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Keywords: Climate change, temperature, poverty, inequality, subnational data

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Does Hotter Temperature Increase Poverty and Inequality?
Global Evidence from Subnational Data Analysis

Hai-Anh H. Dang, Stephane Hallegatte, Minh Cong Nguyen, and Trong-Anh Trinh*

Abstract
Despite a vast body of literature documenting the harmful effects of climate change on various socio-economic outcomes, little cross-country analysis exists on the global impacts of higher temperatures on poverty and inequality. Analyzing a new global panel dataset of subnational poverty in 137 countries covering the past decade, we find that a one-degree Celsius increase in temperature leads to a 17.1% increase in poverty, employing the US$2.15 daily poverty threshold, and a 1.1% increase in the Gini inequality index. We also find negative effects of colder temperature on poverty and inequality. Yet, while poorer countries—particularly those in Sub-Saharan Africa—are more affected by climate change, household adaptation could have mitigated some adverse effects in the long run. The findings provide relevant and timely inputs for the global fight against climate change as well as the current policy debate on cost-sharing between richer and poorer countries.

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Introduction

The increasingly prominent threats of climate change have inspired a significant body of economic research on a variety of outcomes, such as economic growth (Dell et al., 2012; Callahan and Mankin, 2022), agriculture (Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009; Cinner et al., 2022), labor productivity (Ortiz-Bobea et al., 2021; Somanathan et al., 2021), human health (Deschênes and Greenstone, 2011; Kephart et al., 2022; Salas et al., 2024), and crime and conflict (Burke et al., 2015a; Heilmann et al., 2021). Yet, while studies generally observe negative impacts of higher temperature on poverty, existing evidence on the global impacts of climate change on inequality appears inclusive (Dang et al., 2024).

A possible explanation for the limited empirical evidence on global warming's impacts is the challenge of obtaining appropriate measures of poverty and inequality. While household surveys—the main source of poverty statistics—are increasingly available, they remain unavailable or infrequent in many poor countries. Additionally, poverty and inequality vary significantly within and across countries. Ignoring subnational variations could easily mask the dynamic relationship between these outcomes and climatic conditions, which are often location-specific. Indeed, recent studies suggest that country-level data aggregation may fail to capture the true effects of climate change on economic growth, which are better revealed through subnational analyses (Damania et al., 2020; Kalkuhl and Wenz, 2020).

Figure 1 illustrates poverty and inequality against temperature at the subnational level for India, a populous country with a major share of the global poor. Subnational variations are substantial: poverty, measured by the headcount poverty rate at US$ 2.15 a day, ranges from 0.5% in the Northern regions to 52.8% in the Central and Eastern regions. Similarly, inequality, measured by the Gini index, ranges from 18.9% to 47%. Temperature also widely varies, from 4.3°C to 28.7°C. These variations are not revealed by simply looking at India's country-level averages of poverty, inequality, and temperature (16%, 31%, and 22°C, respectively), suggesting the need for subnational data to accurately assess global warming's impacts on poverty and inequality.

This study identifies strong and statistically significant global effects of both higher and lower temperature on poverty and inequality. Our (preferred) panel model with subnational fixed effects shows that a one-degree Celsius (i.e., 1°C) annual increase in temperature causes headcount poverty increases of 1.42, 1.39, and 0.67 percentage points, respectively, using the daily poverty lines of $2.15, $3.65, and $6.85 (which correspond to 17.1%, 7.5%, and 1.8% increases). The long differences model indicates smaller effects, suggesting household adaptation to gradual warmer temperature over time. For inequality, a 1°C rise in temperature leads to 1.1% and 4.1% increases in the Gini and Theil indices, respectively. For both poverty and inequality, we find stronger climate change effects at the subnational level compared to country-level data, indicating that aggregated analyses may overlook critical impacts. Heterogeneity analysis reveals that Sub-Saharan African countries are particularly vulnerable to warmer temperatures, while colder weather effects are notable in Europe and Central Asia.

Our study contributes to the literature by providing the first global assessment of warmer temperature on *both* poverty and inequality, exploiting a novel global subnational panel database covering 137 countries over the past decade. Recent studies focus on either poverty or inequality, but not both. For example, Azzarri and Signorelli (2020) show that a one degree increase in long-term temperature is associated with a 2.8 percentage point increase in poverty. Paglialunga et al. (2022) find that a one percent temperature increase is associated with a 0.5 percentage point increase in the Gini index. While these results are qualitatively consistent with earlier estimates based on simulation (Diffenbaugh and Burke, 2019; Budolfson et al., 2021), recent simulation evidence suggests climate change could reduce long-term inequality and increase it slightly in the short term (Emmerling et al., 2024). Consequently, examining both poverty and inequality using cross-country survey data is crucial as it provides a clear picture of the potentially diverse, on-the-ground impacts of climate changes. The results would be more comparable (i.e., thanks to coming from the same data source) and can offer useful inputs to the current public debate on cost-sharing responsibilities between richer and poorer countries.

Second, we offer these new results by analyzing freshly disaggregated data on headcount poverty estimates and inequality indices for 1,695 subnational areas in 137 economies from 2004 to 2022, based on the Subnational Poverty and Inequality Database (SPID) database (Nguyen et al., 2023). Derived from household income and consumption, SPID distinguishes our study from prior cross-national studies focused on country-level datasets, which, although informative, were not able to capture the subnational dynamics of poverty, inequality and temperature change. Our results show that analysis based on subnational data yields more accurate estimates of the impacts of temperature, enabling better global research on climate change, poverty and inequality.

Finally, our paper expands the literature on climate change impacts by examining how rising temperature affects economic growth and other welfare outcomes such as labor productivity and human capital (Barreca, 2012; Graff Zivin et al., 2018; Graff Zivin et al., 2020; Kalkuhl and Wenz, 2020; Sun et al., 2024; Zhang et al., 2024). In particular, while far fewer studies investigate the effects of colder temperature (Dell et al., 2012; Deschênes and Greenstone, 2011; Oudin Åström et al., 2013; Cook and Heyes, 2020), none address distributional effects on poverty and inequality. As colder weather has become more common despite global warming, understanding its adverse effects is important. Our results indicate that the distributional effects across temperature ranges (as well as across subnational regions) should be considered together with their longer-term effects as inputs for designing more effective policies aiming at fighting climate change, poverty, and inequality.

Results

Effects of temperature on poverty

We start examining the effects of temperature change on poverty at both country and subnational levels as shown in Figure 2. For the country analysis, we aggregate the SPID database weighted by the subnational population and examine three poverty indicators ($2.15, $3.65, and $6.85 daily poverty lines). For each outcome, we present the results of the fixed-effects panel model, followed by the results of the long-differences model. In both panels, the results are strongly statistically significant and confirm the negative effects of higher temperature on poverty for all the three different poverty lines.

Yet, the subnational-level analysis (right panel) has stronger magnitudes than the country-level estimates (left panel). The differences between these two sets of estimates are statistically significant (see Supplementary Table S2). This suggests that studies relying on analysis at the country level alone could mask the impacts of warmer temperature, aligning with previous research on economic growth using subnational data (Damania et al., 2020; Kalkuhl and Wenz, 2020). One implication is that the assessment of poverty impacts of climate change and natural disaster cannot be done sequentially by first assessing the macroeconomic impact on national GDP (or national economic growth) and then assessing its subsequent poverty and distributional implications. Even a more direct assessment of subnational GDP and growth would likely miss the stronger impact detected here of temperature change on poverty.

We focus on subnational analysis to interpret the results, finding that a 1°C temperature increase raises poverty by 1.423 percentage points at the $2.15 daily poverty line, equivalent to a 17.1% rise given the mean poverty rate of 8.3%. For higher poverty lines, the impacts are smaller: 1.390 and 0.673 percentage point increases for the $3.65 and $6.85 lines, translating to relative increases of 7.5% and 1.8%, respectively.

Using the long-differences model (see the Methods section for more discussion on the different models), we show the estimated longer-term effects of temperature on poverty. The results remain similar, though smaller in magnitude than the panel FE estimates. Specifically, a 1°C increase in temperature is estimated to result in a poverty increase of 0.615 percentage points (7.4%) (using the daily poverty line $2.15). The differences between the fixed-effects estimates and the long-differences estimates are statistically significant ($p < 0.01$), implying that potential longer-run household adaptation may have offset the negative short-run impacts of temperature on poverty by 0.808 percentage point (or 9.7%). These findings are consistent with previous studies on adaptation's role in mitigating temperature effects on economic production, agriculture, and human capital (Graff Zivin et al., 2018; Kalkuhl and Wenz, 2020; Chen and Gong, 2021).

While focusing on temperature impacts, Supplementary Table S2 reveals mixed effects of precipitation. Higher rainfall is linked to lower poverty rate in the long-differences model (e.g., Column 2, Panel B), but the opposite is found in the panel FE model (e.g., Column 1, Panel B), and both are statistically insignificant. This ambiguity is, however, perhaps consistent with previous findings showing both negative (Damania et al., 2020; Kotz et al., 2022) and positive impacts (Dell et al., 2012; Burke et al., 2015b) of rainfall on economic growth.

Effects of temperature on inequality

Figure 3 presents estimates of warmer temperature effects on income inequality, which are statistically significant at both country and subnational levels. A 1°C increase in temperature raises the Gini index by 0.379 percentage points (1.1%) and the Gini index by 1.010 percentage point (4.1%). Similar to the estimation results for poverty (Figure 2), subnational-level estimates (right panel) are stronger than country-level ones (left panel), supporting the idea that global warming might exacerbate inequality because poorer countries or individuals could be more vulnerable to climate change. Our results are qualitatively similar to, but offer slightly smaller estimates than, those found in Paglialunga et al. (2022), who found a 0.5 percentage point increase in the Gini index with a 1% temperature rise.

Regarding the potential long-run effects, we find significant long-term effects of hotter temperatures on income inequality at both country and subnational levels, with stronger impacts at the subnational level. Specifically, a 1°C increase raises the Gini index and the Theil index by 0.147 (0.4%) and 0.325 (1.3%) percentage points. Long-differences models show smaller effects than fixed-effects models, as confirmed by the t-tests (see Supplementary Table S3), suggesting that household adaptation may mitigate inequality over time.

To contextualize our findings, Finland has one of the lowest Gini indexes (i.e., less inequality), with a value of 26.5, while the Central African Republic has one of the highest Gini indexes (i.e., more inequality), at 53.7. Given this, our estimated increase in the Gini index of 0.379 percentage points (using fixed-effects model) suggests that 1°C increase in temperature widens the gap in inequality between these countries by 1.4%. This shift is substantial, considering the cumulative impacts over time and across different countries. Another way to contextualize the impacts of temperature on inequality is by examining the progression of inequality. In our sample, the average Gini index has decreased from 28.4 in 2004 to 34.2 in 2022, showing a movement towards increased inequality. However, our estimates suggest that a 1°C increase in temperature could counteract this positive trend, offsetting approximately 1.2 years of progress made in reducing inequality.

Nonlinear effects

The effects of hotter temperature on poverty and income inequality discussed earlier are linear. To explore potential nonlinear effects, we categorize temperature into 3°C bins, where coefficients can be interpreted as the effects of falling into a given bin relative to the reference “comfortable” bin (i.e., 18-21°C). We define hotter weather as temperature being in the top decile of the temperature range (i.e., greater than 27°C), and colder weather as temperature being in the bottom decile of the temperature range (i.e., less than 6°C). Figure 4 presents the results, showing both contemporaneous (left panel) and cumulative effects (right panel). The findings indicate that an additional day of hotter temperatures leads to significantly higher poverty and inequality, with consistent magnitudes across hotter temperature bins. These results strongly support our earlier conclusions on the adverse effects of warmer temperatures.

We replicate the results in Figure 4 but using alternative thresholds to define hot and cold days, including using the 2-degree bin, the 4-degree bin and the 5-degree bin. We find that when our definition of hot and cold days is less (or more) demanding, the implied effects on income inequality remain consistent (Supplementary Figure S4).

Furthermore, the results in Figure 4 also show that colder weather worsens poverty and inequality. Our findings concur with several studies finding negative effects of colder weather on productivity, health, and economic growth (Deschênes and Moretti, 2009; Dell et al., 2012; Cook and Heyes, 2020) and add fresh evidence for the impacts of colder weather on poverty and inequality.

