using Financial Data

3.2.2.1 Spanning Tests

We assess whether the estimated temperature anomaly factors contain information already captured by existing asset pricing factors. If they reflect a distinct source of systematic physical climate risk, they should not be spanned by traditional market factors or climate transition risk factors. We therefore estimate time-series regressions of each temperature factor on the Fama-French five factors and, for the post-2009 sample, augment the specification with the Green Minus Brown (GMB) and Green factors of Pástor et al. (2022) to test distinctiveness from transition risk factors.

[4] In Panel B of Table A.1, we estimate a county-by-county regression of temperature anomalies on a linear time trend and collect the estimated trend coefficients. We then regress the absolute values of factor loadings on trend coefficients. The R^2 from these cross-sectional regressions is 3.1%, 18.2%, 3.2%, and 1.6% for Factors 1 through 4, respectively. If the extracted factors merely repackaged county-specific warming trends, trend coefficients would explain most of the variation in loadings. The low R^2 values make this an unlikely scenario and indicate that the loadings capture sensitivity to common temperature fluctuations rather than county-specific warming trends.

Table 3 reports the spanning tests. In all specifications, the first two temperature anomaly factors exhibit very low explanatory power, with R^2 values below 4% even when both traditional and transition risk factors are included, and none of the Fama-French or transition risk factors load significantly. These findings indicate that the temperature anomaly factors are largely distinct from conventional asset pricing and transition risk factors. We also conduct reverse spanning tests, reported in Panel B of Table 3, by regressing the GMB and green factors on the temperature anomaly factors. The temperature factors alone explain little variation in the GMB and green factors, with R^2 values of 7% and 4%, respectively. When we add the Fama-French factors, the explanatory power increases substantially, with R^2 rising to 29% and 51%, respectively. These results indicate that transition risk factors remain closely related to traditional asset pricing factors and are not explained by the temperature factors.

[Insert Table 3 Here]

3.2.2.2 Cross-Sectional Tests

We next evaluate whether adding the temperature factors improves the time-series and cross-sectional explanatory power of standard asset pricing models across a broad set of test assets. We estimate factor models for 123 test assets (48 industry, 25 size-book-to-market, 25 size-profitability, and 25 size-investment portfolios) and compare the explanatory power of models with and without the temperature factors. Panel C reports changes in *adjusted* R^2, while Panel D reports cross-sectional R^2 (Jagannathan & Wang, 1996).

Adding the temperature factors improves both the time-series and cross-sectional performance of standard asset pricing models. Augmenting the Fama-French five-factor model increases the average adjusted R^2 across test assets by 3%, with the incremental explanatory power rising to 10.3% when augmented with transition risk factors. Similarly, the cross-sectional R^2 increases from 18% to 25% when the temperature factors are added to the Fama-French model and from 30% to 40% when transition risk factors are included. These results indicate that exposure to the temperature factors explains meaningful variation in asset returns beyond existing conventional and transition risk factors. Despite their incremental explanatory power, we find no evidence that the temperature factors command risk premium raising the possibility that perhaps systematic physical climate risk is reflected primarily through changes in volatility, which provides a complementary perspective on how risk is incorporated into financial markets. We therefore examine whether the temperature factors influence the conditional volatility of financial sector returns. We estimate a Dynamic Conditional Correlation Multivariate GARCH (DCC-MGARCH) model in which the four temperature factors enter the conditional variance equation as exogenous variables. The analysis uses equally weighted returns for the banking, financial, and insurance industries from the Fama-French 48 industry portfolios.

Panel E of Table 3 reports the results. The first two temperature factors are positively associated with the conditional volatility of bank and financial sector returns, indicating that systematic temperature variation increases financial market uncertainty. These findings suggest that the economic effects of systematic physical climate risk are reflected through changes in volatility, providing further evidence that the estimated temperature factors contain economically meaningful information for financial markets.

3.3 Estimating Banks' Exposure to Physical Climate Risk

Building on the validation evidence presented above, we next estimate banks' exposure to the temperature factors, which we refer to as bank climate betas. Conceptually, bank climate betas are the financial analog of county factor loadings: whereas county loadings measure exposure to systematic temperature variation, bank climate betas measure how bank fundamentals co-vary with the same underlying factors through equity returns.

Because the latent temperature factors are estimated from physical climate data rather than financial asset returns, they are not directly traded and therefore cannot be used directly in return regressions. Following the standard factor-mimicking portfolio approach in the empirical asset pricing literature, we therefore construct traded portfolios whose returns proxy for realizations of the latent temperature factors.[5] Using the full universe of publicly traded US firms in CRSP, we estimate each stock's factor loading on the latent temperature factors using time-series regressions, requiring a minimum of 60 monthly observations. We sort stocks into quintiles based on their estimated factor loadings and form value-weighted long-short portfolios by taking positions in the highest and lowest quintiles, respectively. The resulting portfolios serve as traded proxies for the latent temperature factors, enabling standard return regressions to recover banks' exposures.[6]

We estimate bank climate betas by regressing excess bank equity returns on the market factor and the four climate factor-mimicking portfolios:

$$r_{bt} = \alpha_b + \beta_{b,\mathrm{m}} r_{mt} + \sum_{k=1}^{4} \beta_{b,k} \mathbb{P}_{f_k t} + u_{bt}, \quad \forall \quad b \tag{4}$$

where r_{bt} denotes the excess return on bank b, r_{mt} denotes the excess return on the market portfolio, and $\mathbb{P}_{f_k t}$ denotes the return on the portfolio mimicking temperature

[5] Our procedure follows the standard approach for constructing traded proxies for non-traded factors. The mimicking-portfolio methodology originates with Huberman et al. (1987) and Breeden et al. (1989), and is developed further by Lamont (2001), Vassalou (2003), and Balduzzi & Robotti (2008). Our two-step implementation, estimating stock-level betas with respect to the non-traded factor and forming long-short portfolios from beta-sorted extremes, follows Pástor & Stambaugh (2003), who construct a traded liquidity factor from stocks sorted on estimated liquidity betas, and is likewise employed by Ang, Hodrick, et al. (2006) for aggregate volatility risk, Ang, Chen, & Xing (2006) for downside risk, Boons (2016) for macroeconomic state variables, and Bali et al. (2017) for economic uncertainty. Our methodological contribution is therefore not the construction of factor-mimicking portfolios per se, but the identification of latent systematic temperature factors from temperature anomalies and their mapping into stock returns.

[6] An alternative method for constructing traded proxies for non-traded factors is the projection-based tracking portfolio of Lamont (2001). Specifically, each latent temperature factor is projected onto contemporaneous value-weighted excess returns of eleven non-financial Fama–French industry portfolios, controlling for the lagged factor and lagged market return. For the lending analysis, projection coefficients are estimated recursively using an expanding window to obtain out-of-sample mimicking portfolio returns and rolling bank climate betas. For the stress-testing analysis, we use full-sample projection coefficients to construct the corresponding climate portfolios. Across both applications, the estimated bank climate betas produce similar results to the baseline specification. We therefore retain the beta-sorted mimicking portfolios throughout the paper because this construction has become the standard approach for obtaining traded proxies for non-traded factors in the empirical asset-pricing literature (Pástor & Stambaugh, 2003; Ang, Chen, & Xing, 2006; Bali et al., 2017, among others), facilitating comparison with prior studies.

factor k. Bank climate betas are estimated using a rolling 60-month window, allowing them to vary over time. The estimated coefficients, $\beta_{b,k}$, summarize each bank's financial *exposure* to the corresponding latent temperature factor.

[Insert Figure 3 Here]

Figure 3 presents the cross-sectional distribution of bank climate betas over time. The estimated betas exhibit substantial dispersion across banks and meaningful time-series variation, indicating considerable heterogeneity in banks' exposure to the latent temperature factors. For the first factor, the within-bank variation exceeds the between-bank variation, suggesting that climate exposures evolve gradually over time as banks adjust their geographic lending activities and portfolio composition. Detailed summary statistics are reported in Table A.2. The economic interpretation of the leading temperature factor is developed in Section 4.2, where we show that it closely tracks aggregate temperature anomalies and use this relationship to motivate the subsequent analysis of bank balance sheets and lending decisions.

4 Physical Climate Risk and Bank Exposure

4.1 Systemic Physical Climate Risk Measure

Building on the estimated bank climate betas, we adapt the systemic capital shortfall framework of Jung et al. (2025) to quantify the banking system's vulnerability to systematic physical climate risk under extreme realizations of the latent temperature factors estimated from observed temperature anomalies. For each bank, we compute the implied capital shortfall separately for each of the four temperature anomaly factors. Following Jung et al. (2025), we evaluate capital shortfalls under a severe stress scenario corresponding to a 50% in each climate factor-mimicking portfolio. The objective is not to forecast the probability of such an event, but rather to quantify the banking sector's vulnerability conditional on a severe realization of systematic physical climate risk.[7]

[7]Using the historical relationship between each latent temperature factor and its corresponding factor-mimicking portfolio, a 50% change in the mimicking portfolio corresponds to an implied realization

The four temperature anomaly factors are orthogonal by construction, and each represents an independent dimension of systematic physical climate risk. We therefore estimate four separate bank-level capital shortfalls, one for each factor, and retain only positive capital shortfalls, as these correspond to situations in which regulatory capital falls below the required threshold. Aggregate systemic physical climate risk is then computed by summing the remaining positive shortfalls across all four factors and across all banks. This procedure provides a *conservative* measure of the capital required to recapitalize the banking system across the independent dimensions of systematic physical climate risk.

[Insert Figure 4 Here]

Figure 4a presents the time series of aggregate systemic physical climate risk. The estimated capital shortfall rises substantially over the sample period and peaks at approximately $980 billion. To put this magnitude into perspective, the aggregate market capitalization of publicly listed US banks is approximately $5.6 trillion during the final year of our sample. The estimated shortfall therefore represents roughly 17% of the market value of the listed US banking sector under the adopted severe climate stress scenario. Figure 4b decomposes aggregate systemic physical climate risk across the four latent temperature factors. The contribution of each factor varies considerably over time, indicating that distinct dimensions of systematic temperature variation contribute differently to aggregate banking sector vulnerability.

The estimated capital shortfalls increase most during periods of broad financial stress, including the Global Financial Crisis and the COVID-19 pandemic. This pattern is expected. The stress test measures the capital required to recapitalize banks conditional on severe adverse realizations of systematic physical climate risk. Such capital shortfalls are naturally amplified when banks are simultaneously financially vulnerable. The

of approximately 2.6, 5.52, 4.7, and 3.1 standard deviations of the standardized latent factor 1 through 4, respectively. These mappings are reported only to calibrate the stress scenario and should not be interpreted as probabilities of observing monthly temperature anomalies of comparable magnitudes.

results therefore indicate that physical climate risk compounds existing financial stress.

One possibility is that the estimated climate exposures simply proxy for aggregate market risk. Two features of the empirical design mitigate this concern. First, market returns are controlled for both when constructing the factor-mimicking portfolios and when estimating bank climate betas. Second, aggregate market returns explain less than 4% of the variation in any of the four climate factor-mimicking portfolios. These results indicate that the estimated capital shortfalls reflect a dimension of banking sector vulnerability beyond that implied by aggregate market movements alone.

4.2 Interpreting the First Temperature Anomaly Factor

The four latent temperature factors capture distinct dimensions of systematic variation in temperature anomalies. Since the first dominant factor alone explains approximately 60% of the cross-county variation in temperature anomalies, the remainder of the paper focuses on the first factor when examining banks' balance sheet management and lending decisions. This parsimonious approach substantially reduces dimensionality while retaining the majority of the systematic variation identified by the factor model. Emphasizing the leading factor is standard practice when the objective is to summarize the dominant source of common variation, as in Baker & Wurgler (2006).

[Insert Figure 5 Here]

To better understand the economic content of the first factor, Figure 5 plots its realizations against the cross-sectional average of temperature anomalies. The two series move closely together, with a correlation exceeding 98%, indicating that the first factor closely tracks aggregate fluctuations in realized temperature anomalies.[8] Unlike the cross-sectional mean, however, the factor model also estimates county-specific

[8]The close relationship between the first latent factor and the cross-sectional mean does not imply that the two approaches are equivalent. The cross-sectional mean assigns equal weights to counties, whereas factor analysis estimates the dominant source of common variation from the data's covariance structure. This distinction is analogous to empirical asset pricing, where the first principal component of returns is often highly correlated with the market portfolio, yet latent factor methods remain valuable because they recover the common covariance structure rather than imposing a particular weighting scheme ex ante (Kelly et al., 2019).

loadings that quantify heterogeneous exposure to the common temperature factor and underpin the subsequent empirical analysis. By contrast, Figure 6 shows substantially weaker correlations between the cross-sectional average of temperature anomalies and the GMB and Green factors, indicating that the first temperature factor is considerably more closely aligned with aggregate temperature dynamics than existing transition risk factors.

The close correspondence between the first latent factor and aggregate temperature anomalies provides a natural economic orientation for the factor. Throughout the remainder of the paper, we orient the first temperature factor so that higher realizations correspond to higher aggregate temperature anomalies. Under this normalization, counties with larger factor loadings and banks with higher associated betas are interpreted as having greater *exposure* to systematic physical climate risk.

Because the first factor explains the majority of systematic variation in temperature anomalies and closely tracks aggregate temperature fluctuations, we use it as our primary empirical proxy for systematic physical climate risk in the remainder of the paper. Accordingly, we refer to the bank beta associated with the first temperature factor as the *physical climate risk beta*.