Finally, we consider the model specification that incorporates lag of temperature bins to examine cumulative effects on income inequality. The cumulative effects remain negative and slightly larger than the contemporaneous effects as shown in Figure 4. Our results therefore suggest that when accounting for non-linearity of temperature effects, we find strong evidence of the adverse impacts of both colder temperature and hotter temperature on poverty and inequality, observed in both the short-term and long-term. While we identify non-linear effects of temperature, we also note that the distribution of temperature in our sample predominantly aligns with the hotter ranges, as shown in Supplementary Figure S1. Therefore, we focus on the linear models (fixed-effects and long-differences) as the primary models for analysis in our study, but we provide supplementary analysis using the non-linear model where relevant.

Heterogeneity analysis

We expect the impacts of warmer temperature to be heterogenous across regions. Poorer countries, particularly in low-income regions, are less prepared for climate change and face greater damages, higher material losses, and more significant challenges in recovery and reconstruction. To explore this, we split our sample into six regions and plot the coefficient estimates of temperature in Figure 5 (Panels A and B) using the temperature bin approach. As expected, hot temperatures are found to increase poverty and income inequality in most regions, especially in Sub-Saharan Africa and South Asia. Furthermore, cold temperature have negative effects in East Asia and Pacific and Europe and Central Asia. To account for temperature variation across countries, we divide each country's temperature distribution into deciles, using the 60th percentile as the baseline group. Supplementary Figure S2 confirms similar patterns of extreme weather effects.

We also provide further support to the regional heterogeneity by estimating the effects of temperature on poverty and inequality by country, adjusted by their real GDP per capital in 2018. Figure 6 shows that countries bearing the largest effect of global warming are also those with the lowest income such as Uganda, Ghana, and Mozambique.

Further heterogeneity analysis (in the Methods section) suggests that countries with a democratic regime or a higher share of manufacturing in its economy appear to be less vulnerable to the impacts of global warming. The opposite holds for countries near the equator or those with higher share of agriculture.

Potential mechanisms

Having demonstrated strong evidence of warming temperatures' effects on poverty at the subnational level, we explore why impacts vary across regions. Poor countries, often located in tropical areas with higher average temperatures, rely heavily on climate-sensitive agriculture. Evidence suggests that extreme temperature has negative effects on crop yields, particularly in these countries (Deschênes and Moretti, 2009; Schlenker and Lobell, 2010; Jacoby et al., 2015). To investigate agriculture's mediating role in the link between temperature and socio-economic outcomes, we use causal mediation analysis. Given the challenges of obtaining consistent crop production data across geographies and time, we rely on the Normalized Difference Vegetation Index (NDVI) as a proxy for vegetation health and crop yields. NDVI offers consistent satellite data across large spatial and temporal scales, making it a reliable indicator in the absence of direct measurements.

The results confirm a direct correlation between temperature increases and higher poverty and inequality, as shown by consistent coefficients in Supplementary Table S5. A 1°C increase is associated with 2.095 and 0.355 percentage point rises in poverty and the Gini index, respectively. Agriculture plays a significant role in these effects, explaining about 2.5% of poverty variation and 20% of inequality variation.

Projected impacts under future climate change

We project future temperature effects on poverty to assess potential impacts under different scenarios. Using model estimates from Figures 2 and 3, combined with simulated weather data from the Coupled Model Intercomparison Project Phase 6 (CMIP6), we generate projections following established methods (Burke and Emerick, 2016; Kalkuhl and Wenz, 2020 Annual temperature data from ERA-5 is used to construct historical averages and probability distributions for 1979–2022. Projected temperature changes are calculated as the difference between CMIP6 projections and historical averages. Finally, the temperature changes are used to calculate poverty (inequality) rates by multiplying with the baseline estimates in Columns (1), (3), and (5) of Supplementary Table S2 (Columns (1) and (3) of Supplementary Table S3).

Supplementary Table S6 summarizes projected temperature and poverty changes under different emission pathways. By 2099, temperatures are expected to rise by 1.4°C to 5.0°C, leading to a poverty increase of 2.0 to 7.1 percentage points (23.9% to 85.5%) at the $2.15 daily poverty threshold (Panel A). Similarly, inequality is projected to rise, with the Gini index increasing by 0.53 to 1.9 percentage points (1.5% to 5.4%) (Panel B). The largest increases in poverty and inequality are predicted under scenarios lacking renewable energy strategies to mitigate climate change.

Discussion

Although evidence of climate change's macroeconomic impacts is growing, its effects on poverty and inequality at a global scale remain underexplored. A major limitation has been the lack of disaggregated data for accurate analysis across and within countries. Using a global panel dataset covering subnational areas in 137 countries, we find that both hotter and colder temperatures increase poverty and inequality, with stronger impacts at the subnational level. This suggests that country-level analyses underestimate the consequences of global warming. Long-term effects are smaller, indicating that households may adapt to permanent changes in weather conditions.

Our findings contribute to policy discussions on reducing future losses from global warming. Specifically, certain countries (e.g., those with democratic regimes) appear less vulnerable to climate impacts, whereas those with higher agricultural shares are more affected. Improved vegetation health, however, reduces poverty and inequality. Subnational poverty data also opens new research opportunities. While our study highlights agriculture's role in climate-induced poverty and inequality, alternative factors such as civil conflicts and labor productivity merit further exploration. Research on these areas can provide valuable policy insights for addressing global warming.

Online Methods

This study relies on an extensive and diverse range of data sources to investigate poverty, inequality, and their interactions with climate variables. The core of our analysis is grounded in a novel dataset that offers a detailed view of poverty and inequality at the subnational level.

Poverty data. We employ a novel dataset that provides a granular perspective on poverty and inequality at the subnational level. In particular, we draw on the Subnational Poverty and Inequality Database (SPID), a collaborative effort among different teams at the World Bank over a period of time. The SPID is built on countries' official household income (consumption) surveys, covering over 1,695 subnational units across 137 countries, with more than 90% of the data ranging from 2010 to 2022. In most cases, a subnational unit refers to a province or state (i.e., first-level administrative boundaries – ADM1) but can also be a group of regions determined by the specific sampling strategy of household surveys.

Poverty rates at the subnational level are derived from official household or income surveys for global poverty tracking. These rates correspond to the specific household or income survey they originate from. Creating a consistent panel data for poverty at an area level is challenging due to potential changes in country borders and survey representation over time. To maintain a consistent and comparable dataset across different regions and periods, the World Bank team has employed different measures including redefining areas to align with previous definitions or increasing the granularity of geographical breakdown over time. In the current panel data version, a typical country has information for 14 regions over the period of three years.

For the main outcomes, we utilize the (headcount) poverty rate at US$2.15 a day, as estimated by the percentage of the population living on less than $2.15 a day at the 2017 purchasing power parities (PPP) prices. For richer analysis, we also employ other poverty lines of \$3.65 and \$6.85 a day. Supplementary Figure S3 shows that Sub-Saharan Africa currently has the highest poverty rates, with the poorest countries including Tanzania (51.3%), Mozambique (54.7%), and the Democratic Republic of Congo (72.9%).

Inequality data. We use the Gini index and Theil index, which are the most commonly used measures of income inequality. These indices are computed on the income available to households after government taxes and transfers, excluding indirect and value-added taxes, public services, and indirect government transfers. For robustness checks, we also use the distribution of income (consumption) shares held by each decile and calculate different percentile ratios, namely the 90/10 ratio, the 80/20 ratio, and the 90/40 ratio (i.e., the Palma ratio). All income measures are converted to real terms using 2017 PPP dollars. Supplementary Figure S3 provides a global map of income inequality at the subnational level, which shows substantial variation of inequality across regions within a country.

Weather and other data. We match our poverty and inequality data with the ERA5 satellite reanalysis data from the European Centre for Medium-Range Weather Forecasts Reanalysis 5 (ECMWF). The ERA5 provides hourly estimates of several climate-related variables at a grid of approximately 0.25 longitude by 0.25 latitude degree resolution with data available since 1979. An advantage of the ERA5 data is that it combines information from ground stations, satellites, weather balloons, and other inputs with a climate model, and therefore is less prone to station weather bias. Our measures of weather variables include air temperature and precipitation, both denoted as annual averages. We then aggregate the gridded data to the region level by computing area-weighted averages (i.e., averaging all grid cells that fall into a region).

To understand the potential effects of climate change on poverty and inequality, we utilize weather data from the Coupled Model Intercomparison Project Phase 6 (CMIP6). This project provides various scenarios including SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5. Each scenario shows a different path for global growth, energy use, policy actions, and climate responses and thus allows for a detailed study of the possible impacts of climate change in different situations.

For a more comprehensive analysis, our paper utilizes data from different sources. To examine the role of agriculture as a mechanism, we rely on the gridded daily Normalized Difference Vegetation Index (NDVI) derived from the Surface Reflectance Climate Data Record (CDR) provided by the National Oceanic and Atmospheric Administration (NOAA). This dataset presents global, grid-based vegetation index, with a 0.05° resolution, spanning from 1981 to present. We provide description and summary statistics of the main variables in Supplementary Table S1.

Empirical Specifications. Our first empirical approach identifies the effects of hotter temperature on poverty and inequality by estimating the following panel data model with fixed effects (FE):

$$Y_{i,t} = \beta_{FE} T_{i,t} + \gamma_{FE} W_{i,t} + \alpha_i + \pi_t + \varepsilon_{i,t} \tag{1}$$

where $Y_{i,t}$ represents the poverty rate and inequality in location *i* in year *t*. Depending on the specific specification, location *i* is either country in the country-level analysis or subnational unit in the subnational analysis. $T_{i,t}$ is the temperature variable, and the coefficient of interest β_{FE} is expected to be positive (i.e., global warming likely increases poverty and inequality).

Following previous studies' suggestion that precipitation and temperature are historically correlated and should be included in the same regression to obtain unbiased coefficients (Dell et al., 2012), we control for other weather conditions ($W_{i,t}$) including precipitation and humidity in all the regressions. α_i is the location (country or sub-national) fixed effects that controls for unobserved time-invariant factors that may be correlated with location-specific climate or economic patterns; π_t is the year fixed effects that controls for unobserved temporal changes affecting poverty and inequality each year. We cluster the errors $\varepsilon_{i,t}$ at the specified location level to allow for potential serial correlation over time within a region (or a country). All the regressions are weighted with population weights at the subnational (country) level.

While we can causally interpret β_{FE} in Equation (1), it is likely derived from short-run responses to temperature change given the nature of the annual panel data analyzed in this equation. Consequently, β_{FE} is not necessarily representative of households' responses to temperature change in the longer term. In other words, long-term responses to temperature change may fundamentally differ from short-term responses to weather fluctuations because the former type of responses better accounts for potential household adaptation over time. Therefore, we address the shortcoming of Equation (1) by utilizing the long-differences approach to estimate the accumulated effects of temperature change over longer periods of time (Deschênes and Moretti, 2009):

$$\Delta Y_i = \beta_{LD}\Delta T_i + \gamma_{LD}\Delta W_i + \omega_i \tag{2}$$

In Equation (2), ΔY_i represents changes in poverty (or inequality) in the same location between two periods, and ΔT_i and ΔW_i are the corresponding changes in temperature and other weather conditions. To provide more stable estimates that are robust to data fluctuations in any single year, we use 3-year difference averages. That is, for all the variables in Equation (2) in our study period of 2004–2022, we analyze the differences between their averages of the earliest 3-year period 2004–2006 and their averages of the latest 3-year period 2020–2022 (e.g., $\Delta Y_{i,2004-2022} = \frac{\sum_{2020}^{2022} Y_{i,t}}{3} - \frac{\sum_{2004}^{2006} Y_{i,t}}{3}$). Under the long-differences approach, any time-invariant location-specific factors are differenced out. As with Equation (1), the coefficients of interest, β_{LD}, is expected to be positive.

In both the panel FE and long-differences models, we assume the effects of temperature change to be in linear form. To allow for a more flexible functional form of temperature, we further employ a temperature bin approach that offers estimates of nonlinear effects:

$$Y_{i,t} = \sum_{j=1}^{12} \beta_{TB,j} T_{i,j,t} + \gamma_{TB} W_{i,t} + \alpha_i + \pi_t + \vartheta_{i,t} \quad (3)$$

Specifically, we categorize daily temperature into 13 temperature bins, where each bin captures temperature change in increments of 3°C (e.g., the first bin is [0°C, less than 3°C), the second bin is [3°C, less than 6°C), and so on). The two extremes of low and high temperature are respectively defined as less than 0°C and greater than 33°C. The temperature shock variable, $T_{i,j,t}$, reflects the number of days when the daily average temperature in a region is within a specific bin in a particular year. We use the most thermally comfortable temperature bin, which is [18°C, less than 21°C), as the reference group. The coefficients of interest $\beta_{TB,j}$ are thus interpreted as the effects of exchanging a day in the 18–21°C reference bin with a day in the other bins.

Finally, we also estimate the cumulative effects of temperature on poverty and inequality with a distributed lag model. Specifically, we capture the contemporaneous effects as well as the lag effects on each temperature bin for the last four periods. The distributed lag model is specified as

$$Y_{i,t} = \sum_{j=1}^{12} \delta_{TB,j} T_{i,j,t} + \sum_{k=1}^{4} \sum_{j=1}^{12} \delta_{TB,j,t-k} T_{i,j,t-k} + \theta_{TB} W_{i,t} + \alpha_i + \pi_t + \epsilon_{i,t} \quad (4)$$

Further heterogeneity analysis

We further assess the heterogeneity of the effects of temperature across different country characteristics. First, we examine whether a country's institution may affect the impacts of temperature. This is motivated by the fact that institutions may affect adaptation to climate change through which incentives for individuals and collective action are structured. We use the democracy index from the 2020 report of the Economist Intelligence Unit and categorize countries into different types of regimes: (i) democracy; (ii) authoritarian; and (iii) hybrid. The results presented in Supplementary Table S4 show evidence that countries with a democratic regime appear to be less vulnerable to the impacts of global warming (Panel A). We also examine the heterogenous impacts of temperature by other country characteristics. For example, countries near the equator have a higher poverty rate caused by an increase in temperature (Panel B). In addition, the effects of temperature are more pronounced in countries whose economy has a higher share of agriculture, while the opposite is found in those with higher share of manufacturing (Panels C and D). Finally, we find a stronger effect among countries with lower share of trade, but our estimates are not statistically significant (Panel E).

We further provide a number of robustness checks in the Supplementary Information (Appendix B), including alternate modelling specifications, different thresholds to define hot and cold days, different measures of poverty (including poverty gap measures that focus on the poorer groups) and income inequality, varying choices of temperature measures, different data subsamples and time periods, and analyzing poverty and inequality data from other sources, as well as conducting a placebo test that randomizes the temperature of a region.

Competing interests

The authors declare no competing interests.

Author contributions

H.A. D.: methodology, writing, final editing, supervision; S. H.: feedback, supervision; T.A. T.: data analysis, methodology, writing; M. N.: data curation

Data availability statement

The data are fully described in the Online Methods section. The links to the data sources are provided in Supplementary Table S1.

Code availability statement

Weather data were collected using QGIS. The data analysis was performed in STATA. All the codes will be provided from the corresponding author upon request.

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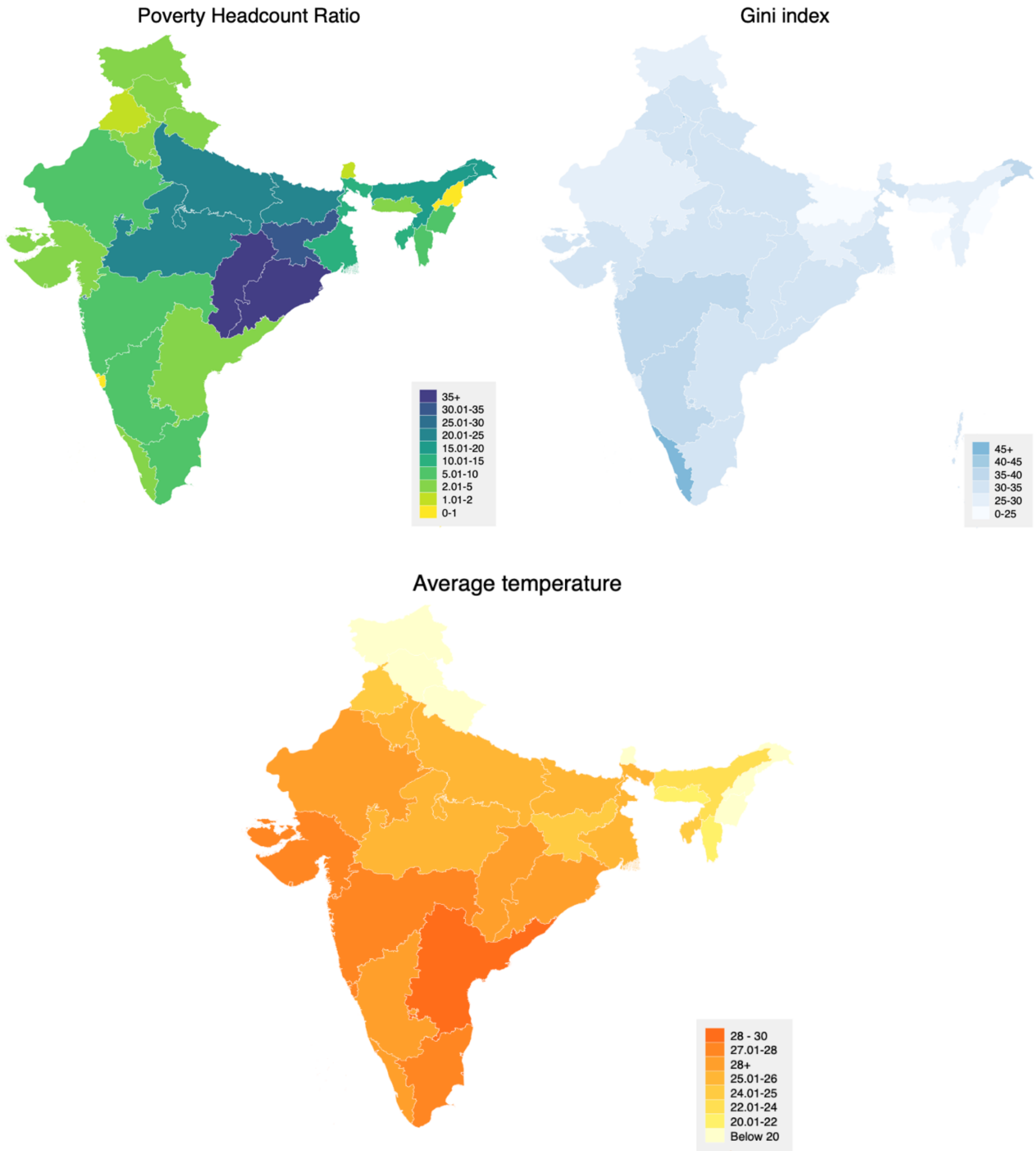
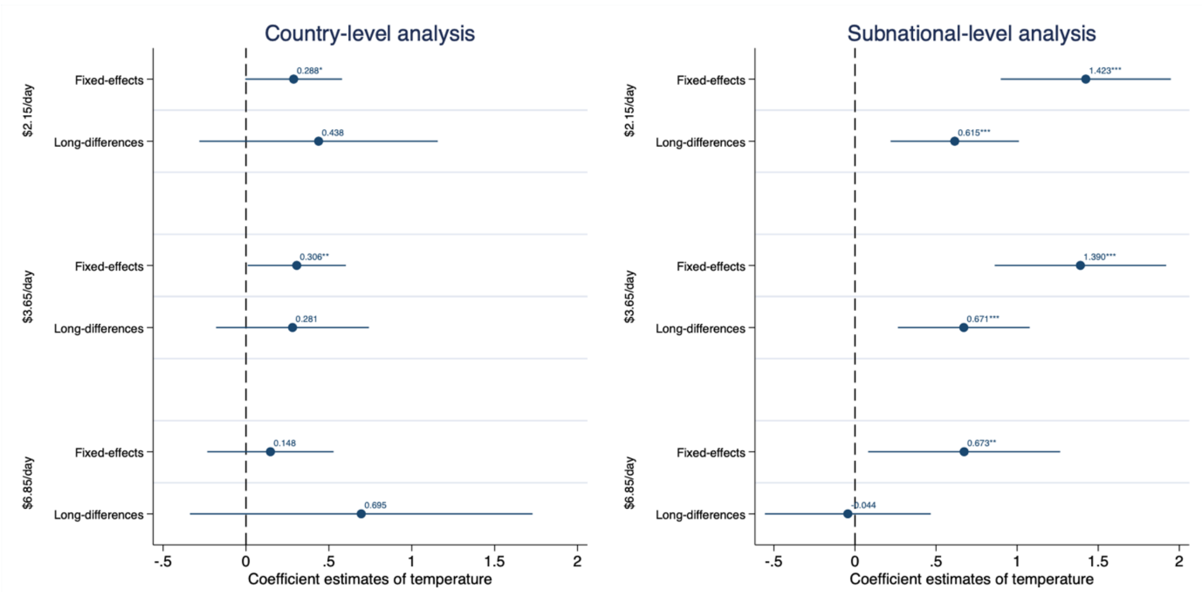
Figures and Tables

Figure 1: Subnational poverty, inequality and temperature in India



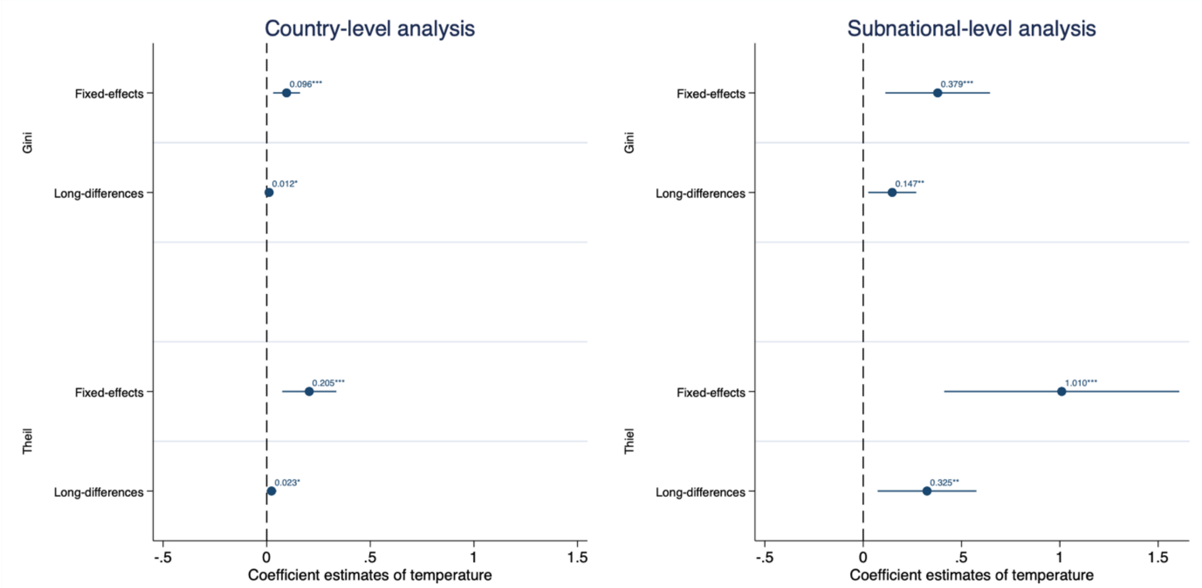
Notes: Poverty is measured by Global Subnational Poverty Headcount Ratio using the daily threshold of US$ 2.15. Inequality is measured by the Gini index. Temperature data is taken from the European Centre for Medium-Range Weather Forecasts Reanalysis 5 (ERA-5). Poverty rate, inequality and temperature data are measured in the period 2004 – 2022 (*n*=70).

Figure 2: The effects of temperature on poverty



Notes: Figure presents regression coefficients and 95% level confidence intervals of regressions of poverty on temperature, controlling for weather conditions (rainfall and humidity) and fixed effects. Poverty is measured by Global Subnational Poverty Headcount Ratio. Temperature data is taken from the European Centre for Medium-Range Weather Forecasts Reanalysis 5 (ERA-5). The left panel shows country-level analysis using two models: a fixed-effects model (n=528) and a long-differences model (n=100). The right panel shows subnational-level analysis using two models: a fixed-effects model (n=6,169) and a long-differences model (n=1,402). Results with controls are presented in Supplementary Table S2.