4.3 Sample Characteristics and Physical Climate Risk Beta

We begin by describing the sample and documenting variation in physical climate beta. Panel A of Table 4 compares listed banks, which constitute our sample, with unlisted banks. Listed banks are larger, operate more branches, and are present in more counties, reflecting greater geographic diversification. They also rely less on deposit funding and maintain lower capital ratios. Profitability is similar across groups, while listed banks have marginally lower non-performing loans. These differences reflect the larger scale and broader geographic footprint of publicly listed banks.

Panel B of Table 4 shows that, even among listed banks, there is substantial heterogeneity in both bank characteristics and physical climate risk beta across banks and over time. This dispersion ensures that exposure to physical climate risk is not uniform, providing the cross-sectional heterogeneity required for identification. Next, we validate the physical climate risk beta by relating it to independently constructed measures of banks' geographic exposure based on county loadings for the first temperature factor (Panel C of Table 4). Banks with greater exposure to counties that load more heavily on this factor have higher physical climate risk betas. This positive and statistically significant relationship holds for both equally weighted and deposit-weighted county loadings aggregated to the bank level. These results provide further validation that the market-based climate beta aligns with banks' geographic exposure to systematic temperature variation.

[Insert Table 4 Here]

[Insert Table 5 Here]

We next examine whether banks' physical climate risk beta is reflected in their fundamentals. Table 5 reports regressions of bank balance sheet, funding, and performance outcomes on the lagged physical climate risk beta, controlling for bank and time fixed effects. Banks with higher climate betas hold more capital, originate fewer loans relative to assets, and rely less on deposit funding, consistent with more conservative balance sheet and funding policies. These adjustments do not coincide with lower profitability and are only weakly related to non-performing loan ratios, suggesting that they do not simply reflect deteriorating bank performance or realized credit losses. These findings indicate that banks incorporate systematic physical climate exposure into financial policy before disaster losses are realized. The results suggest that physical climate risk influences banks' financial decisions before it becomes visible in conventional balance sheet measures, motivating our subsequent analysis of how climate exposure shapes credit allocation across regions.

4.4 Physical Climate Risk and Bank Lending

4.4.1 Identification

The previous section shows that banks with higher physical climate risk beta adopt more conservative balance sheet policies. We next examine whether these adjustments extend to the supply of credit. We proceed in two steps. First, we ask whether increases in a bank's physical climate risk exposure are associated with changes in its lending activity. Second, conditional on a lending response, we examine whether banks reallocate credit away from counties that are themselves more exposed to the same systematic climate factor.

We begin by estimating the following specification:

$$\begin{aligned}\Delta\text{Lending Outcome}_{cbt} = \gamma_1 \Delta\text{Physical Climate Risk Beta}_{bt} + \Gamma'\text{Controls}_{bt} + \\ \text{Bank}_b \times \text{County}_c + \text{County}_c \times \text{Year}_t + v_{cbt}.\end{aligned} \tag{5}$$

The dependent variable is the log change in either the number or total volume of small business loan originations by bank *b* in county *c* during year *t*. The coefficient of interest, γ_1, measures whether changes in a bank's physical climate risk beta are associated with changes in lending. A negative estimate implies that banks experiencing larger increases in physical climate risk reduce lending on average across their lending portfolio. Bank-level controls account for changes in size, capitalization, profitability, and loan quality.

To examine where these lending adjustments occur, we augment the baseline specification with an interaction between the physical climate risk beta and the county loading on the first temperature factor:

$$\begin{aligned}\Delta\text{Lending Outcome}_{cbt} = \gamma_1 \Delta\text{Physical Climate Risk Beta}_{bt} + \\ \gamma_2 \left(\Delta\text{Physical Climate Risk Beta}_{bt} \times \text{County Loading}_c\right) \\ + \Gamma'\text{Controls}_{bt} + \text{Bank}_b \times \text{County}_c + \text{County}_c \times \text{Year}_t + v_{cbt}.\end{aligned} \tag{6}$$

The interaction coefficient, γ_2, measures whether banks experiencing larger increases in physical climate risk adjust lending differentially across counties with different exposure to the same systematic climate factor. A negative estimate implies that more exposed banks reduce lending disproportionately in counties where temperature anomalies load more heavily on the first temperature factor. In Equation (6), the interaction is identified from two dimensions of exposure to the same latent climate factor: bank exposure varies over time through changes in the physical climate risk beta, whereas county exposure is captured by the time-invariant loading on the first temperature factor. The interaction coefficient identifies whether banks experiencing larger increases in physical climate risk reallocate credit toward less climate-exposed counties.[9]

In both specifications (Equations (5) and (6)), county-year fixed effects ensure that identification comes from differences in lending across banks operating in the same county-year, thereby absorbing local credit demand, realized climate shocks, and other economic conditions shared by all borrowers within a county-year (Gilje et al., 2016; Cortés & Strahan, 2017; Islam & Singh, 2025). Bank-county fixed effects absorb persistent lending relationships between individual banks and counties, and time invarying bank heterogeneity. Standard errors are clustered at the bank and county levels.

4.4.2 Results

Table 6 examines whether changes in banks' physical climate risk exposure affect overall lending activity. Across all specifications, increases in the physical climate risk beta are associated with statistically significant reductions in both the number and the volume of small business loan originations. The estimated effects are economically meaningful. A 1-standard-deviation increase in the physical climate risk beta is associated with approximately a 10.7% decline in loan originations and a 5.6% decline in total loan volume. The results are robust to the inclusion of bank-level controls and indicate that banks systematically contract lending as their exposure to physical climate risk increases. In our sample, the average bank-county pair originates 45 small business loans totaling $2.6 million annually. Based on these sample means, a unit increase in the

[9] We demean the county loadings on the first temperature factor for interpretation purposes and to capture how the lending response varies with county exposure.

physical climate risk beta corresponds to approximately 5 fewer loans and $145,000 less lending per bank-county-year. These findings complement the balance sheet evidence presented earlier: as banks become more exposed to systematic physical climate risk, they not only hold more capital and maintain lower loan shares but also tighten the flow of new credit.

[Insert Table 6 Here]

Next, in Table 7, we next examine whether this contraction is uniformly distributed across counties or concentrated in counties more exposed to the same systematic climate factor. To facilitate interpretation, we demean the county loading before constructing the interaction term. The coefficient on the physical climate risk beta remains negative and statistically significant. The interaction between the physical climate risk beta and county loading indicates that banks experiencing larger increases in physical climate risk reduce lending disproportionately in counties whose temperature anomalies covary more strongly with the first systematic climate factor. This pattern is consistent with our conceptual framework, whereby banks respond to increases in systematic physical climate risk by reallocating credit away from regions that are more exposed to the same underlying source of climate variation. Relative to the median demeaned county loading (0.1), a one-unit increase in the physical climate risk beta is associated with a reduction of approximately 5 fewer loans and about $159,000 less lending per year.

[Insert Table 7 Here]

Our specification in Equation (6) assumes that the effects of bank characteristics do not vary with counties' exposure. Table A.4 relaxes this assumption by interacting county loadings with the full set of bank characteristics. The estimated coefficient on the interaction between the physical climate risk beta and the county loading remains economically and statistically similar, indicating that the baseline results are not driven by omitted-variable bias in the effects of bank characteristics across counties.

A confounding explanation is that the estimated lending effects reflect heterogeneous responses to realized natural disasters rather than exposure to systematic physical climate risk. Although county-year fixed effects absorb the direct effects of realized disasters and other county-year shocks common to all lenders, they do not allow banks with different characteristics to respond differently to those events. To address this possibility, Tables A.5 and A.6 augment Equations (5) and (6), respectively, by interacting contemporaneous and lagged major disaster indicators with both the physical climate risk beta and bank characteristics. The estimated coefficients of interest remain economically and statistically similar to the baseline estimates. This evidence indicates that the results are not driven by heterogeneous responses to realized disasters but instead reflect banks' exposure to systematic physical climate risk.

4.4.3 Role of bank branch network

We next examine whether these lending responses differ between relationship-based and arm's-length lending. We distinguish between core markets, where a bank maintains a branch presence, and non-core markets, where it does not. Existing research shows that banks typically adjust lending more strongly in non-core markets, where informational frictions are greater and relationship-specific rents are weaker (Cortés & Strahan, 2017). Table 8 reports the results.

[Insert Table 8 Here]

The coefficient on the physical climate risk beta remains negative and statistically significant, indicating that increases in physical climate risk reduce lending in non-core markets. The interaction between the physical climate risk beta and the core-market indicator is economically small and statistically insignificant across specifications, suggesting that banks' lending responses to physical climate risk do not differ systematically between counties where they maintain branch networks and those where they do not.

These results complement the evidence in Table 7. There, we show that banks reallocate lending according to counties' exposure to the first temperature factor. Here, we show that this response is similar in both core and non-core markets. These findings suggest that geographic climate exposure, rather than the presence of local lending relationships, determines banks' responses to physical climate risk.

4.4.4 State-Dependent Effects of Physical Climate Risk

The physical climate risk beta captures a bank's underlying exposure to systematic physical climate risk, whereas the contemporaneous value of the first temperature factor summarizes the common component of temperature anomalies during a given period. If banks actively manage these exposures, lending responses should become more pronounced during periods when the underlying climate factor takes higher values. In this section, we test this conjecture, and report results in Table 9.

[Insert Table 9 Here]

The interaction between the physical climate risk beta and the first temperature factor is negative for both lending measures, indicating that banks' responses to physical climate risk intensify when the systematic component of temperature anomalies becomes more pronounced. Figure 7 shows that the marginal effect of the physical climate risk beta becomes increasingly negative as the first temperature factor rises. Thus, banks experiencing similar increases in physical climate risk exposure adjust lending differently depending on the contemporaneous state of the common temperature factor. This evidence suggests that physical climate risk influences credit supply through both banks' underlying exposure and the contemporaneous state of the climate system.

An implication of these results is that periods when the first temperature factor runs high are precisely those in which climate-related disruption, adaptation, and post-disaster reconstruction should intensify borrowers' need for credit. Demand, in other words, ought to strengthen. Yet lending does the opposite: it contracts exactly where banks most exposed to physical climate risk face higher realizations of the first factor. A demand-side explanation is therefore difficult to reconcile with the evidence, whereas a tightening of credit supply provides a natural interpretation. Viewed together with the county-year fixed effects, which absorb local credit demand and other county-specific shocks, these findings suggest that physical climate risk constrains the supply of bank credit.

5 Additional Analyses

5.1 Rotational Indeterminacy

Factor models are identified only up to a rotation, implying that multiple mathematically equivalent representations span the same covariance structure. To examine whether the estimated temperature factors nevertheless align with economically intuitive geographic patterns, we construct an alternative set of location-based factors using county latitude and longitude. Comparing the two sets of factors provides a benchmark for assessing whether the statistical factors recover systematic geographic variation in temperature anomalies rather than arbitrary rotations of the latent factor space.

We standardize county latitude and longitude by centering the coordinates around the geographic midpoint of the contiguous US. Using these standardized coordinates, we estimate a cross-sectional regression each month to construct location-based factors:

$$\begin{aligned}\Delta\mathbb{T}_c =& \alpha + \beta_{1t}\text{Latitude}_c + \beta_{2t}\text{Longitude}_c + \beta_{3t}\text{Latitude}_c \times \text{Longitude}_c + \\ & \beta_{4t}\text{Latitude Squared}_c + \beta_{5t}\text{Longitude Squared}_c + u_{ct} \qquad \forall \quad t\end{aligned} \tag{7}$$

In equation (7), $\Delta\mathbb{T}_c$ represents the temperature anomaly for county c. The linear, interaction, and quadratic terms allow for flexible geographic gradients in temperature anomalies across the US. The monthly coefficients on these geographic basis functions constitute an alternative set of location-based factors.

[Insert Table 10 Here]

Panel A of Table 10 reports summary statistics for the location-based factors. Panel B compares the location-based factors with the estimated statistical factors. Each statistical factor is correlated with one or more location-based factors, indicating that the latent factors closely align with systematic geographic variation in temperature anomalies. These results show that the statistical factors recover the same broad geographic patterns without imposing geographic information during estimation. Because the location-based factors are constructed entirely from observable geographic information, this comparison provides an external benchmark for interpreting the latent statistical factors, as the covariance structure spanned by statistical factors aligns closely with economically intuitive geographic variation in temperature anomalies.

5.2 Global Temperature Anomaly Factors

The temperature anomaly factors in our analysis are constructed from US county-level data. An important question is whether the proposed approach generalizes beyond the US and whether the resulting factors reflect global climate variation or geographic patterns specific to the sample under consideration. To examine this, we construct a global dataset of temperature anomalies by mapping gridded data to 1,785 sub-national regions and apply the same factor extraction procedure as in Section 3.1. Because latent factors recover the covariance structure of the estimation sample, factors estimated from the global temperature panel need not coincide with those estimated from US counties. Differences between the two sets of factors should therefore be interpreted as differences in the underlying covariance structure of temperature anomalies rather than as evidence that one set of factors is preferable to the other.

Panel A of Table 11 shows that the first four global factors explain 46% of the cross-sectional variation in global temperature anomalies, with the leading factor accounting for 20%. This demonstrates that a low-dimensional factor structure also characterizes global temperature anomalies. Panel B compares the global factors with those estimated from US counties. The low correlations indicate that the two sets of factors summarize different covariance structures, implying that local temperature dynamics are not well represented by factors extracted from global temperature data.

[Insert Table 11 and Figure 8 Here]

Figure 8 illustrates the geographic distribution of the global factor loadings. The estimated factors align with broad climatic regions, including tropical and high-latitude zones, indicating that the extracted covariance structure remains geographically interpretable even at the global scale. Together, these results show that the proposed methodology is readily applicable beyond the US and highlight that latent temperature factors are inherently sample-specific summaries of systematic climate variation. Consequently, analyses of bank exposure are most naturally based on factors estimated from the geographic domain relevant to the institutions under study.