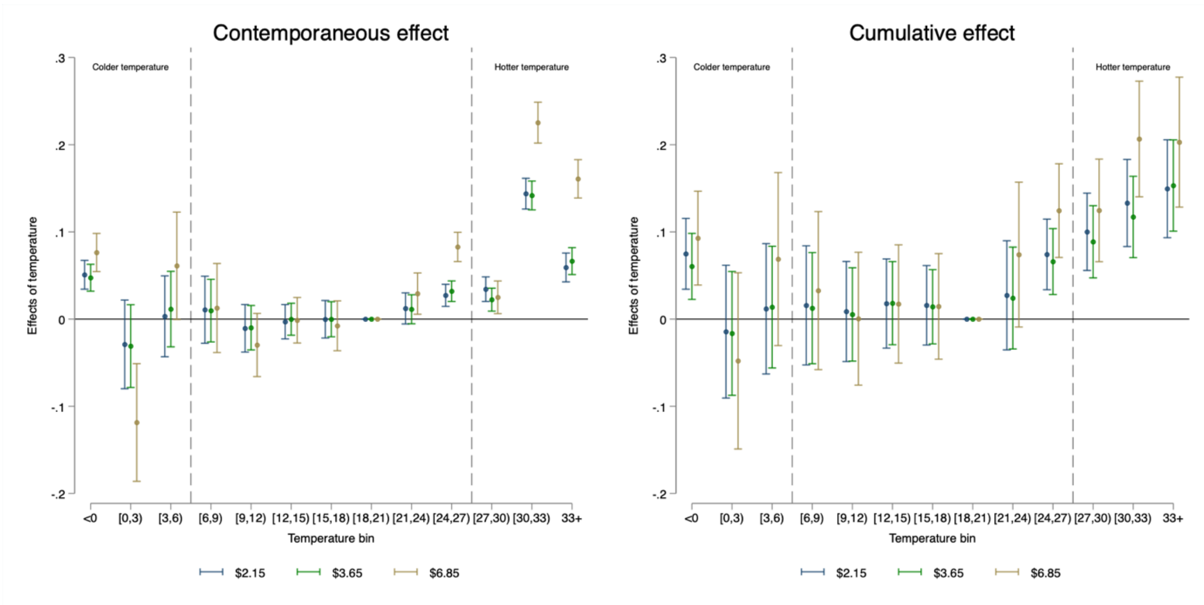
Figure 3: The effects of temperature on inequality



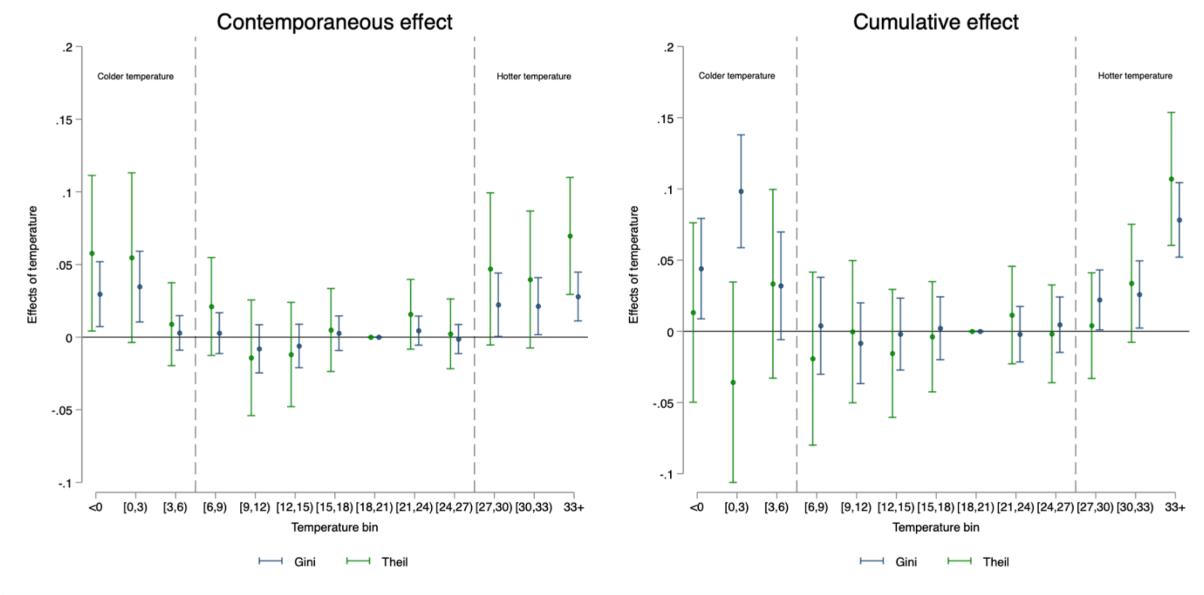
Notes: Figure presents regression coefficients and 95% level confidence intervals of regressions of inequality on temperature, controlling for weather conditions (rainfall and humidity) and fixed effects. Inequality is measured by Gini and Theil indices. Temperature data is taken from the European Centre for Medium-Range Weather Forecasts Reanalysis 5 (ERA-5). The left panel shows country-level analysis using two models: a fixed-effects model (n=468) and a long-differences model (n=108). The right panel shows subnational-level analysis using two models: a fixed-effects model (n=5,260) and a long-differences model (n=1,308). Results with controls are presented in Supplementary Table S3.

Figure 4: Nonlinear effects of temperature on poverty and inequality

Panel A: Poverty



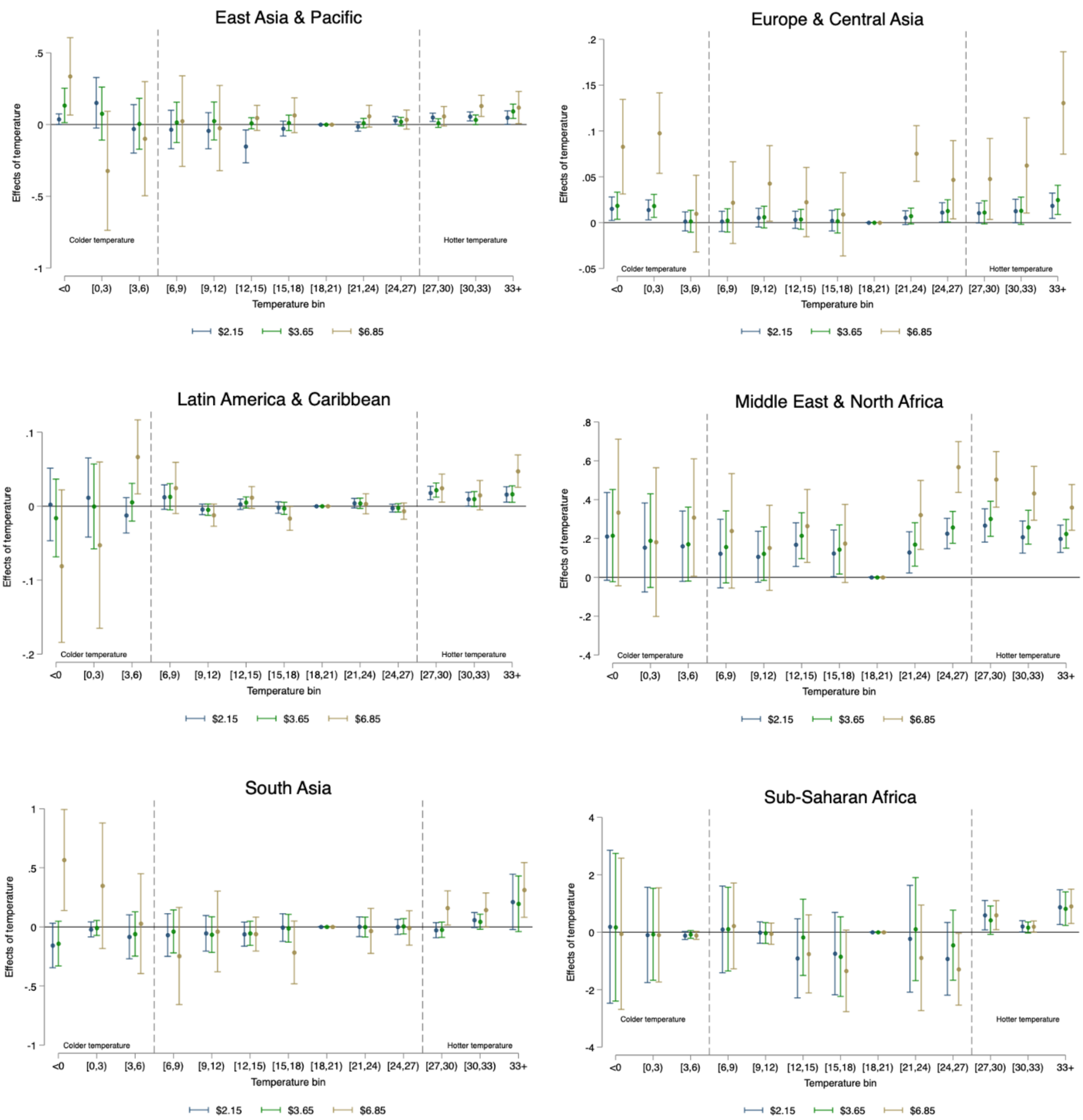
Panel B: Inequality



Notes: The figures show the point estimates and their 95% confidence intervals of temperature bins using regression with weather conditions (rainfall and humidity) and subnational fixed effects. Robust standard errors are clustered at the subnational level. Panel A reports results for poverty (*n*=6,169), while Panel B focuses on inequality (*n*=5,260). The reference temperature bin is [18,21). The cumulative effects are obtained by estimating the model with three lags of weather variables. Hotter temperature and colder temperature are defined as temperature being in the top decile (i.e., greater than 27°C) and bottom decile (i.e., less than 6°C) of the temperature range, respectively.