5.3 Robustness to Alternative Temperature Dynamics

A potential concern is that the estimated factor structure reflects persistent features of county-level temperature anomalies. To examine this possibility, we construct an alternative set of factors using innovation terms. For each county, we estimate an AR(1)-GARCH(1,1) model of temperature anomalies and obtain standardized residuals, thereby removing both serial dependence and conditional heteroskedasticity. We then apply the same factor analysis procedure to these innovation series. We also estimate an alternative specification in which county-specific linear trends are first removed using an AR(1)-Trend model before estimating latent factors.

[Insert Figure 9 Here]

Figure 9a compares the factor scores from the baseline specification with those obtained using the AR(1)-GARCH innovation series, while Figure 9b compares the baseline factor scores with those obtained after removing county-specific linear trends. In both cases, the estimated factor scores lie close to the 45-degree line, indicating that the alternative specifications recover essentially the same latent factors as the baseline model. These results show that the estimated covariance structure is robust to alternative representations of county-level temperature dynamics, including serial dependence, conditional heteroskedasticity, and deterministic warming trends. The baseline specification therefore provides a parsimonious representation of systematic temperature variation.

6 Conclusion

A central challenge in climate finance is measuring systematic physical climate risk in a way that links physical climate conditions to financial outcomes. Existing approaches typically infer physical climate risk from realized disasters or financial asset prices, both of which reflect many forces beyond the underlying climate process. This paper develops an alternative framework that estimates latent factors directly from temperature anomalies, allowing systematic climate variation to be measured before it is reflected in disaster outcomes or financial markets. The estimated factors summarize the dominant covariance structure of temperature anomalies and are supported by a broad set of validation exercises, indicating that they capture economically meaningful variation consistent with systematic physical climate risk.

Using these factors, we estimate banks' exposure to physical climate risk. We show that more exposed banks hold more capital, maintain lower loan shares, and generate economically meaningful systemic capital shortfalls under severe climate scenarios, despite exhibiting little deterioration in conventional measures of profitability or loan performance. These findings suggest that banks adjust their balance sheets in anticipation of physical climate risk rather than merely reacting to realized losses.

We find that banks experiencing larger increases in physical climate risk reduce overall lending and disproportionately reallocate credit away from counties with greater exposure to the same latent climate factor. These lending responses do not differ systematically between relationship-based and arm's-length lending markets, but become stronger when the common temperature factor takes larger values. Together, these findings point to a credit supply channel through which physical climate risk is transmitted to the real economy.

More broadly, the framework developed in this paper provides a tractable way to link physical climate data with financial outcomes. Although the analysis focuses on banks, the same methodology can be applied wherever exposure to systematic climate variation is economically relevant, providing a unified framework for studying how physical climate risk propagates through financial markets and institutions. As climate risks continue to evolve, approaches that integrate physical climate science with financial economics will become increasingly important for understanding financial system resilience and capital allocation.

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Table 1: **Factor analysis of temperature anomaly across US counties**
This table presents the output of factor analysis implemented on the county-month-year level temperature anomaly for US counties. Here, temperature anomaly, denoted $\Delta\mathbb{T}_{cmy} = \mathbb{T}_{cmy} - \frac{1}{30}\sum_{y=1951}^{1980}\mathbb{T}_{cmy}$. The subscripts c, m, and y represent county, month, and year, respectively. In Panel A, we present the eigenvalues of the first four factors and the proportion of the total variation in monthly temperature anomaly across US counties. The sample period spans 504 months (1981:M1–2022:M12). In Panel B, we present summary statistics of factor scores. In Panel C, we present summary statistics of factor loadings estimated for 3,108 US counties.

Panel A: Factor analysis output

Factor	Eigenvalue	Difference	Variance explained:	
			Proportion	Cumulative
Temperature Anomaly Factor 1	1,868.942	1,342.165	0.601	0.601
Temperature Anomaly Factor 2	526.777	272.609	0.170	0.771
Temperature Anomaly Factor 3	254.168	137.762	0.082	0.853
Temperature Anomaly Factor 4	116.406	34.959	0.038	0.890

Panel B: Summary statistics – Factor Scores (T = 504)

	Mean	SD	Min	Max
Temperature Anomaly Factor 1	0.000	1.000	-3.867	3.906
Temperature Anomaly Factor 2	0.000	1.000	-4.441	3.602
Temperature Anomaly Factor 3	0.000	1.000	-3.297	2.841
Temperature Anomaly Factor 4	0.000	1.000	-3.122	2.659

Panel C: Summary statistics – County loadings (N = 3,108)

	Mean	SD	Min	Max
County loading – Factor 1	0.737	0.241	-0.127	0.971
County loading – Factor 2	0.073	0.405	-0.583	0.839
County loading – Factor 3	0.027	0.285	-0.461	0.641
County loading – Factor 4	0.041	0.189	-0.243	0.680

Table 2: **Local factor scores and loadings, and natural disasters**
This table presents validation results for latent factors and their loadings, estimated using factor analysis of county-level monthly temperature anomalies. The analysis examines how these factors relate to one-period-ahead disaster outcomes. In column (1), the dependent variable is *Disaster*, an indicator set to one if SHELDUS records positive total damages in a given county-month. Column (2) uses *Major Disaster* as the dependent variable, which equals one if per capita total damages, adjusted to 2022 dollars, are at or above the 75th percentile among disaster observations. Columns (3) through (5) use the logarithm of inflation-adjusted per capita crop, property, and total damages as dependent variables. The sample covers the period from January 1981 to December 2022. Standard errors are clustered at the county level, and t-statistics are shown in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)
	Dependent variable:				
			Ln(· Damages) ∣ Disaster		
	Disaster	Major Disaster ∣ Disaster	Crop	Property	Total
County loading - Factor 1 × Factor 1 scores	0.0031*	0.0134***	0.2431***	0.0705***	0.0648***
	(1.9381)	(4.0098)	(2.7789)	(3.2839)	(2.8115)
County loading - Factor 2 × Factor 2 scores	0.0082***	0.0012	0.7064***	0.0425***	0.0491***
	(9.0764)	(0.6002)	(16.0050)	(3.3017)	(3.7760)
County loading - Factor 3 × Factor 3 scores	0.0144***	0.0105***	0.5231***	-0.0036	0.0343*
	(9.5858)	(3.3641)	(8.4865)	(-0.1822)	(1.7262)
County loading - Factor 4 × Factor 4 scores	0.0049**	-0.0226***	0.3218***	-0.3244***	-0.3512***
	(1.9713)	(-5.0991)	(3.5028)	(-10.2241)	(-10.4258)
Residual temperature anomaly	-0.0071***	-0.0066***	-0.2233***	-0.0479***	-0.0371***
	(-12.1637)	(-5.8855)	(-8.8658)	(-6.4251)	(-4.8876)
N	1,563,324	334,767	62,846	321,422	334,767
R^2	0.1215	0.1687	0.5104	0.2772	0.2880
County FE	✓	✓	✓	✓	✓
Year × Month FE	✓	✓	✓	✓	✓

Table 3: **Validating Temperature Anomaly Factors**
This table examines whether temperature anomaly factors capture variation in asset returns not explained by standard asset pricing factors. Panel A implements spanning tests by regressing each of the four temperature anomaly factors on established factors. Model (1) uses the full sample from 1981 to 2022 and includes the Fama–French five-factor model. Model (2) restricts the sample to 2009–2022, while Model (3) adds the Green Minus Brown (GMB) and green factors, which are available from 2009 onward. If the temperature anomaly factors are not spanned by the existing factors, we expect low explanatory power in these regressions. Panel B reverses the spanning tests, regressing the GMB and green factors on the temperature anomaly factors, both with and without the Fama–French factors, to assess whether temperature anomaly factors subsume information in sustainability-related factors. Panel C evaluates the incremental explanatory power of temperature anomaly factors for 123 test assets, including 48 industry, 25 size–book-to-market, 25 size–profitability, and 25 size–investment portfolios. For each asset, we estimate four models: the Fama–French five-factor model; the five-factor model plus GMB and green factors; the five-factor model plus temperature anomaly factors; and a model that includes all factors. We report the change in *adjusted* R^2 from adding temperature anomaly factors and summarize the distribution of these changes across portfolios. Panel D presents cross-sectional R^2. Panel E estimates Dynamic Conditional Correlation multivariate GARCH models for Fama–French industry portfolios in the Banks, Financials, and Insurance sectors over 1981–2022. Standard errors in Panels A and B are Newey–West corrected with 12 lags, and t-statistics are reported in parentheses. Panel E reports z-statistics in parentheses.

Panel A: Spanning Tests

	(1)	(2)	(3)	(4)
	Dependent variable: $(\cdot)$ Scores			
	Factor 1	Factor 2	Factor 3	Factor 4
Model 1: FF5 (N = 504)				
Market	-0.0028	0.0031	-0.0111	-0.0123
	(-0.2347)	(0.2693)	(-1.1177)	(-1.2015)
SMB	0.0104	-0.0044	-0.0251	-0.0131
	(0.5509)	(-0.2716)	(-1.5751)	(-0.7149)
HML	-0.0126	-0.0096	-0.0329*	-0.0035
	(-0.5818)	(-0.3928)	(-1.7670)	(-0.1718)
RMW	-0.0104	-0.0501**	-0.0299	-0.0132
	(-0.4946)	(-2.1071)	(-1.4522)	(-0.6294)
CMA	-0.0207	0.0496	0.0221	-0.0542*
	(-0.5800)	(1.3352)	(0.7023)	(-1.7416)
R^2	0.0082	0.0190	0.0163	0.0147
Model 2: FF5 (N = 168)				
Market	-0.0086	0.0210	-0.0237*	0.0006
	(-0.4606)	(1.0320)	(-1.7194)	(0.0387)
SMB	0.0148	0.0124	0.0220	-0.0628*
	(0.3950)	(0.4234)	(0.5909)	(-1.7584)
HML	-0.0485	-0.0320	-0.0416*	0.0466
	(-1.5807)	(-0.8756)	(-1.9668)	(1.6078)
RMW	0.0299	-0.0416	0.0708*	-0.0924**
	(0.6796)	(-0.9148)	(1.9042)	(-2.4010)
CMA	0.0498	0.0834	-0.0011	-0.1109**
	(0.7549)	(1.2231)	(-0.0326)	(-2.0665)
R^2	0.0199	0.0264	0.0527	0.0658
Model 3: FF5+GMB+GF (N = 168)				
Market	-0.0177	0.0204	-0.0019	-0.0019
	(-1.0355)	(0.9357)	(-0.0999)	(-0.0999)
SMB	0.0414	0.0077	-0.0492	-0.0492
	(1.0630)	(0.2506)	(-1.2621)	(-1.2621)
HML	-0.0281	-0.0313	0.0529	0.0529
	(-1.0050)	(-0.8912)	(1.5251)	(1.5251)
RMW	0.0431	-0.0589	-0.0715	-0.0715
	(1.0725)	(-1.4494)	(-1.5822)	(-1.5822)
CMA	0.0637	0.0636	-0.0873	-0.0873
	(0.9485)	(0.8799)	(-1.6222)	(-1.6222)
GMB	0.1684	-7.6994	7.3819	7.3819
	(0.0283)	(-1.5952)	(1.4042)	(1.4042)
Green Factor	8.4187	2.9124	0.1125	0.1125
	(1.5215)	(0.4733)	(0.0207)	(0.0207)
R^2	0.0337	0.0405	0.0853	0.0853

Panel B: Reverse Spanning

	Dependent variable:			
	GMB		Green Factor	
Temperature Anomaly Factor 1	0.0015	0.0013	0.0024	0.0017
	(0.8194)	(0.7938)	(1.5321)	(1.6062)
Temperature Anomaly Factor 2	-0.0021	-0.0018	-0.0006	-0.0002
	(-1.2386)	(-1.3751)	(-0.3981)	(-0.1745)
Temperature Anomaly Factor 3	-0.0003	-0.0010	-0.0004	-0.0019**
	(-0.3062)	(-1.0225)	(-0.4520)	(-2.2383)
Temperature Anomaly Factor 4	0.0048***	0.0028	0.0031**	0.0012
	(2.9161)	(1.5223)	(2.3766)	(0.9322)
Fama-French 5-Factors	✗	✓	✗	✓
p-value for joint significance	0.2678	0.7409	0.1722	0.7624
N	168	168	168	168
R^2	0.0652	0.2913	0.0387	0.5095

Panel C: △Adjusted R^2

	Mean	p25	p50	p75
△Adjusted R^2–FF5	0.0281	-0.0477	0.0051	0.0487
△Adjusted R^2– FF5+GMB+GF	0.1030	-0.0727	0.0277	0.2041

Panel D: △Cross-Sectional R^2

	Model			
	FF5	FF5+T4	FF5+GM+GF	FF5+GM+GF+T4
R^2	0.1769	0.2428	0.2978	0.3992
Number of Assets	123	123	123	123
Number of Months	504	504	168	168
Sample Period	1981-2022	1981-2022	2009-2022	2009-2022

Panel E: DCC-MGARCH Estimates

	(1)	(2)	(3)
	Banks	Financials	Insurance
Variance Equation			
Temperature Anomaly Factor 1	0.3667**	0.8595***	0.0063
	(2.5630)	(5.2250)	(0.0303)
Temperature Anomaly Factor 2	0.4548**	0.1587	-0.3154
	(2.4092)	(0.8312)	(-1.6133)
Temperature Anomaly Factor 3	-0.3876**	0.4351*	0.4099
	(-2.4902)	(1.7916)	(1.5720)
Temperature Anomaly Factor 4	-0.3028**	0.0002	0.4852
	(-1.9870)	(0.0008)	(1.7409)
α	0.2214***	0.1160***	0.2171***
	(4.1352)	(3.3838)	(4.4081)
β	0.6377***	0.8200***	0.7188***
	(7.8226)	(16.7510)	(15.1942)
$\rho(Banks, Financials)$		0.5742*** (6.4603)	
$\rho(Banks, Insurance)$		0.1980 (1.6082)	
$\rho(Financials, Insurance)$		0.1020 (0.7671)	

Table 4: **Physical Climate Risk Beta and Sample Characteristics**
This table describes the sample, summarizes key variables, and validates the physical climate risk beta. Panel A compares listed and unlisted banks using cross-sectional regressions with standard errors clustered by bank and time. Panel B reports summary statistics for listed banks, including within- and between-bank variation. Panel C relates the market-based physical climate risk beta to geographic exposure constructed from county-level temperature loadings aggregated across each bank's branch network using equal and deposit weights; estimates are obtained from Fama–MacBeth regressions with Newey–West (5 lags) standard errors. Physical climate risk beta is estimated from bank equity returns using a mimicking portfolio for the first temperature anomaly factor derived from factor analysis. The sample period is 1981–2022. t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable:						
	Bank Size	Deposits-to-Assets	Capital Ratio	Profitability	NPL-to-Assets	Branches	Counties
Listed bank	1.8537***	-0.0395***	-0.0123***	0.0001	0.0004**	2.9271***	2.2060***
	(21.7299)	(-12.7526)	(-16.3402)	(0.8989)	(2.2885)	(12.6881)	(11.7835)
N	298,451	298,451	298,451	298,451	298,451	144,831	144,831
R^2	0.1963	0.0481	0.0302	0.0001	0.0004		

Panel B

	Mean	Standard Deviation			P10	P50	P90
		Overall	Between	Within			
Bank size	13.3775	2.0831	1.6632	0.5228	11.0793	12.9638	16.2389
Deposit-to-Assets	0.8233	0.0934	0.0783	0.0491	0.6948	0.8493	0.9132
Capital Ratio	0.0829	0.0241	0.0278	0.0134	0.0588	0.0784	0.1128
Profitability	0.0068	0.0047	0.0037	0.0040	0.0019	0.0065	0.0130
NPL-to-Assets	0.0080	0.0080	0.0079	0.0058	0.0014	0.0054	0.0177
Physical climate risk beta	-0.5710	1.2653	0.9152	1.0876	-2.3110	-0.3617	0.8763

Panel C

	(1)	(2)
	Dependent variable: Physical climate risk beta	
Factor 1 Loading–Equally-weighted	0.1834***	
	(4.7098)	
Factor 1 Loading–Deposit-weighted		0.1677***
		(4.3172)
Bank size	-0.0065	-0.0059
	(-0.9644)	(-0.8779)
Capital ratio	-0.8094**	-0.8245**
	(-2.2099)	(-2.2489)
Profitability	-3.7976	-3.3696
	(-0.8103)	(-0.7173)
NPL-to-Assets	-0.5398	-0.2211
	(-0.3978)	(-0.1629)
N	47,374	47,374
R^2	0.1143	0.1139

Table 5: **Physical Climate Risk Beta and Bank Balance Sheets**
This table examines how bank balance sheet composition, funding structure, and performance relate to physical climate risk beta. The dependent variables are capital ratio, loans-to-assets, deposits-to-assets, log deposits, non-performing loans (NPL) to assets, and profitability. The key explanatory variable, *Physical climate risk beta*, measures bank-level exposure to physical climate risk, estimated from bank equity returns using a mimicking portfolio for the first temperature anomaly factor. All explanatory variables are lagged by one period. The data are quarterly, and the sample period is from 1986:Q1 to 2022:Q4. Standard errors are clustered at the bank level, and $t-$statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Asset Side		Funding Side		Performance	
	(1)	(2)	(3)	(4)	(5)	(6)
	Capital ratio	Loans-to-Assets	Deposits-to-Assets	Ln(Deposits)	NPL-to-Assets	Profitability
Physical climate risk beta	0.0012***	-0.0061***	-0.0029*	-0.0087***	-0.0002	-0.0001
	(3.3159)	(-3.0975)	(-1.7687)	(-3.3336)	(-1.4256)	(-1.3532)
Bank size	0.0019**	-0.0147***	-0.0141***	0.9214***	0.0006*	-0.0004***
	(1.9666)	(-3.1319)	(-2.7608)	(96.3453)	(1.8922)	(-2.7469)
Capital ratio		0.1145	-0.2149**	0.1582	0.0114*	0.0195***
		(1.1020)	(-2.5236)	(1.0552)	(1.7247)	(6.2272)
NPL-to-Assets	0.0609*	1.6046***	0.2037	0.1453		-0.1434***
	(1.8170)	(7.4889)	(1.4069)	(0.5838)		(-20.2707)
Profitability	0.3461***	1.9336***	-0.0682	0.7418*	-0.5008***	
	(6.2513)	(6.6157)	(-0.3306)	(1.9108)	(-18.1661)	
N	42,969	42,969	42,969	42,969	42,969	42,969
R^2	0.7840	0.7666	0.7860	0.9970	0.6131	0.7307
Bank FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓

Table 6: **Physical Climate Risk Exposure and Small Business Lending**
This table presents results linking credit outcomes at the county-bank-year level and the physical climate risk beta. In columns (1)–(2), the dependent variable is the change in the logarithm of the number of loan originations by a bank to small businesses in a county-year. In columns (3)–(4), the dependent variable is the change in the logarithm of the total loan amount extended by a bank to small businesses in a county-year. *Physical climate risk beta* is the beta with respect to the portfolio that mimics the first temperature anomaly factor, measured in December (year-end). The differenced control variables are the *capital ratio* that equals tier 1 capital as a fraction of total assets, *bank size* measured by the logarithm of the total assets of a bank, *profitability* that equals the return on assets, and *NPL-to-assets* that equals non-performing loans as a fraction of total assets of a bank. Δ represents change. The sample period is from 1997 to 2022. The standard errors are clustered by county and bank, and *t*-statistics are 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	
ΔPhysical climate risk beta	-0.1003**	-0.0995**	-0.0563*	-0.0516*
	(-2.0098)	(-2.0187)	(-1.7499)	(-1.7083)
ΔBank size		0.3049		0.3264*
		(1.4718)		(1.8119)
ΔCapital ratio		-1.4587		1.7598
		(-0.5618)		(0.8571)
ΔProfitability		8.3967		9.4834
		(1.4483)		(1.4146)
ΔNPL-to-Assets		9.8057		13.0714**
		(1.4642)		(2.0683)
N	388,603	388,603	388,603	388,603
R^2	0.2647	0.2686	0.2598	0.2625
County × Bank FE	✓	✓	✓	✓
County × Year FE	✓	✓	✓	✓

Table 7: **Physical Climate Risk Exposure and Small Business Lending**
This table presents results linking credit outcomes at the county-bank-year level and the physical climate risk beta. In columns (1)–(2), the dependent variable is the change in the logarithm of the number of loan originations by a bank to small businesses in a county-year. In columns (3)–(4), the dependent variable is the change in the logarithm of the total loan amount extended by a bank to small businesses in a county-year. *Physical climate risk beta* is the beta with respect to the portfolio that mimics the first temperature anomaly factor, measured in December (year-end). The differenced control variables are the *capital ratio* that equals tier 1 capital as a fraction of total assets, *bank size* measured by the logarithm of the total assets of a bank, *profitability* that equals the return on assets, and *NPL-to-assets* that equals non-performing loans as a fraction of total assets of a bank. Δ represents change. The sample period is from 1997 to 2022. The standard errors are clustered by county and bank, and t-statistics are 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	
ΔPhysical climate risk beta	-0.0998**	-0.0991**	-0.0558*	-0.0512*
	(-1.9983)	(-2.0089)	(-1.7520)	(-1.7078)
ΔPhysical climate risk beta× County loading	-0.0693***	-0.0605**	-0.0812***	-0.0705**
	(-2.9962)	(-2.5271)	(-2.9552)	(-2.5449)
N	388,603	388,603	388,603	388,603
R^2	0.2648	0.2687	0.2599	0.2625
Bank Controls	✗	✓	✗	✓
County × Bank FE	✓	✓	✓	✓
County × Year FE	✓	✓	✓	✓

Table 8: **Physical Climate Risk Exposure, Branch Network and Small Business Lending**
This table presents results linking credit outcomes at the county-bank-year level and the physical climate risk beta. In columns (1)–(2), the dependent variable is the change in the logarithm of the number of loan originations by a bank to small businesses in a county-year. In columns (3)–(4), the dependent variable is the change in the logarithm of the total loan amount extended by a bank to small businesses in a county-year. *Physical climate risk beta* is the beta with respect to the portfolio that mimics the first temperature anomaly factor, measured in December (year-end). *Core market* is a dichotomous variable that equals 1 (0 otherwise) if a bank has a branch in a given county. The differenced control variables are the *capital ratio* that equals tier 1 capital as a fraction of total assets, *bank size* measured by the logarithm of the total assets of a bank, *profitability* that equals the return on assets, and *NPL-to-assets* that equals non-performing loans as a fraction of total assets of a bank. Δ represents change. '#' represents interaction with the grouping variable (Core Market). The sample period is from 1997 to 2022. The standard errors are clustered by county and bank, and *t*-statistics are 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	
ΔPhysical climate risk beta	-0.0906*	-0.0985**	-0.0519*	-0.0514
	(-1.7697)	(-2.0106)	(-1.6738)	(-1.5072)
Core Market	-0.0187		-0.0451	
	(-0.6147)		(-1.1962)	
ΔPhysical climate risk beta×Core Market	-0.0255*	-0.0103	0.0011	0.0132
	(-1.6568)	(-0.4456)	(0.0876)	(0.4618)
N	388,603	388,603	388,603	388,603
R^2	0.2688	0.3491	0.2625	0.3276
Bank controls	✓	✓	✓	✓
Bank controls×Core Market	✗	✓	✗	✓
County × Bank FE	✓	✓#	✓	✓#
County × Year FE	✓	✓#	✓	✓#

Table 9: **Physical Climate Risk Exposure, Realizations and Small Business Lending**
This table presents results linking credit outcomes at the county-bank-year level and the physical climate risk beta and physical climate risk realizations. In columns (1)–(2), the dependent variable is the change in the logarithm of the number of loan originations by a bank to small businesses in a county-year. In columns (3)–(4), the dependent variable is the change in the logarithm of the total loan amount extended by a bank to small businesses in a county-year. *Physical climate risk beta* is the beta with respect to the portfolio that mimics the first temperature anomaly factor, measured in December (year-end). The differenced control variables are the *capital ratio* that equals tier 1 capital as a fraction of total assets, *bank size* measured by the logarithm of the total assets of a bank, *profitability* that equals the return on assets, and *NPL-to-assets* that equals non-performing loans as a fraction of total assets of a bank. Δ represents change. The sample period is from 1997 to 2022. The standard errors are clustered by county and bank, and *t*-statistics are in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)
	Dependent variable: Growth in (.)	
	Number of originations	Loan volume
ΔPhysical climate risk beta	-0.0721	-0.0354
	(-1.5718)	(-1.4051)
ΔPhysical climate risk beta$\times$Factor 1 Scores	-0.0577***	-0.0342
	(-2.6770)	(-1.2679)
N	388,603	388,603
R^2	0.2697	0.2626
Bank Controls	✓	✓
County $\times$ Bank FE	✓	✓
County $\times$ Year FE	✓	✓

Table 10: **Factor Rotation and Geographic Interpretation of Temperature Anomaly Factors**
This table addresses the rotational indeterminacy of factor analysis, where factors are interpretable only up to a rotation of the underlying space spanning temperature anomalies. Panel A presents summary statistics for the pre-specified geography-based factors. Panel B reports the correlations between the geography-based factors and the local temperature anomaly factors extracted from the factor analysis and used in the main analysis. The sample period is from January 1981 to December 2022.