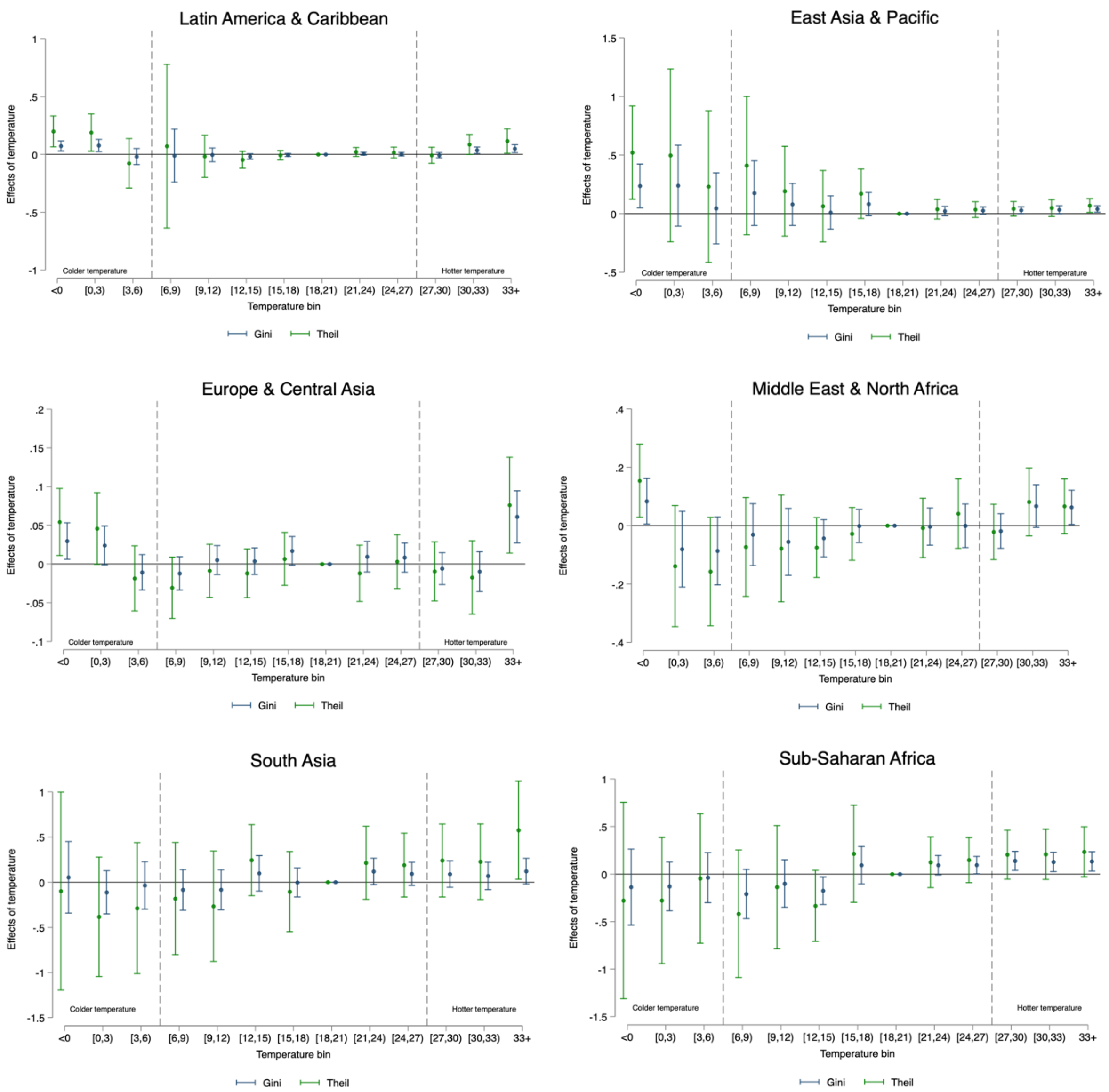
Figure 5: Heterogeneity analysis

Panel A: Effects of temperature on poverty by region



Notes: The figures show the point estimates and their 95% confidence intervals of temperature bins using regression with weather conditions (rainfall and humidity) and subnational fixed effects. Robust standard errors are clustered at the subnational level. The reference temperature bin is [18,21). Hotter temperature and colder temperature are defined as temperature being in the top decile (i.e., greater than 27°C) and bottom decile (i.e., less than 6°C) of the temperature range, respectively. The analytical sample is divided into six regions: East Asia & Pacific (*n*=1,265), Europe & Central Asia (*n*=1,702), Latin America & Caribbean (*n*=1,055), Middle East & North Africa (*n*=319), South Asia (*n*=247), and Sub-Saharan Africa (*n*=963).

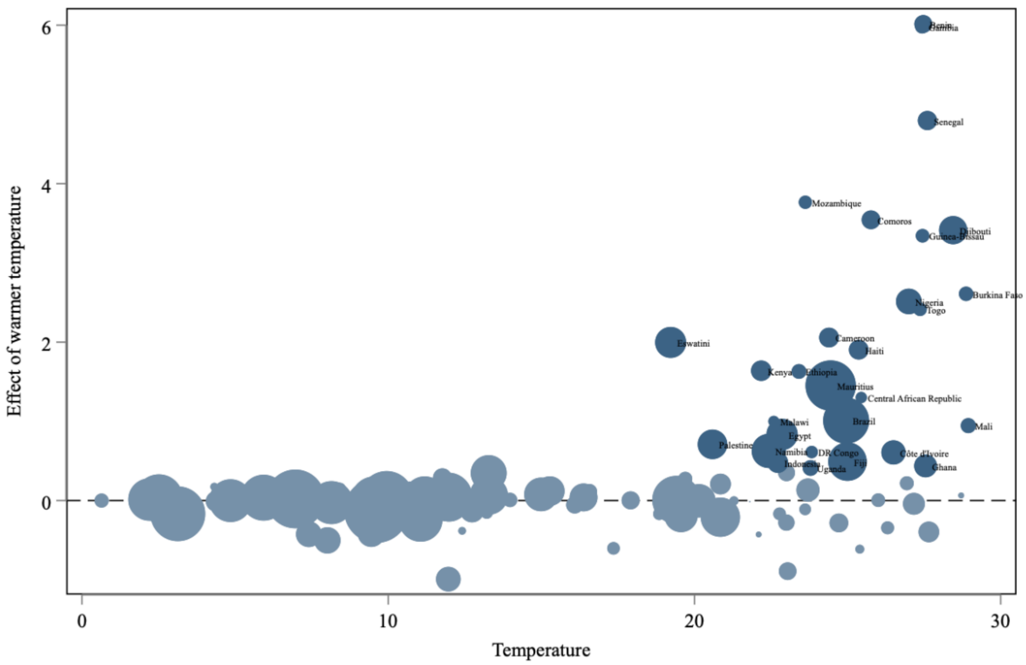
Panel B: Effects of temperature on inequality by region



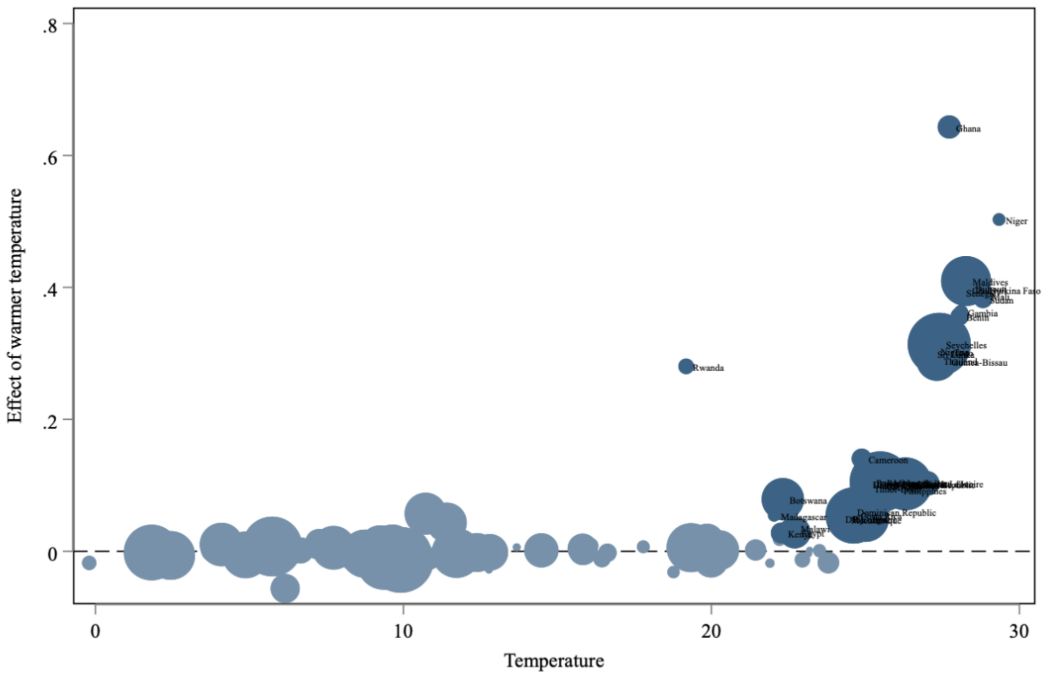
Notes: The figures show the point estimates and their 95% confidence intervals of temperature bins using regression with weather conditions (rainfall and humidity) and subnational fixed effects. Robust standard errors are clustered at the subnational level. The reference temperature bin is [18,21). Hotter temperature and colder temperature are defined as temperature being in the top decile (i.e., greater than 27°C) and bottom decile (i.e., less than 6°C) of the temperature range, respectively. The analytical sample is divided into six regions: East Asia & Pacific (*n*=1,180), Europe & Central Asia (*n*=1,542), Latin America & Caribbean (*n*=1,055), Middle East & North Africa (*n*=319), South Asia *(n*=247), and Sub-Saharan Africa (*n*=963).

Figure 6: The effects of temperature on poverty and inequality across countries adjusted by real GDP

Panel A: Poverty



Panel B: Inequality

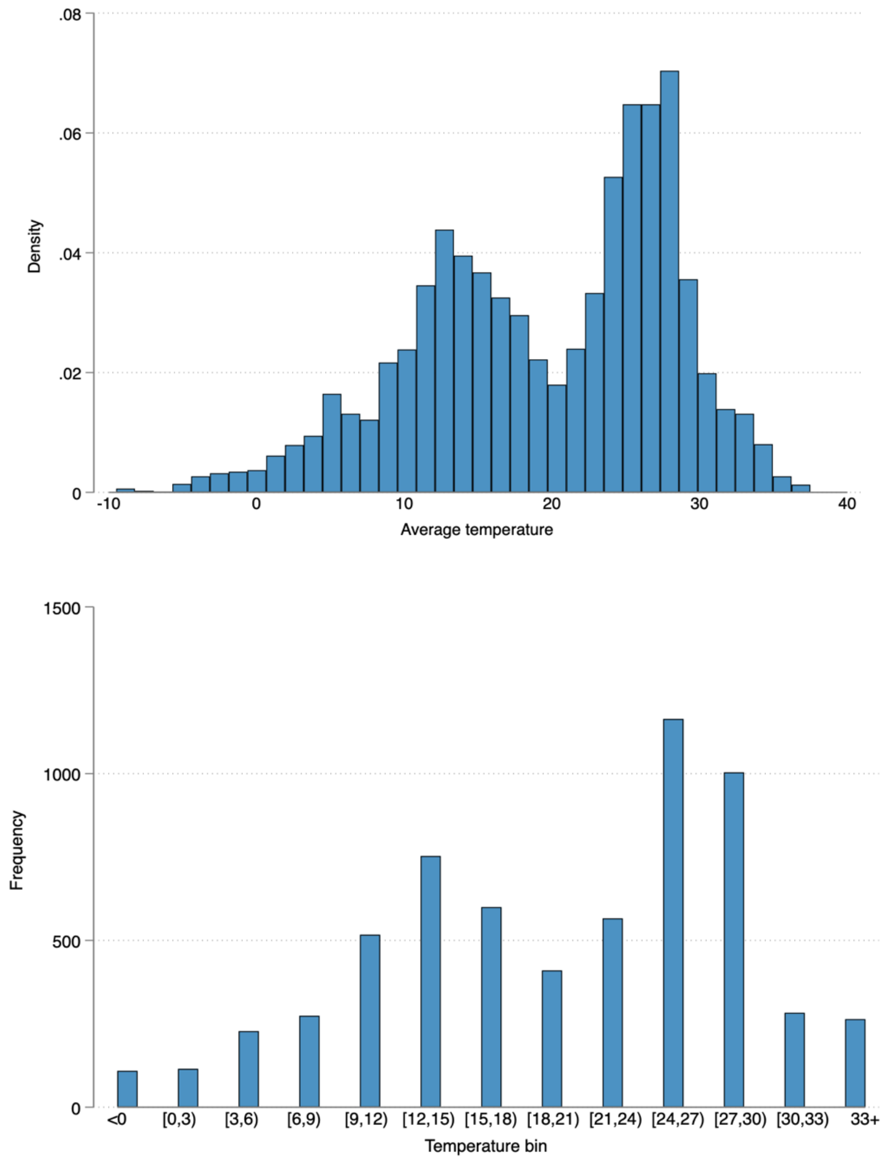


Notes: Poverty rate is measured by the Subnational Poverty Headcount Ratio at $2.15 a day (*n*=536). Inequality is measured by the Gini index (*n*=488). The figure shows the point estimates of temperature and the country dummies using regression with weather conditions (rainfall and humidity) and subnational fixed effects. Each country's marker is proportional to its real GDP per capital using the WDI database (i.e., a larger size indicates a higher GDP per capita level).