Panel A: Summary Statistics

	N	Mean	SD	Min	Max
Latitude Factor	504	0.0153	0.1140	-0.3985	0.3949
Longitude Factor	504	-0.0023	0.0454	-0.1459	0.1807
Latitude × Longitude Factor	504	-0.0003	0.0027	-0.0092	0.0083
Latitude Squared Factor	504	0.0013	0.0095	-0.0406	0.0296
Longitude Squared Factor	504	0.0001	0.0017	-0.0056	0.0080

Panel B: Correlations with Local Temperature Anomaly Factors

	Temperature Anomaly Factor				Highest |value|
	Factor 1	Factor 2	Factor 3	Factor 4	
Latitude Factor	0.3731	0.5456	-0.7290	-0.0661	0.7290
Longitude Factor	-0.5483	0.5946	0.5714	0.0806	0.5946
Latitude × Longitude Factor	-0.2242	-0.5311	0.5289	0.2563	0.5311
Latitude Squared Factor	0.0291	0.7483	-0.4543	-0.3387	0.7483
Longitude Squared Factor	-0.3953	-0.7880	0.0332	0.3857	0.7880
Highest |value|	0.5483	0.7880	0.7290	0.3857	0.7880

Table 11: **Global Temperature Anomaly Factors and Correlation with Local Temperature Anomaly Factors**

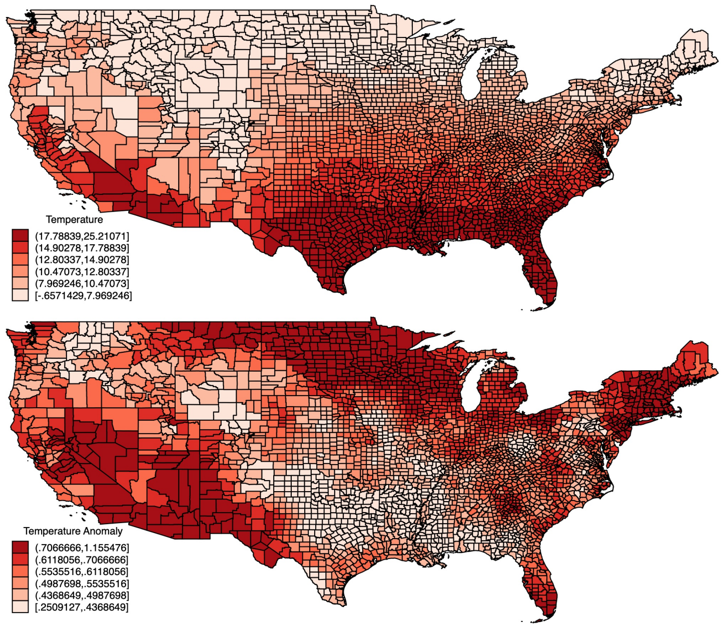
This table presents the output of *global* factor analysis implemented on the sub-national-month-year level temperature anomaly. Here, temperature anomaly, denoted $\Delta\mathbb{T}_{smy} = \mathbb{T}_{smy} - \frac{1}{30}\sum_{y=1951}^{1980}\mathbb{T}_{smy}$. The subscripts *s*, *m*, and *y* represent sub-national region, month, and year, respectively. In Panel A, we present the eigenvalues of the first four factors and the proportion of the total variation in monthly temperature anomaly across the globe. In Panel B, we present correlations between the first four local temperature anomaly factors, estimated from US county-level temperature anomaly data, and global temperature anomaly factors. The sample period spans 42 years (1981:M1–2022:M12).

Panel A: Global factor analysis output

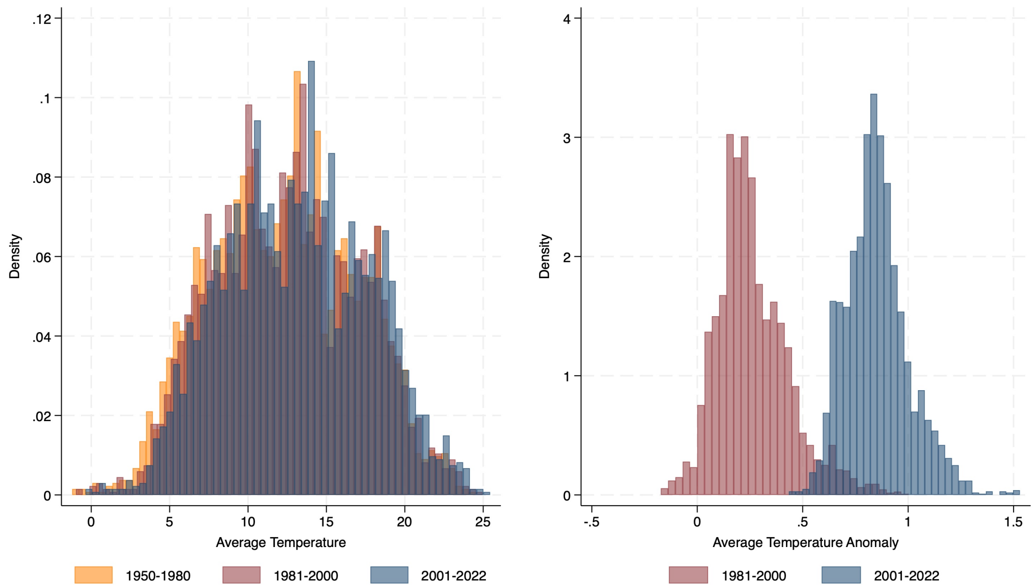
	Eigenvalue	Difference	Proportion	Cumulative
Global - Factor 1	369.9077	143.8368	0.2072	0.2072
Global - Factor 2	226.0709	92.1009	0.1267	0.3339
Global - Factor 3	133.9700	56.8737	0.0751	0.4089
Global - Factor 4	77.0963	8.4560	0.0432	0.4521

Panel B: Correlation between local and global temperature anomaly factors

	Local - Factor 1	Local - Factor 2	Local - Factor 3	Local - Factor 4
Global - Factor 1	0.2205	0.0596	0.0486	0.2732
Global - Factor 2	0.0966	-0.0669	-0.0549	0.1499
Global - Factor 3	-0.2538	0.0828	0.2308	-0.0259
Global - Factor 4	0.3196	-0.1623	0.057	-0.0813

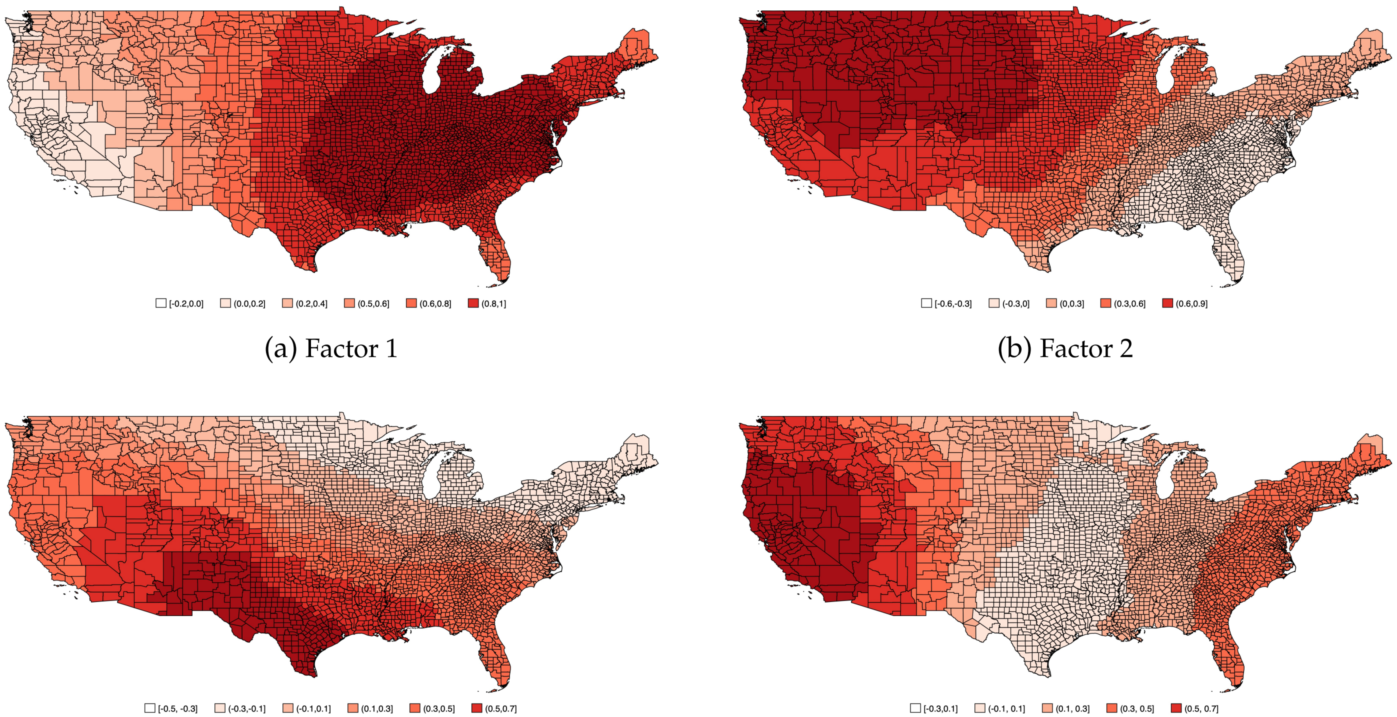


(a) Spatial distribution of monthly temperature and temperature anomaly



(b) Average temperature and temperature anomaly over different time periods

Figure 1: In Panel (a), the figure displays spatial maps of average temperature (top) and average temperature anomaly (bottom). Both are computed using data from 1981 to 2022. In Panel (b), the figure on the left shows the distribution of average temperatures across three non-overlapping periods: 1951–1980 (reference period), 1981–2000, and 2001–2022. The figure on the right in Panel (b) presents the distribution of temperature anomalies for 1981–2000 and 2001–2022, measured relative to the 1951–1980 baseline.



(a) Factor 1

(b) Factor 2

(c) Factor 3

(d) Factor 4

Figure 2: The figure shows the spatial distribution of counties' exposures to the first four temperature anomaly factors derived from factor analysis, based on monthly temperature anomaly data from 1981 to 2022.

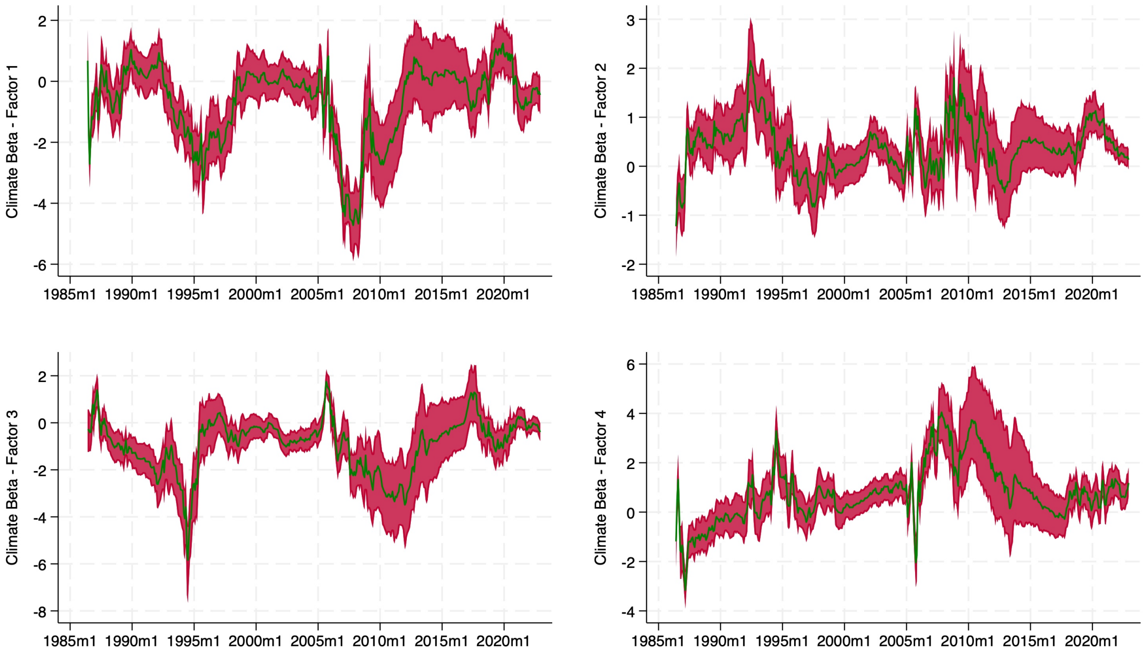
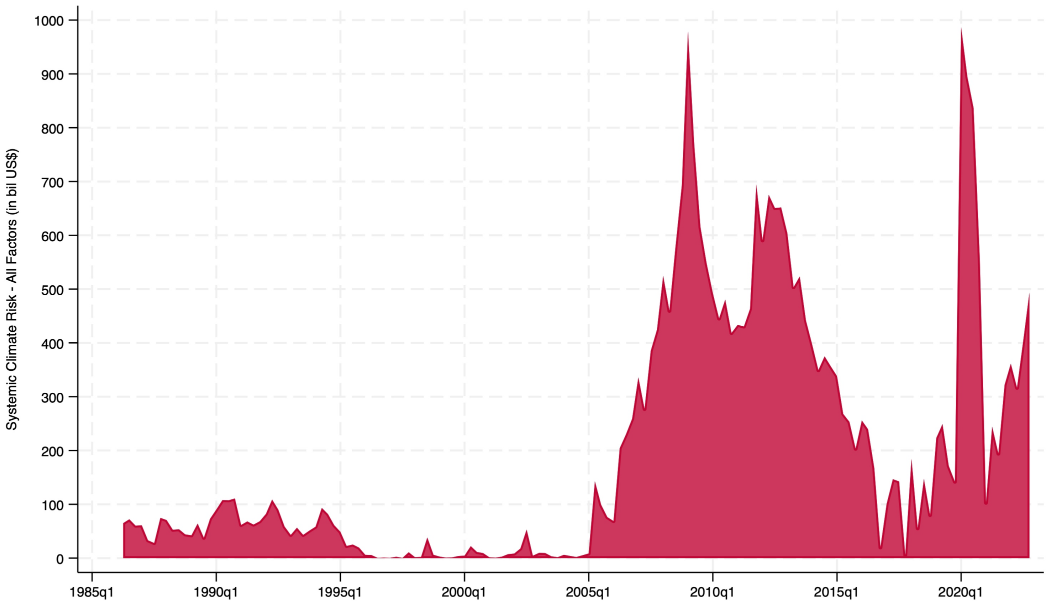
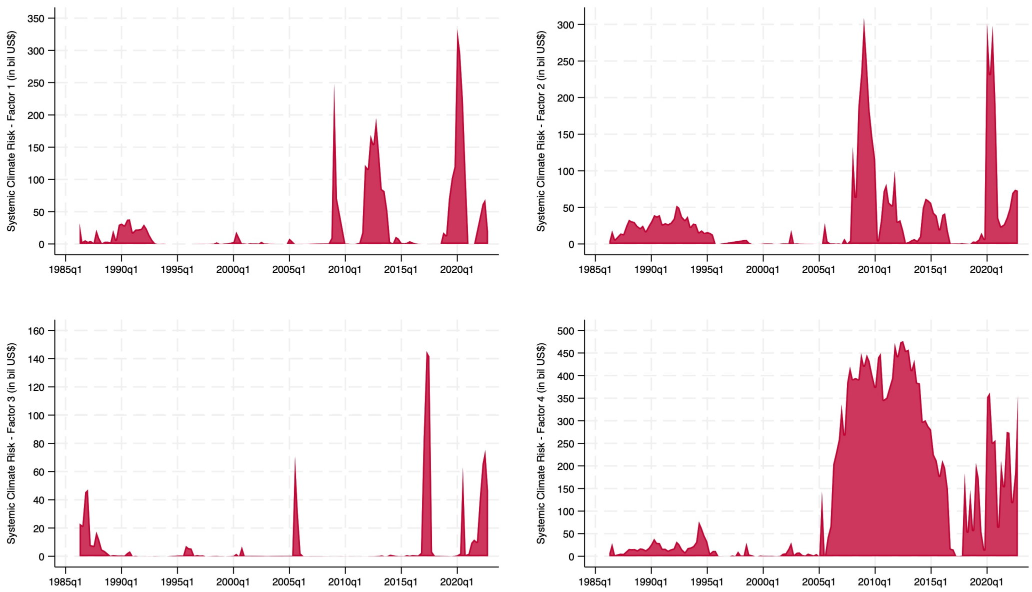


Figure 3: The figure shows the time series of the cross-sectional average of climate betas (line plot). The shaded area represents the 90th and 10th percentiles of the cross-sectional distribution. The sample period is from 1986:M1 to 2022:M12.



(a) Systemic Physical Climate Risk



(b) Systemic Physical Climate Risk Disaggregated by Factor

Figure 4: The figure presents the time series of systemic physical climate risk for publicly traded US banks from 1986:Q1 to 2022:Q4. Panel (a) shows the aggregate measure, aggregating the contributions of all four temperature anomaly factors. Panel (b) disaggregates this risk, displaying separate time series for each factor's contribution to systemic physical climate risk.

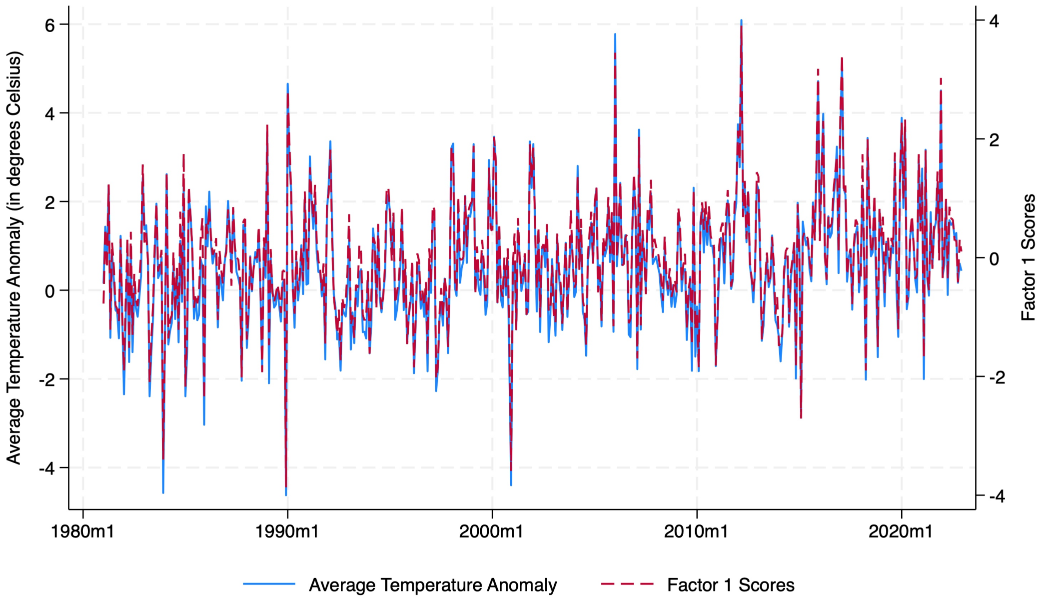


Figure 5: The figure shows the time series of scores for the first factor derived from factor analysis of temperature anomalies and the cross-sectional average of temperature anomalies across contiguous US counties. The sample period spans from 1980:M1 to 2022:M12.

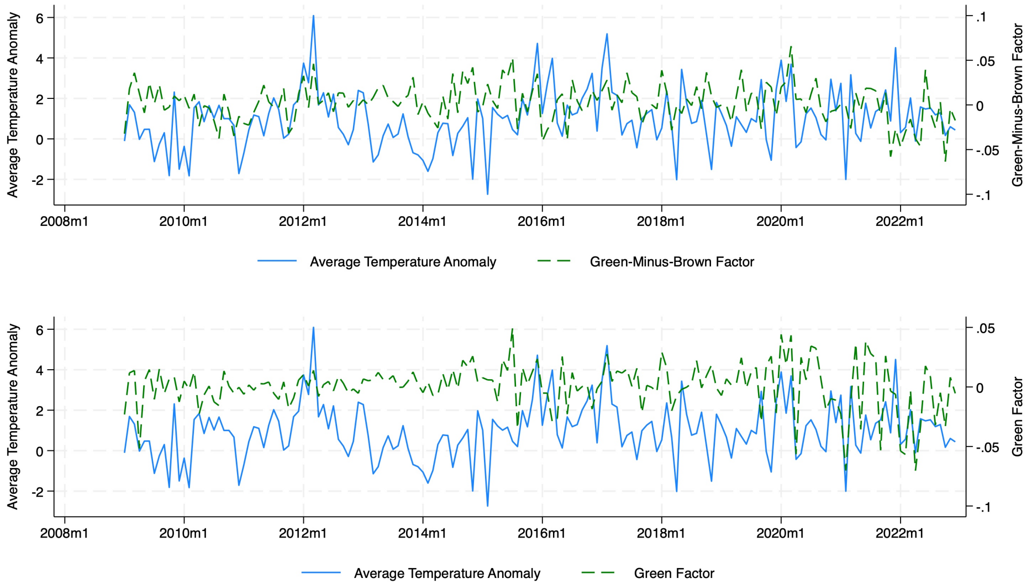
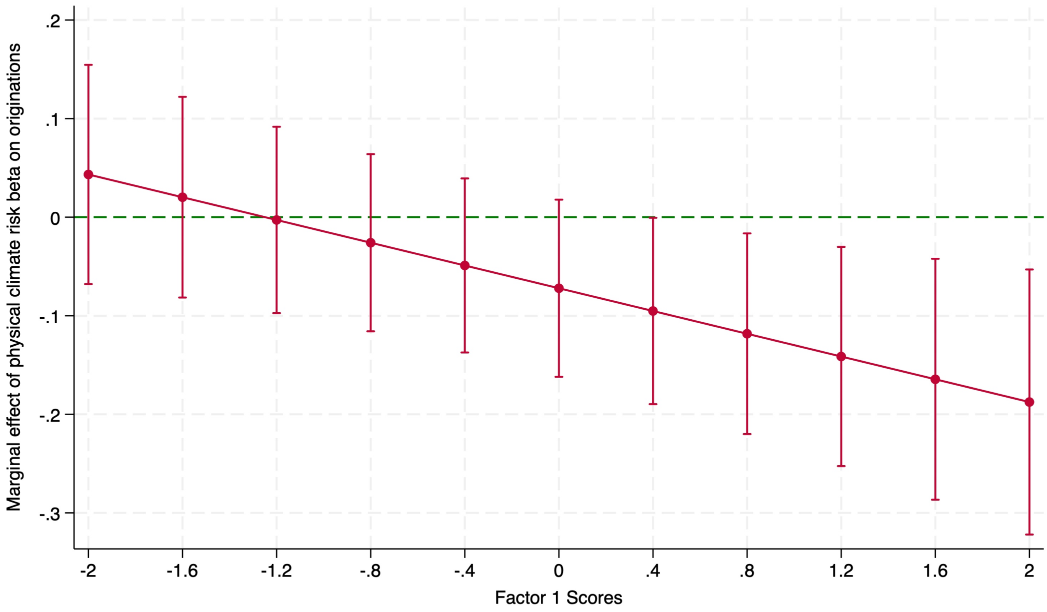
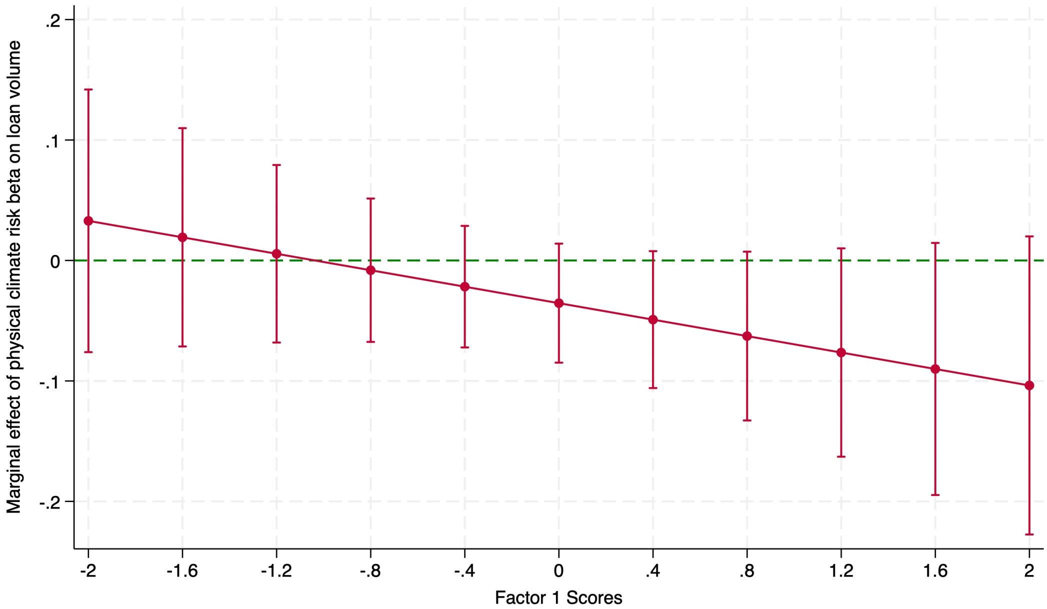


Figure 6: The figure shows the time series of scores for the first factor derived from factor analysis of temperature anomalies across contiguous US counties and the Green-Minus-Brown factor (top) and the Green factor (bottom). The sample period spans from 2009:M1 to 2022:M12.

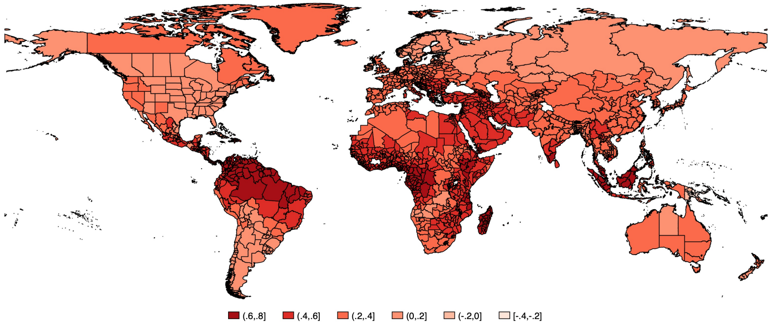


(a) Number of Originations

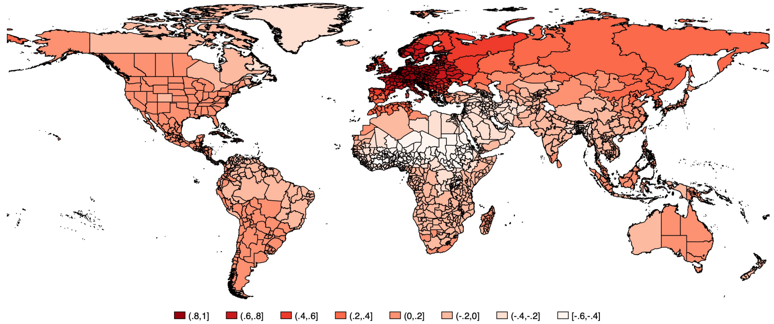


(b) Loan Volume.

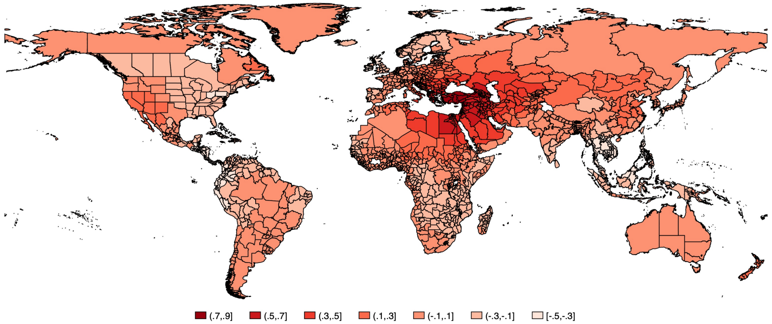
Figure 7: The figure presents the marginal effect of a unit increase in a bank's physical climate risk beta for various values of return on factor portfolio mimicking the first temperature anomaly factor for number of originations (Panel (a)) and loan volume (Panel (b)).