Supplementary Information

Appendix A. Additional figures and tables

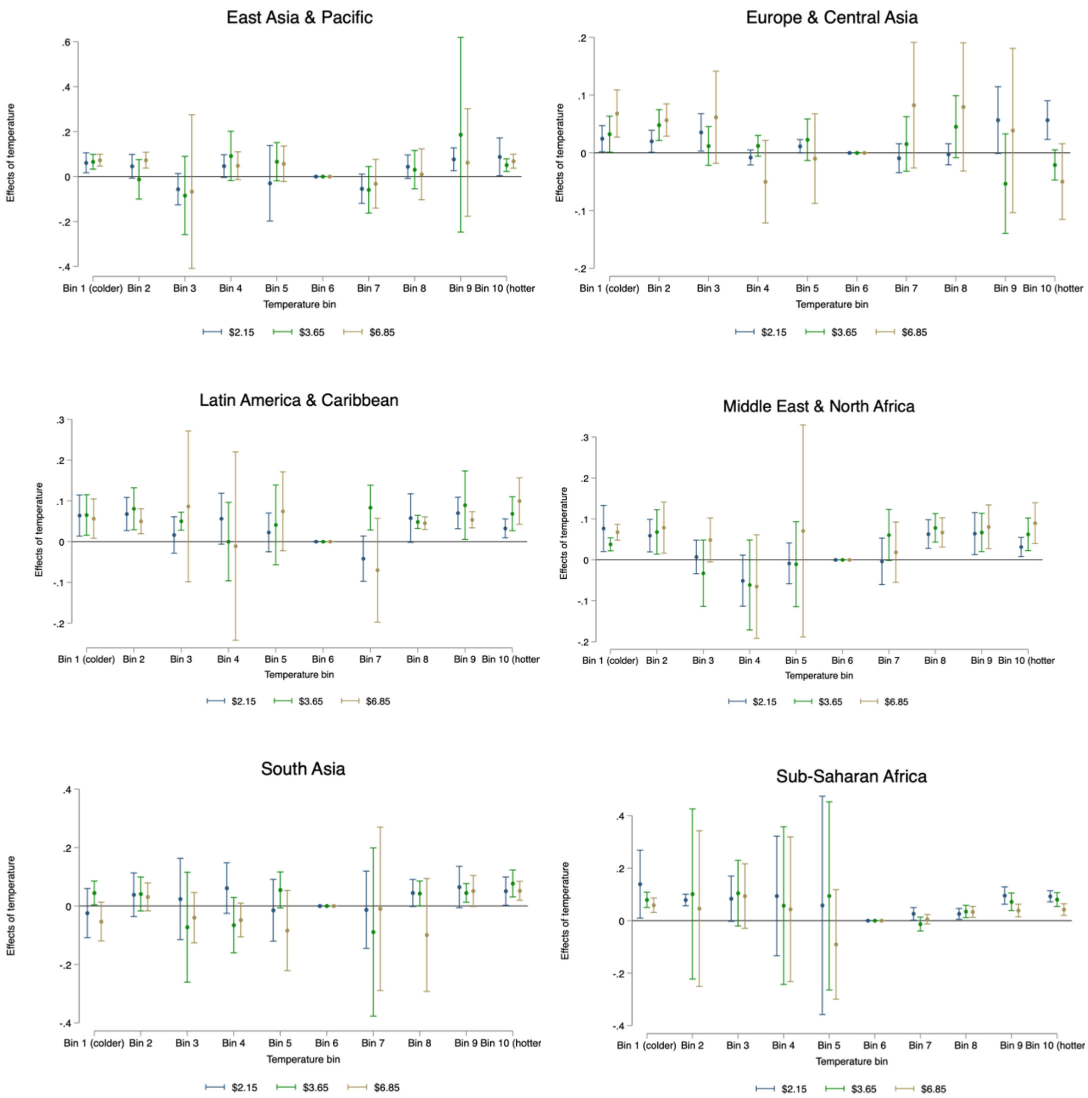
Figure S1: Distribution of temperature



Notes: Temperature data are sourced from the European Centre for Medium-Range Weather Forecasts Reanalysis 5 (ERA-5). The figure displays the distributions of subnational regions across the temperature range (top panel) and temperature categories (bottom panel) (*n*=6,287).

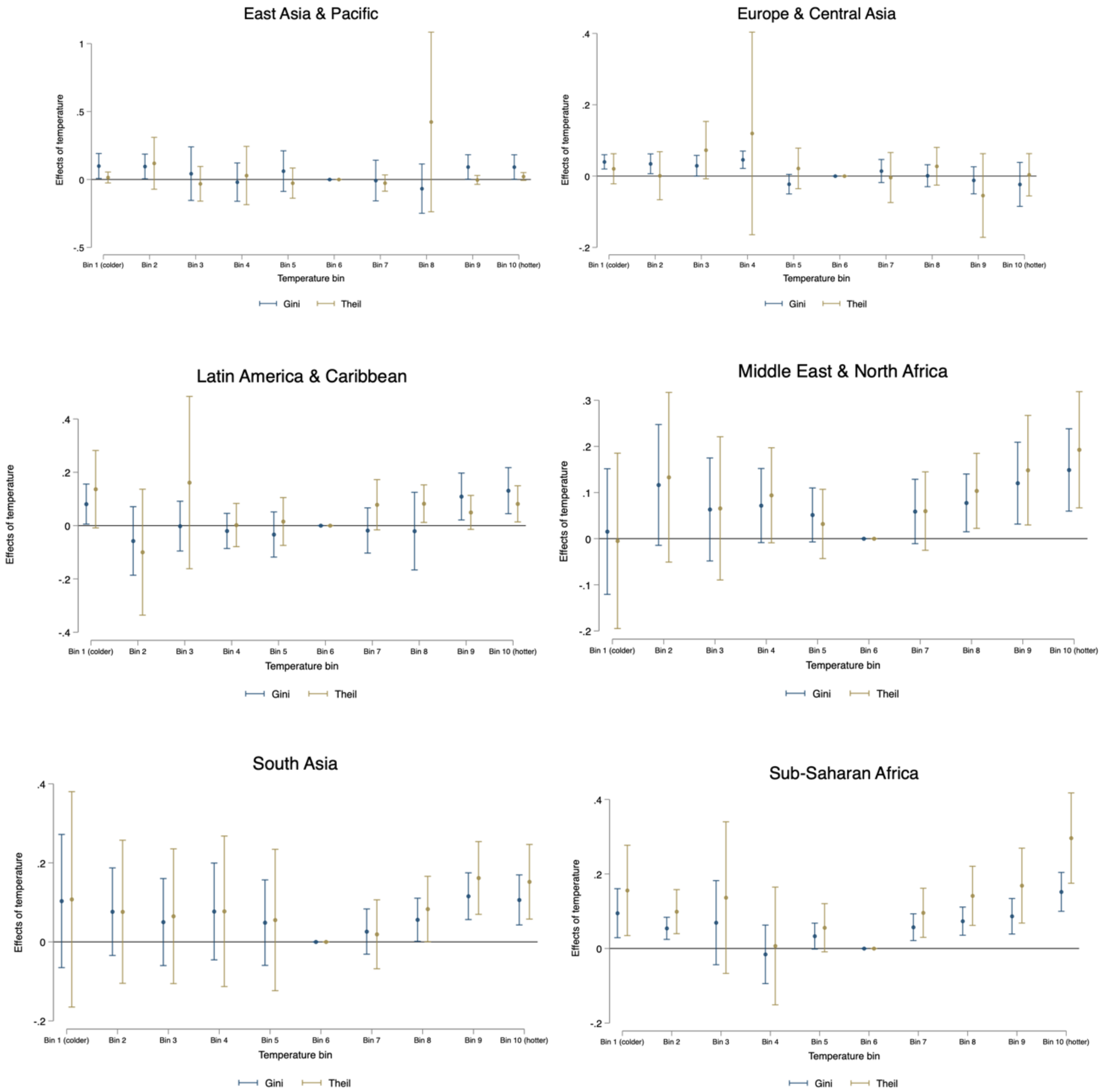
Figure S2: Heterogeneity analysis using regional temperature

Panel A: Effects of temperature on poverty by region



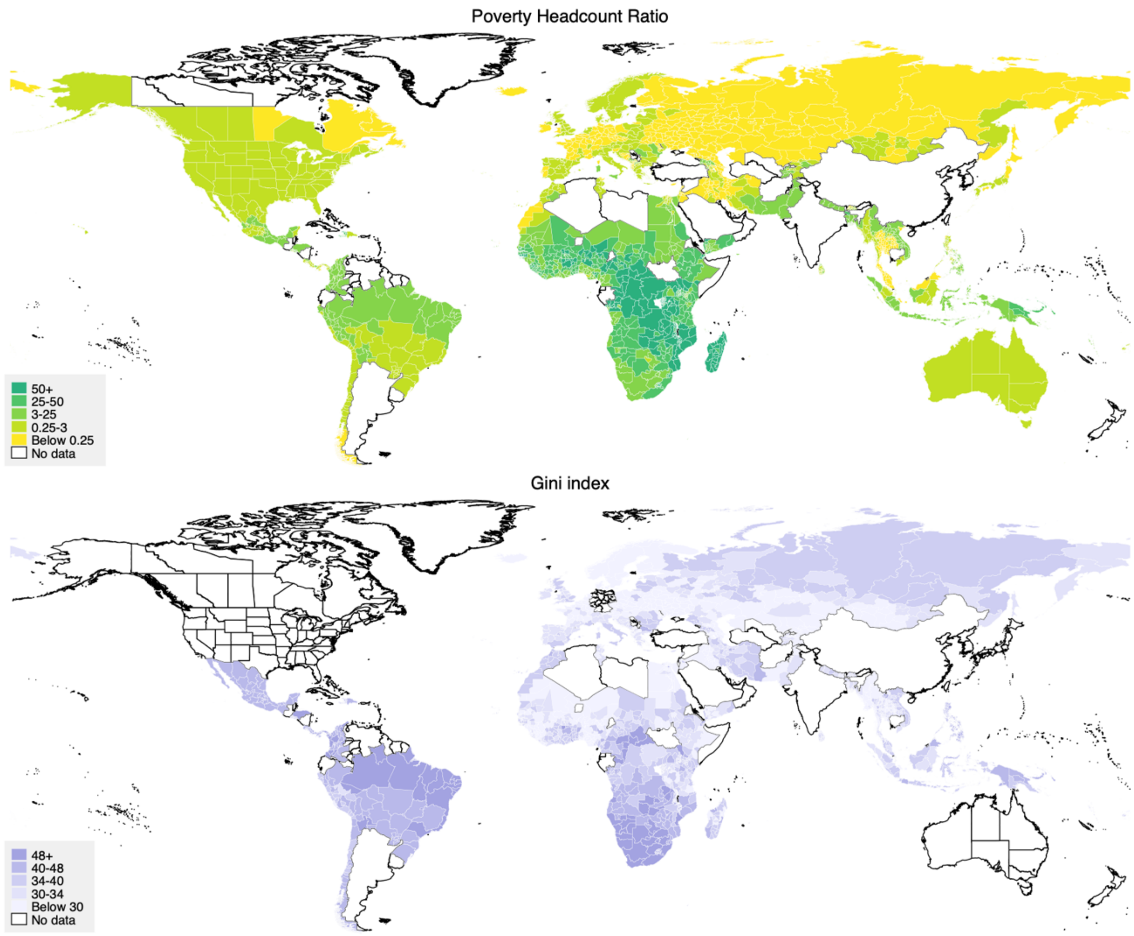
Notes: The figure shows the point estimates and their 95% confidence intervals of temperature bins using regression with weather conditions (rainfall and humidity) and subnational fixed effects. Robust standard errors are clustered at the subnational level. Temperature bins are identified by dividing regional average temperature into deciles with the temperature bin in the 6th decide being the reference group. Hotter temperature and colder temperature are defined as temperature being in the top decile (i.e., bin 10) and bottom decile (i.e., bin 1) of the temperature range, respectively. The analytical sample is divided into six regions: East Asia & Pacific (*n*=1,265), Europe & Central Asia (*n*=1,702), Latin America & Caribbean (*n*=1,055), Middle East & North Africa (*n*=319), South Asia *(n*=247), and Sub-Saharan Africa (*n*=963).

Panel B: Effects of temperature on inequality by region



Notes: The figure shows the point estimates and their 95% confidence intervals of temperature bins using regression with weather conditions (rainfall and humidity) and subnational fixed effects. Robust standard errors are clustered at the subnational level. Temperature bins are identified by dividing regional average temperature into deciles with the temperature bin in the 6th decide being the reference group. Hotter temperature and colder temperature are defined as temperature being in the top decile (i.e., bin 10) and bottom decile (i.e., bin 1) of the temperature range, respectively. The analytical sample is divided into six regions: East Asia & Pacific (n=1,180), Europe & Central Asia (n=1,542), Latin America & Caribbean (n=1,055), Middle East & North Africa (n=319), South Asia *(n*=247), and Sub-Saharan Africa (n=963).