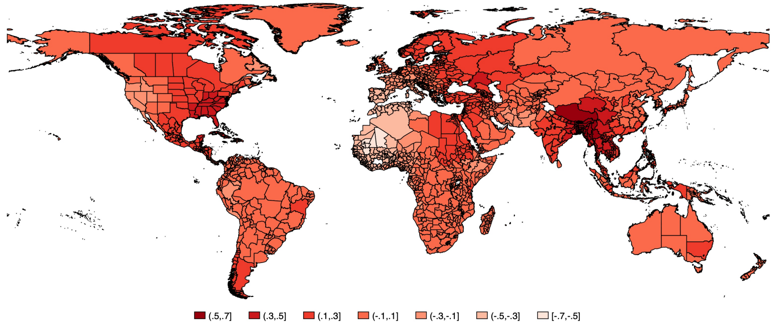
(a) Loadings - Global Factor 1



(b) Loadings - Global Factor 2

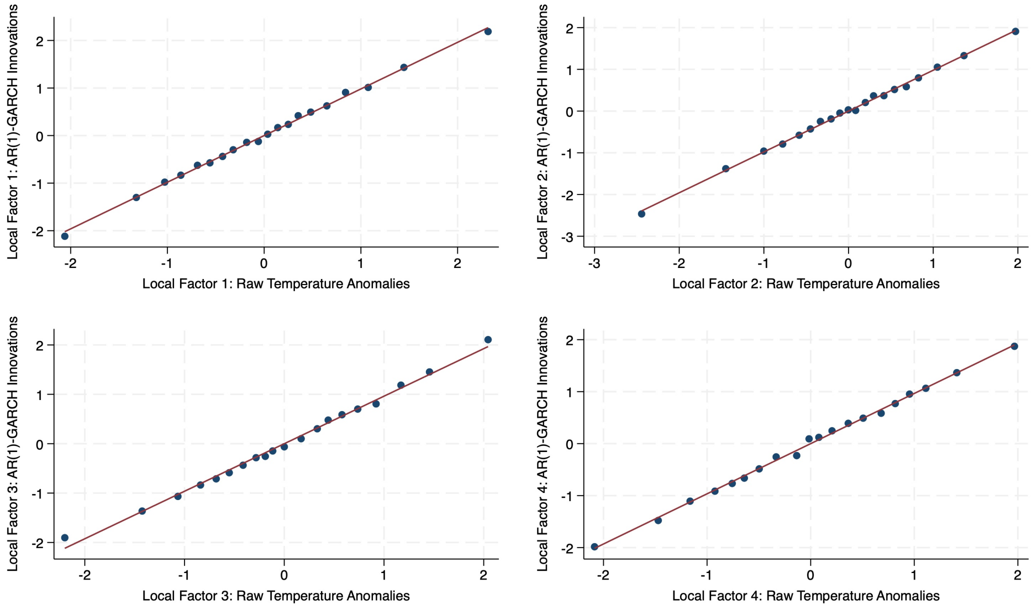


(c) Loadings - Global Factor 3

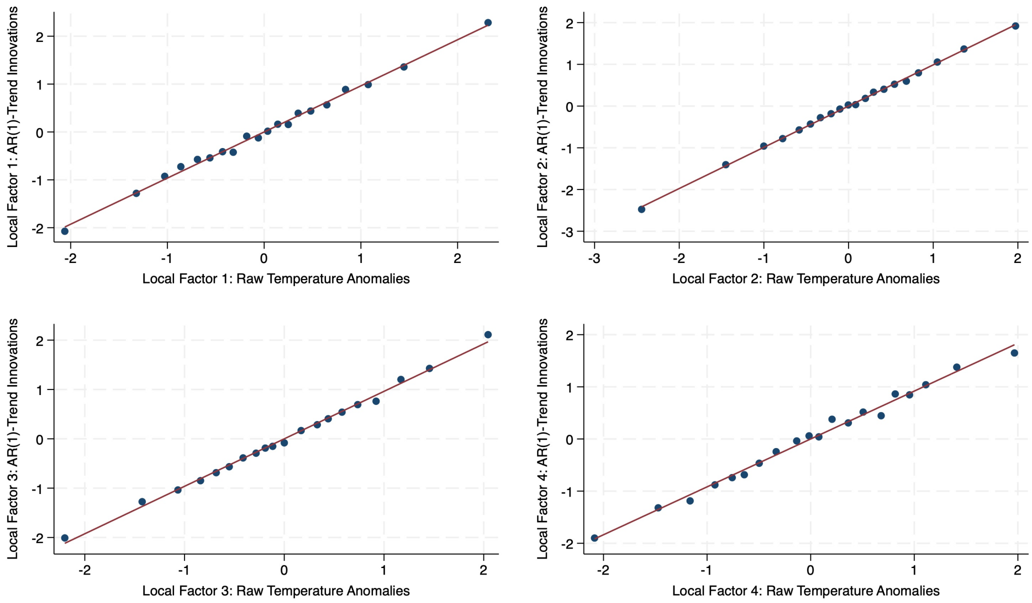


(d) Loadings - Global Factor 4

Figure 8: The figure shows the spatial distribution of exposures of global sub-national regions to the first four temperature anomaly factors derived from factor analysis, based on monthly temperature anomaly data from 1981:M1 to 2022:M12.



(a) AR(1)-GARCH(1,1) Innovations



(b) AR(1)-Trend Innovations

Figure 9: This figure presents a binscatter plot of factor scores, where the first set of factors (along the $y-$axis) is estimated from innovations of AR(1)-GARCH(1,1) model (Panel (a)) and AR(1)-Trend (Panel (b)) implemented on temperature anomaly, and the second set of factors (along the $x-$axis) corresponds to those used in the main analysis studies (described in Section 3.1). The sample period is from 1981:M1 to 2022:M12.

Online Appendix

Physical Climate Risk Exposure and Bank Lending

Table A.1: **Temperature anomaly factor loadings, historical warming trends, and long-term projected warming**

This table examines whether county-level temperature anomaly factor loadings primarily reflect historical warming trends or long-term projected warming. The dependent variable in all regressions is the absolute value of the estimated county loading for each of the four temperature anomaly factors. Panel A reports cross-sectional R^2 values from 16 regressions of absolute factor loadings on long-term projected warming under the four CMIP6 Shared Socioeconomic Pathway (SSP) scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5). Long-run projected warming is defined as the difference between the average projected temperature anomaly over 2081–2100 and that over 2023–2042 for each county. Panel B reports R^2 of cross-sectional regressions of absolute factor loadings on county-specific historical warming trends. For each county, the historical warming trend is estimated as the coefficient from a time-series regression of monthly temperature anomalies on a linear time trend using observations from January 1981 through December 2022. The table reports the cross-sectional R^2 from regressing absolute factor loadings on these estimated trend coefficients across counties.

Panel A: Cross-sectional explanatory power of long-term projected warming

	(1)	(2)	(3)	(4)
	Dependent variable: |Loading|			
	Factor 1	Factor 2	Factor 3	Factor 4
Long-Term Projected Warming - SSP1–2.6	0.0070	0.0012	0.0501	0.0698
Long-Term Projected Warming - SSP2–4.5	0.0592	0.0197	0.0029	0.0012
Long-Term Projected Warming - SSP3–7.0	0.0027	0.0106	0.1765	0.1105
Long-Term Projected Warming - SSP5–8.5	0.0291	0.0030	0.1047	0.0056

Panel B: Cross-sectional explanatory power of historical warming trends

	(1)	(2)	(3)	(4)
	Dependent variable: |Loading|			
	Factor 1	Factor 2	Factor 3	Factor 4
Historical warming trend	0.0305	0.1817	0.0318	0.0158

Table A.2: **Climate Beta – Summary Statistics**

This table presents the summary statistics of monthly physical climate risk betas. The sample period spans 37 years, starting in 1986 and ending in 2022.

	N	n	T	Mean	Standard Deviation			p1	p5	p10	p25	p50	p75	p90	p95	p99
					Overall	Between	Within									
Climate Beta - Factor 1	140,916	1,121	125.706	-0.734	1.589	0.898	1.452	-5.267	-3.823	-2.913	-1.571	-0.431	0.304	0.916	1.309	2.235
Climate Beta - Factor 2	140,916	1,121	125.706	0.387	0.778	0.529	0.679	-1.362	-0.752	-0.472	-0.070	0.333	0.782	1.298	1.695	2.695
Climate Beta - Factor 3	140,916	1,121	125.706	-0.990	1.526	0.884	1.370	-5.612	-3.839	-2.951	-1.713	-0.746	-0.072	0.568	1.095	2.023
Climate Beta - Factor 4	140,916	1,121	125.706	0.945	1.530	0.951	1.315	-2.339	-1.131	-0.655	0.037	0.744	1.575	2.982	3.863	5.679

Table A.3: **Summary Statistics**

This table presents the summary statistics of key variables used in Tables **??** and 8 in the main text. The number of originations and loan volume corresponds to the total number and volume of small business loans originated by a bank in a county-year. Bank size equals the logarithm of total assets. Capital ratio is defined as the ratio of equity to total assets. Profitability is defined as operating income as a percentage of total assets. NPL-to-Assets is the ratio of loan loss provisions as a fraction of total assets. The sample period spans 26 years, from 1997 to 2022.

	N	Mean	SD	p10	p25	p50	p75	p90
Loan Volume (in 000s)	388,603	2,605.430	8,150.906	23.000	72.000	332.000	1,528.000	5,953.000
Number of Originations	388,603	45.691	132.391	1.000	3.000	8.000	32.000	107.000
Physical Climate Risk Beta	388,603	-0.356	1.234	-1.754	-0.851	-0.158	0.423	0.824
Bank Size	388,603	18.993	2.081	16.007	17.460	19.339	21.027	21.291
Capital Ratio	388,603	0.104	0.023	0.077	0.091	0.101	0.117	0.132
Profitability	388,603	0.011	0.004	0.007	0.009	0.011	0.014	0.015
NPL-to-Assets	388,603	0.009	0.008	0.003	0.004	0.006	0.011	0.018

Table A.4: **Physical Climate Risk, Bank Characteristics and Small Business Lending**

This table presents results linking credit outcomes at the county-bank-year level and the physical climate risk beta. In columns (1)–(2), the dependent variable is the change in the logarithm of the number of loan originations by a bank to small businesses in a county-year. In columns (3)–(4), the dependent variable is the change in the logarithm of the total loan amount extended by a bank to small businesses in a county-year. *Physical climate risk beta* is the beta with respect to the portfolio that mimics the first temperature anomaly factor, measured in December (year-end). The differenced control variables are the *capital ratio* that equals tier 1 capital as a fraction of total assets, *bank size* measured by the logarithm of the total assets of a bank, *profitability* that equals the return on assets, and *NPL-to-assets* that equals non-performing loans as a fraction of total assets of a bank. Δ represents change. The sample period is from 1997 to 2022. The standard errors are clustered by county and bank, and *t*-statistics are in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)
	Dependent variable: Growth in (.)	
	Number of Originations	Loan volume
ΔPhysical climate risk beta	-0.0993**	-0.0512*
	(-2.0110)	(-1.7156)
ΔPhysical climate risk beta × County Loading	-0.0592**	-0.0668**
	(-2.1315)	(-2.5343)
N	388,603	388,603
R^2	0.2688	0.2626
Bank Controls	✓	✓
Bank Controls × County Loading	✓	✓
County × Bank FE	✓	✓
County × Year FE	✓	✓

Table A.5: **Physical Climate Risk, Recent Disaster Realizations and Small Business Lending**
This table presents results linking credit outcomes at the county-bank-year level and the physical climate risk beta. In columns (1)–(2), the dependent variable is the change in the logarithm of the number of loan originations by a bank to small businesses in a county-year. In columns (3)–(4), the dependent variable is the change in the logarithm of the total loan amount extended by a bank to small businesses in a county-year. *Physical climate risk beta* is the beta with respect to the portfolio that mimics the first temperature anomaly factor, measured in December (year-end). The differenced control variables are the *capital ratio* that equals tier 1 capital as a fraction of total assets, *bank size* measured by the logarithm of the total assets of a bank, *profitability* that equals the return on assets, and *NPL-to-assets* that equals non-performing loans as a fraction of total assets of a bank. Δ represents change. The sample period is from 1997 to 2022. The standard errors are clustered by county and bank, and t-statistics are 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: Major Disaster Occurrence				
ΔPhysical risk beta	-0.1267**	-0.1238**	-0.0564*	-0.0535*
	(-2.3075)	(-2.2783)	(-1.8365)	(-1.7310)
ΔPhysical risk beta x Major disaster$_t$	0.0284	0.0278	-0.0099	-0.0120
	(1.4989)	(1.4316)	(-0.5842)	(-0.6936)
ΔPhysical risk beta x Major disaster$_{t-1}$	0.0265*	0.0198	0.0246	0.0193
	(1.8146)	(1.4068)	(1.5183)	(1.1319)
R^2	0.2841	0.2846	0.2757	0.2759
Panel A: Disaster Damages				
ΔPhysical risk beta	-0.1354**	-0.1306**	-0.0563*	-0.0524
	(-2.3339)	(-2.2811)	(-1.6909)	(-1.5813)
ΔPhysical risk beta x Disaster damages$_t$	0.0107*	0.0104*	0.0004	-0.0002
	(1.8216)	(1.7222)	(0.0944)	(-0.0352)
ΔPhysical risk beta x Disaster damages$_{t-1}$	0.0060	0.0036	0.0028	0.0012
	(1.2283)	(0.7647)	(0.4768)	(0.2052)
R^2	0.2841	0.2846	0.2757	0.2758
N	266,600	266,600	266,600	266,600
Bank Controls	✓	✓	✓	✓
Bank Controls × Major Disaster$_t$	✗	✓	✗	✗
Bank Controls × Major Disaster$_{t-1}$	✗	✓	✗	✗
Bank Controls × Disaster Damages$_t$	✗	✗	✗	✓
Bank Controls × Disaster Damages$_{t-1}$	✗	✗	✗	✓
County × Bank FE	✓	✓	✓	✓
County × Year FE	✓	✓	✓	✓