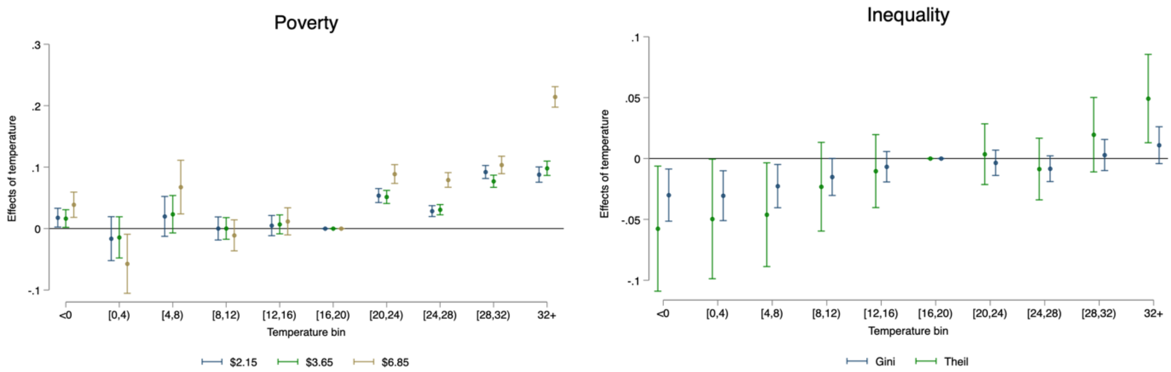
Figure S3: Subnational poverty and inequality – SPID database



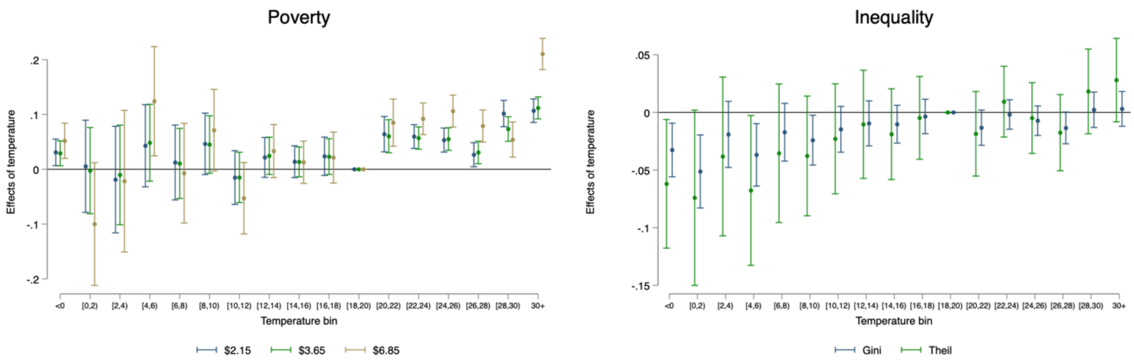
Notes: Poverty is measured by Global Subnational Poverty Headcount Ratio using the daily threshold of US$ 2.15 (*n*=6,169). Inequality is measured by the Gini index (*n*=5,260). Temperature data is taken from the European Centre for Medium-Range Weather Forecasts Reanalysis 5 (ERA-5). Poverty rate, inequality and temperature data are measured in the period 2004 – 2022.

Figure S4: Alternative temperature bin

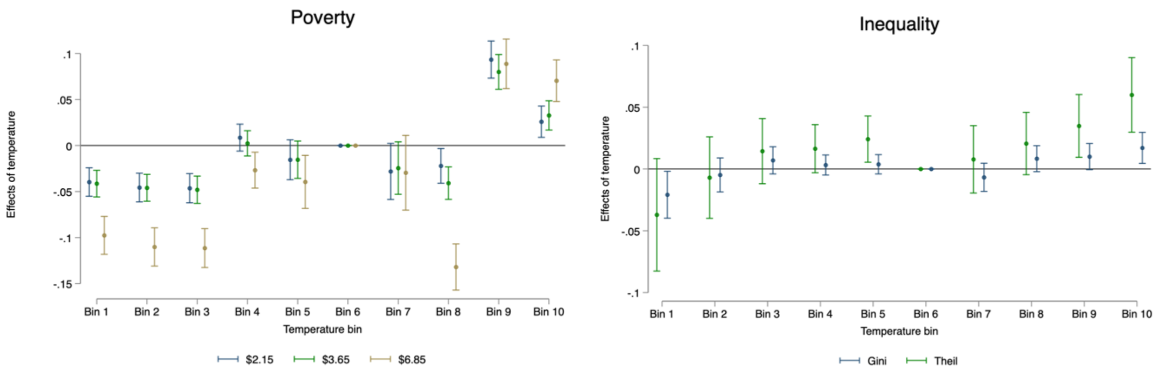
Panel A: 4-degree bin



Panel B: 2-degree bin

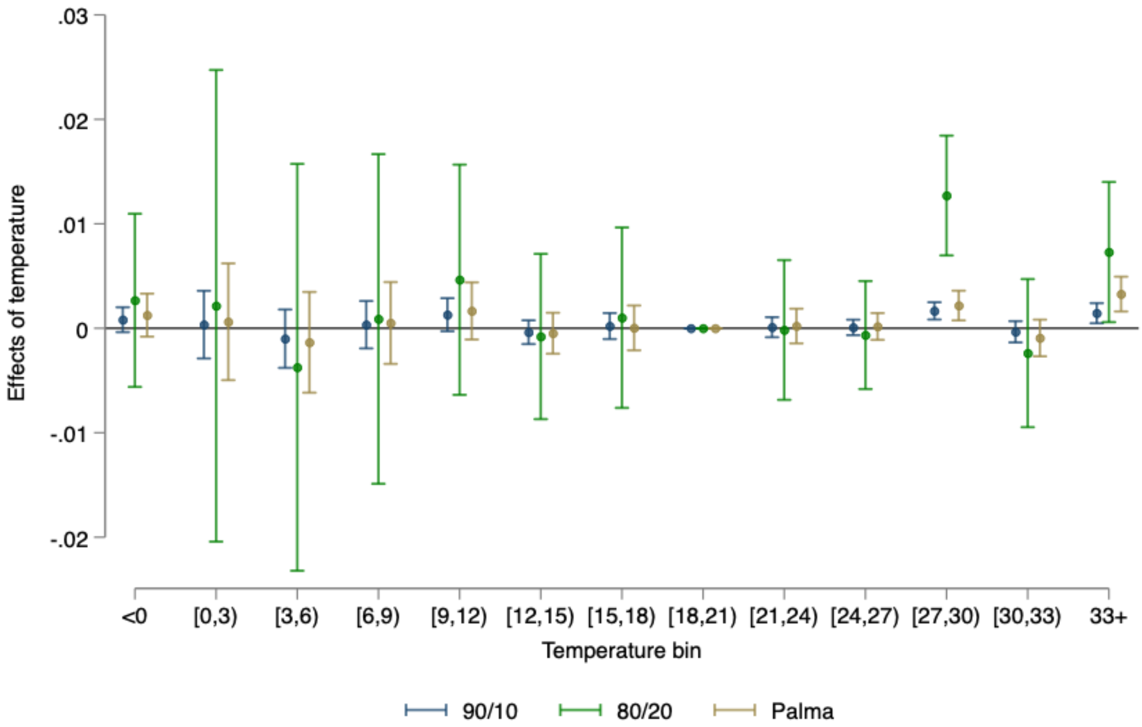


Panel C: decile bin



Notes: The figures show the point estimates and their 95% confidence intervals of temperature bins using regression with weather conditions (rainfall and humidity) and subnational fixed effects. The left-panel figures use the daily headcount ratio of US$2.15 (n=6,169), while the right-panel figures use the Gini index (n=5,260). Robust standard errors are clustered at the subnational level.

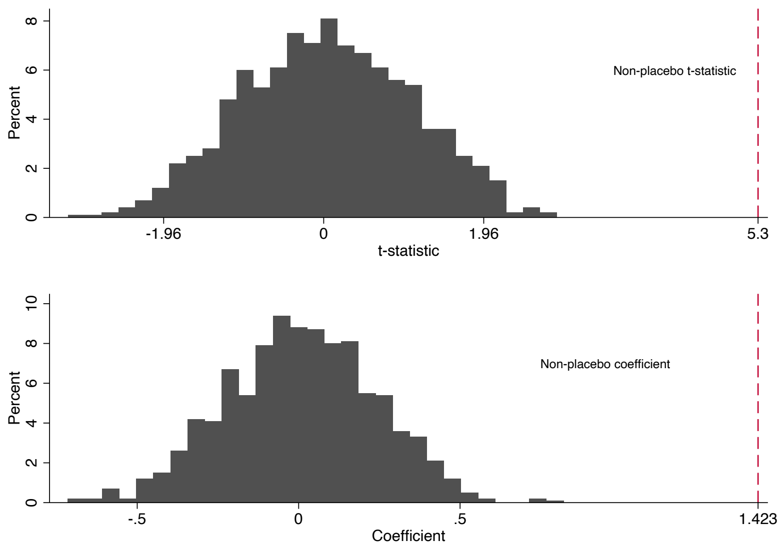
Figure S5: Alternative measures of inequality



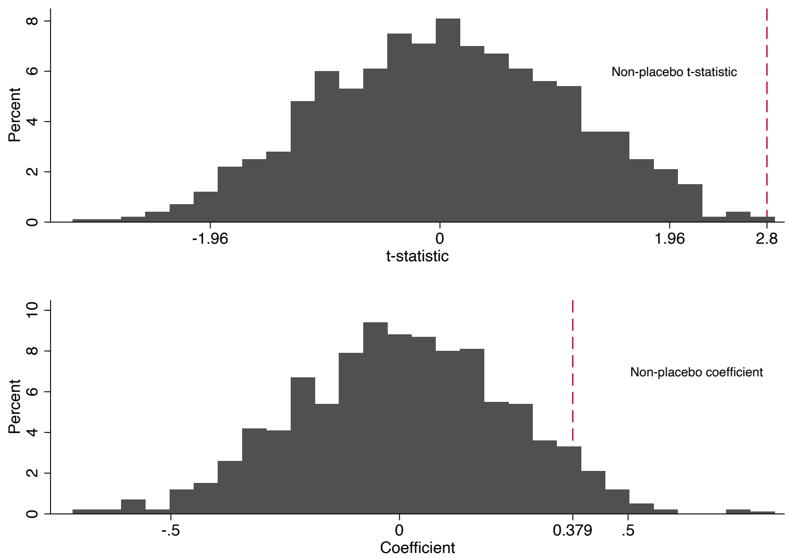
Notes: The figure shows the point estimates and their 95% confidence intervals of temperature bins using regression with weather conditions (rainfall and humidity) and subnational fixed effects. Three alternative measures of inequality are used: the 90/10 ratio (*n*=4,100), the 80/20 ratio (*n* =4,099), and the Palma ratio (*n* =4,150). Robust standard errors are clustered at the subnational level. Robust standard errors are clustered at the subnational level. The reference temperature bin is [18,21).

Figure S6: Placebo test

Panel A: Poverty



Panel B: Inequality



Notes: Results of placebo exercise using 1,000 randomizations of regions. The outcomes are poverty headcount ratio at $2.15 (Panel A, *n*=6,169) and Gini index (Panel B, *n*=5,260). All regressions include weather conditions and subnational fixed effects.