Table A.6: **Physical Climate Risk, Recent Disaster Realizations and Small Business Lending**
This table presents results linking credit outcomes at the county-bank-year level and the physical climate risk beta. In columns (1)–(2), the dependent variable is the change in the logarithm of the number of loan originations by a bank to small businesses in a county-year. In columns (3)–(4), the dependent variable is the change in the logarithm of the total loan amount extended by a bank to small businesses in a county-year. *Physical climate risk beta* is the beta with respect to the portfolio that mimics the first temperature anomaly factor, measured in December (year-end). The differenced control variables are the *capital ratio* that equals tier 1 capital as a fraction of total assets, *bank size* measured by the logarithm of the total assets of a bank, *profitability* that equals the return on assets, and *NPL-to-assets* that equals non-performing loans as a fraction of total assets of a bank. Δ represents change. The sample period is from 1997 to 2022. The standard errors are clustered by county and bank, and t-statistics are 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: Major Disaster Occurrence				
ΔPhysical risk beta	-0.1253**	-0.1223**	-0.0544*	-0.0515*
	(-2.2828)	(-2.2537)	(-1.7991)	(-1.6925)
ΔPhysical risk beta × County Loading	-0.0510*	-0.0509*	-0.0718**	-0.0719**
	(-1.7841)	(-1.7855)	(-2.0419)	(-2.0373)
ΔPhysical risk beta × Major disaster$_t$	0.0280	0.0273	-0.0105	-0.0126
	(1.4797)	(1.4116)	(-0.6221)	(-0.7346)
ΔPhysical risk beta × Major disaster$_{t-1}$	0.0273*	0.0207	0.0258	0.0205
	(1.8597)	(1.4563)	(1.5800)	(1.1914)
R^2	0.2841	0.2847	0.2758	0.2759
Panel A: Disaster Damages				
ΔPhysical risk beta	-0.1341**	-0.1293**	-0.0545*	-0.0505
	(-2.3133)	(-2.2601)	(-1.6589)	(-1.5477)
ΔPhysical risk beta x County Loading	-0.0512*	-0.0517*	-0.0710**	-0.0716**
	(-1.7711)	(-1.7889)	(-2.0178)	(-2.0206)
ΔPhysical risk beta x Disaster damages$_t$	0.0105*	0.0103*	0.0002	-0.0004
	(1.8010)	(1.7004)	(0.0528)	(-0.0804)
ΔPhysical risk beta x Disaster damages$_{t-1}$	0.0063	0.0039	0.0032	0.0016
	(1.2779)	(0.8217)	(0.5450)	(0.2755)
R^2	0.2842	0.2846	0.2758	0.2759
N	266,600	266,600	266,600	266,600
Bank Controls	✓	✓	✓	✓
Bank Controls × Major Disaster$_t$	✗	✓	✗	✗
Bank Controls × Major Disaster$_{t-1}$	✗	✓	✗	✗
Bank Controls × Disaster Damages$_t$	✗	✗	✗	✓
Bank Controls × Disaster Damages$_{t-1}$	✗	✗	✗	✓
County × Bank FE	✓	✓	✓	✓
County × Year FE	✓	✓	✓	✓

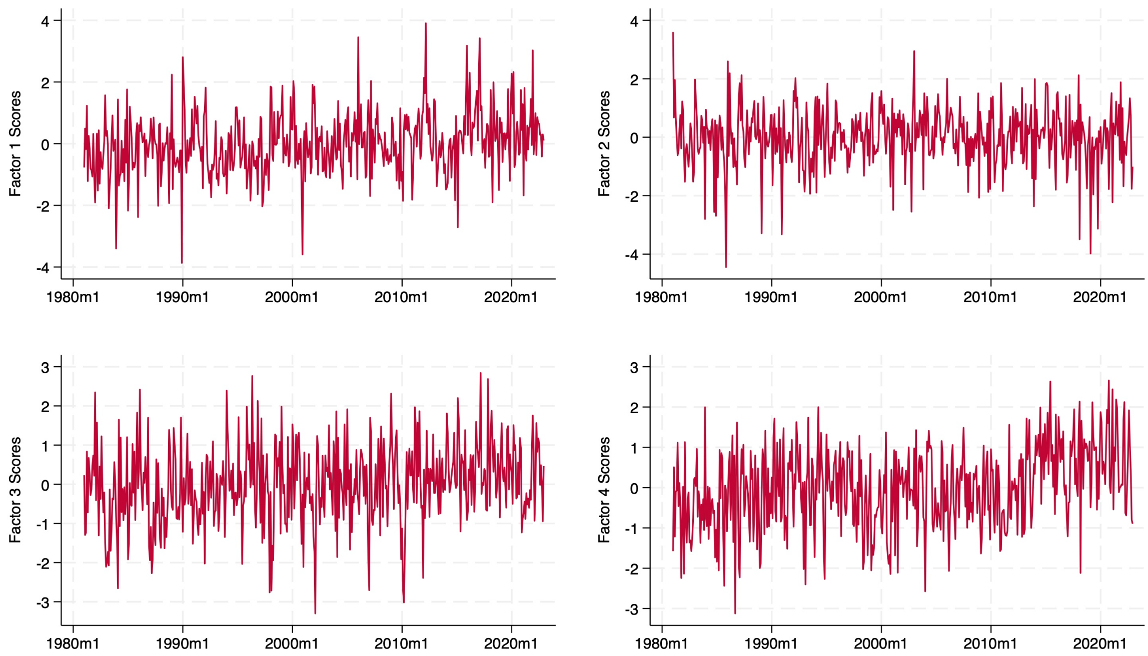


Figure A.1: The figure shows the time series of temperature anomaly factor scores derived from factor analysis of temperature anomaly, covering the period from 1981 to 2022.

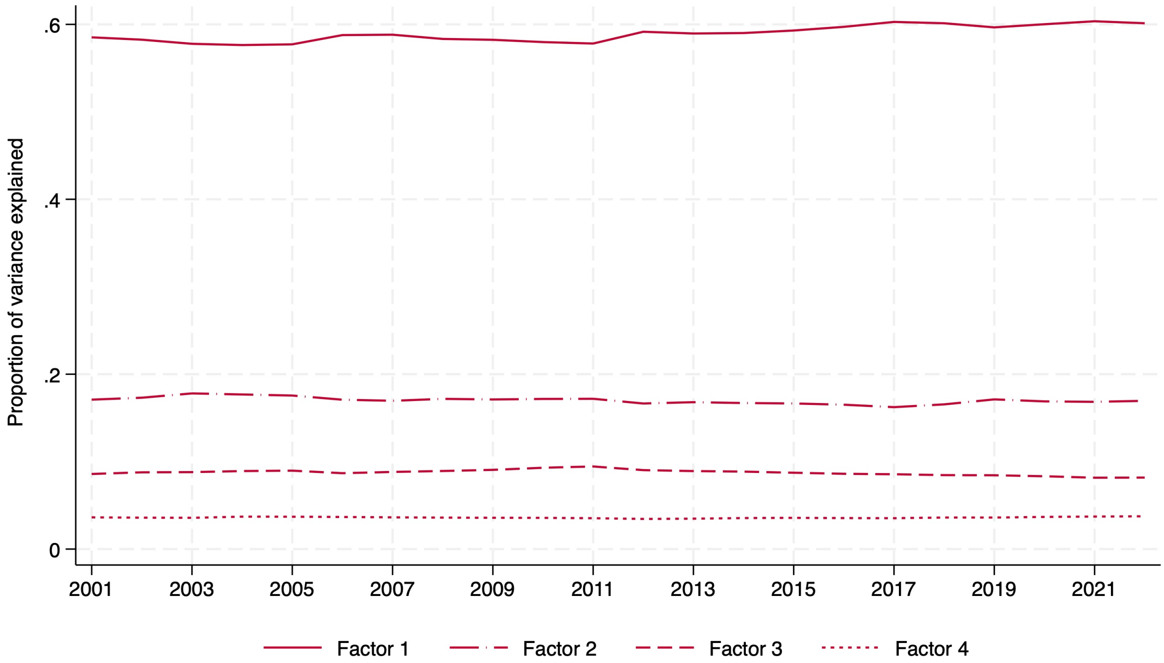


Figure A.2: This figure plots the proportion of total cross-location variation in monthly temperature anomalies explained by the first four common factors. For each end year $Y \in \{2001, 2002, \cdots, 2022\}$, factors are estimated using an expanding monthly sample that begins in January 1981 and ends in December Y. The vertical axis reports the share of total variance explained by each factor, while the horizontal axis indexes the ending year of the expanding estimation window.

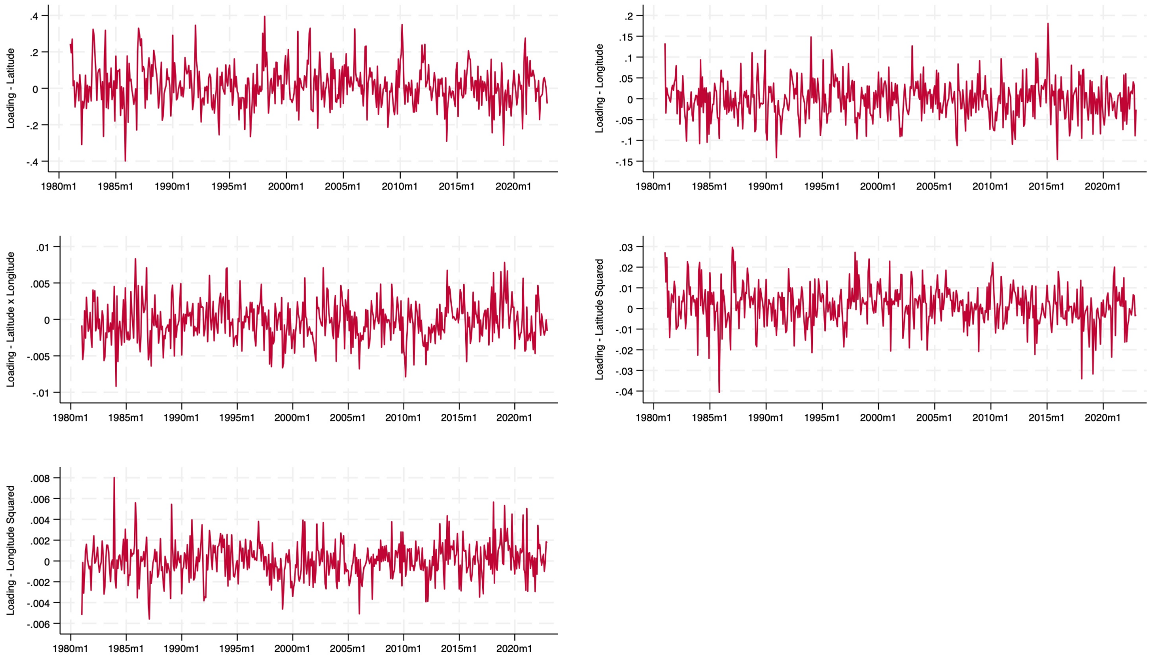


Figure A.3: The figure shows the time series of location-based factor scores, covering the period from 1981 to 2022.

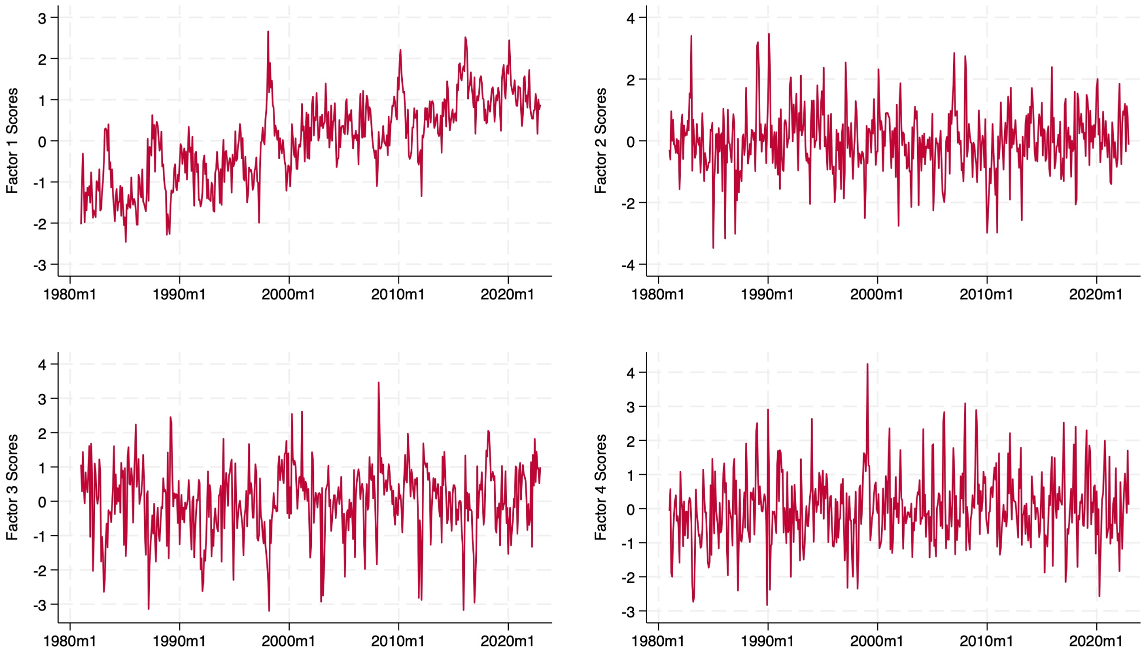


Figure A.4: The figure plots the time series of global temperature anomaly factors, estimated from sub-national data, across 1,785 regions for the period 1981–2022.