Table S1: Data sources and summary statistics

Variable	Descriptions	Country No.	Obs. No.	Mean	S.D.	Min	Max
National poverty rate (Global Subnational Atlas of Poverty – SPID) (%)							
Source: The World Bank (https://pipmaps.worldbank.org/en/data/datatopics/poverty-portal/home)							
Poverty rate $2.15	Poverty Headcount Ratio at US$ 2.15 a day	137	528	7.499	13.028	0.000	98.113
Poverty rate $3.65	Poverty Headcount Ratio at US$ 3.65 a day	137	528	18.585	21.531	0.000	99.724
Poverty rate $6.85	Poverty Headcount Ratio at US$ 6.85 a day	137	528	37.410	28.872	0.000	100.000
Subnational poverty rate (Global Subnational Atlas of Poverty – SPID) (%)							
Source: The World Bank (https://pipmaps.worldbank.org/en/data/datatopics/poverty-portal/home)							
Poverty rate $2.15	Poverty Headcount Ratio at US$ 2.15 a day	137	6,169	8.322	16.769	0.000	98.113
Poverty rate $3.65	Poverty Headcount Ratio at US$ 3.65 a day	137	6,169	18.614	26.234	0.000	99.792
Poverty rate $6.85	Poverty Headcount Ratio at US$ 6.85 a day	137	6,169	36.411	34.137	0.000	100.000
National inequality (Global Subnational Atlas of Poverty – SPID) (%)							
Source: The World Bank (https://pipmaps.worldbank.org/en/data/datatopics/poverty-portal/home)							
Gini	Gini index (%)	128	468	33.947	6.968	22.917	59.433
Theil	Theil index (%)	128	468	22.767	10.851	8.804	73.607
Subnational inequality (Global Subnational Atlas of Poverty – SPID) (%)							
Source: The World Bank (https://pipmaps.worldbank.org/en/data/datatopics/poverty-portal/home)							
Gini	Gini index (%)	131	5,260	35.138	7.853	13.371	66.448
Theil	Theil index (%)	131	5,260	24.676	13.438	3.143	192.672
90/10 ratio	Ratio of the income of the 10% richest to that of the 10% poorest.	131	4,100	2.940	9.837	0.000	131.202
80/20 ratio	Ratio of the income of the 20% richest to that of the 20% poorest.	131	4,099	2.627	7.712	0.000	106.748
Palma ratio	Ratio of the income of the 10% richest to that of the 40% poorest.	131	4,150	0.434	1.933	0.000	64.359
Satellite weather data (1979–2022)							
Source: European Union's Copernicus programme (https://sentinels.copernicus.eu/web/sentinel/missions/sentinel-5p)							
Temperature	Average temperature (C)	137	6,169	18.185	7.996	-9.417	30.790

Rainfall	Average rainfall (mm)	137	6,169	3.880	3.178	0.006	34.882
Humidity	%	137	6,169	70.054	15.895	11.278	92.183
Mechanism							
Source: NOAA (https://www.ncei.noaa.gov/products/climate-data-records/normalized-difference-vegetation-index)							
NDVI	Normalized difference vegetation index [-1, 1]	137	6,117	0.204	0.190	-0.088	0.775
Variables used in heterogeneity analysis							
Regime type in 2018 (*Source: The Economist* - https://www.eiu.com/n/)							
Democracy	=1 if democracy score more than 7	126	3,945	0.193	0.394	0.000	1.000
Hybrid	=1 if democracy score between 4 and 7	126	3,945	0.515	0.500	0.000	1.000
Authoritarian	=1 if democracy score less than 4	126	3,945	0.292	0.455	0.000	1.000
Share of agriculture in GDP *(Source: The World Bank - https://datacatalog.worldbank.org/home)*							
Low share	=1 if share of agriculture in GDP less than 10%	132	4,011	0.605	0.489	0.000	1.000
High share	=1 if share of agriculture in GDP equal to or greater than 10%	132	4,011	0.395	0.489	0.000	1.000
Share of manufacturing in GDP *(Source: The World Bank - https://datacatalog.worldbank.org/home)*							
Low share	=1 if share of manufacturing in GDP less than 10%	132	3,911	0.692	0.462	0.000	1.000
High share	=1 if share of manufacturing in GDP equal to or greater than 10%	132	3,911	0.308	0.462	0.000	1.000
Share of trade in GDP *(Source: The World Bank - https://datacatalog.worldbank.org/home)*							
Low share	=1 if share of trade in GDP less than 10%	132	3,924	0.632	0.482	0.000	1.000
High share	=1 if share of trade in GDP equal to or greater than 10%	132	3,924	0.368	0.482	0.000	1.000

Table S2: The effects of temperature on poverty

Poverty:	$2.15/day		$3.65/day		$6.85/day	
	FE	LD	FE	LD	FE	LD
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Country-level analysis						
Temperature	0.288*	0.114*	0.306**	0.118*	0.148	0.109*
	(0.148)	(0.064)	(0.150)	(0.065)	(0.193)	(0.062)
Rainfall	-0.764*	-3.958**	-0.719	-4.087**	-0.098	-1.876
	(0.451)	(1.788)	(0.473)	(1.804)	(0.388)	(1.621)
Humidity	-0.066**	-0.256	-0.062**	-0.229	-0.078**	-0.265*
	(0.032)	(0.160)	(0.031)	(0.149)	(0.034)	(0.153)
Country/Year FE	Yes	No	No	No	Yes	No
Mean dependent var.	7.499	7.499	18.585	18.585	37.410	37.410
Observations	528	100	528	100	528	100
Equality test (FE vs. LD)	p = 0.196		p = 0.113		p = 0.620	
Panel B: Subnation-level analysis						
Temperature	1.423***	0.615***	1.390***	0.671***	0.673**	-0.044
	(0.267)	(0.202)	(0.270)	(0.207)	(0.302)	(0.261)
Rainfall	0.017	-0.039	0.031	-0.021	0.068	0.081
	(0.035)	(0.047)	(0.039)	(0.047)	(0.056)	(0.065)
Humidity	-0.050***	-0.180***	-0.053***	-0.186***	-0.069***	-0.268***
	(0.013)	(0.047)	(0.013)	(0.046)	(0.017)	(0.052)
Subnational/Year FE	Yes	No	Yes	No	Yes	No
Mean dependent var.	8.322	8.322	18.614	18.614	36.411	36.411
Observations	6,169	1,402	6,169	1,402	6,169	1,402
Equality test (FE vs. LD)	p < 0.01		p = 0.013		p = 0.047	
Equality test (country vs. subnational)	p < 0.01	p = 0.018	p < 0.01	p = 0.011	p = 0.079	p = 0.567
Number of countries	137	115	137	115	137	115
Number of regions	1,695	1,407	1,695	1,407	1,695	1,407

Notes: FE = Fixed-effects model, LD = Long-differences model. Robust standard errors in parentheses. Standard errors are clustered at the country level in Panel A and subnational level in Panel B. Poverty data are taken from SPID. Poverty and weather variables in the long-differences model are measured by the difference between averages of the earliest 3-year period and averages of the latest 3-year period. The long differences estimation is based on cross-sectional data with a smaller sample size compared with panel data. The equality test p-values show the t-test between the FE results vs. LD results, and the country analysis results vs. the subnational analysis results. *** p<0.01, ** p<0.05, * p<0.1.

Table S3: The effects of temperature on subnational inequality

Inequality:	Gini		Theil	
	FE	LD	FE	LD
	(1)	(2)	(3)	(4)
Panel A: Country-level analysis				
Temperature	0.096***	0.012*	0.205***	0.023*
	(0.033)	(0.007)	(0.066)	(0.012)
Rainfall	-0.115	0.421	-0.139	1.224
	(0.095)	(0.445)	(0.194)	(0.824)
Humidity	0.015	0.023	0.036	0.030
	(0.025)	(0.069)	(0.046)	(0.106)
Country/Year FE	Yes	No	Yes	No
Mean dependent var.	33.947	33.947	22.767	22.767
Observations	468	108	468	108
Equality test (FE vs. LD)	p < 0.01		p < 0.01	
Panel B: Subnation-level analysis				
Temperature	0.379***	0.147**	1.010***	0.325**
	(0.136)	(0.062)	(0.305)	(0.128)
Rainfall	-0.051	0.009	-0.117	0.060
	(0.043)	(0.043)	(0.100)	(0.102)
Humidity	0.006	0.014	0.021	0.006
	(0.013)	(0.029)	(0.033)	(0.066)
Subnational/Year FE	Yes	No	Yes	No
Mean dependent var.	35.138	35.138	24.676	24.676
Observations	5,260	1,308	5,260	1,308
Equality test (FE vs. LD)	p = 0.038		p < 0.01	
Equality test (country vs. subnational)	p = 0.014	p = 0.033	p < 0.01	p = 0.021
Number of countries	131	108	131	108
Number of regions	1,597	1,308	1,597	1,308

Notes: FE = Fixed-effects model, LD = Long-differences model. Robust standard errors in parentheses. Standard errors are clustered at the country level in Panel A and subnational level in Panel B. Inequality data are taken from SPID. Inequality and weather variables in the long-differences model are measured by the difference between averages of the earliest 3-year period and averages of the latest 3-year period. The long differences estimation is based on cross-sectional data with a smaller sample size compared with panel data. The equality test p-values show the t-test between the FE results vs. LD results, and the country analysis results vs. the subnational analysis results. *** p<0.01, ** p<0.05, * p<0.1.

Table S4: Heterogeneity analysis by country characteristics

	Poverty \$2.15	Gini index
	(1)	(2)
Panel A: Regime type (Reference group: Democracy)		
Temperature*Hybrid regime	0.735*	-0.004
	(0.444)	(0.003)
Temperature*Authoritarian regime	1.395***	0.008**
	(0.431)	(0.003)
Panel B: Location (Reference group: Countries near equator)		
Temperature* Countries near equator	0.943***	0.011***
	(0.293)	(0.004)
Panel C: Share of agriculture in GDP (Reference group: Low share)		
Temperature*High agriculture share	0.155***	0.001***
	(0.051)	(0.000)
Panel D: Share of manufacturing in GDP (Reference group: Low share)		
Temperature*High manufacturing share	-0.076**	-0.001***
	(0.039)	(0.000)
Panel E: Share of trade in GDP (Reference group: Low share)		
Temperature*High trade share	-0.005	0.000
	(0.003)	(0.000)
Controlling for rainfall and humidity	Yes	Yes
Subnational FE	Yes	Yes

Notes: Results of panel fixed effects model. Robust standard errors in parentheses. Standard errors are clustered at the subnational level. *** p<0.01, ** p<0.05, * p<0.1

Table S5: Causal mediation analysis

	Poverty ($2.15/day)	Gini	Poverty ($2.15/day)	Gini
	(1)	(2)	(3)	(4)
Temperature	2.095***	0.355***	2.756***	0.067***
	(0.068)	(0.038)	(0.062)	(0.020)
NDVI	-2.582**	-4.312***		
	(1.249)	(0.600)		
Soil moisture (%)			-0.050***	-0.041**
			(0.011)	(0.005)
Controlled direct effect	2.095***	0.355***	1.342***	0.067***
	(0.068)	(0.036)	(0.047)	(0.020)
Natural indirect effect	0.054**	0.091***	-0.082***	0.044***
	(0.026)	(0.013)	(0.019)	(0.006)
Total effect	2.150***	0.446***	1.261***	0.111***
	(0.062)	(0.033)	(0.044)	(0.019)
Observations	6,117	6,123	4,016	3,725

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Country-level analysis, agriculture data is taken from WDI database. Causal mediation analysis is conducted using Stata package '*Paramed*', available at: https://ideas.repec.org/c/boc/bocode/s457581.html

Table S6: Simulated effect of temperature on poverty and inequality

Panel A: Poverty

		SSP1-1.9	SSP1-2.6	SSP2-4.5	SSP3-7.0	SSP5-8.5
Increase in temperature	Mean	1.400	2.000	3.000	4.100	5.000
	Upper	2.200	2.900	4.300	6.200	7.400
	Lower	0.900	1.300	2.100	3.000	3.800
Increase in poverty rate $2.15	Mean	1.992	2.846	4.269	5.834	7.115
	Upper	3.131	4.127	6.119	8.823	10.530
	Lower	1.281	1.850	2.988	4.269	5.407
Increase in poverty rate $3.65	Mean	1.946	2.780	4.170	5.699	6.950
	Upper	3.058	4.031	5.977	8.618	10.286
	Lower	1.251	1.807	2.919	4.170	5.282
Increase in poverty rate $6.85	Mean	0.942	1.346	2.019	2.759	3.365
	Upper	1.481	1.952	2.894	4.173	4.980
	Lower	0.606	0.875	1.413	2.019	2.557

Notes: Data on simulated temperature are from the Coupled Model Intercomparison Project (CMIP6) climate projections. The projection is estimated using the coefficient on the effects of temperature on inequality reported in Columns (1), (3), and (5) (Panel B) of Supplementary Table S2.

Panel B: Inequality

		SSP1-1.9	SSP1-2.6	SSP2-4.5	SSP3-7.0	SSP5-8.5
Increase in temperature	Mean	1.400	2.000	3.000	4.100	5.000
	Upper	2.200	2.900	4.300	6.200	7.400
	Lower	0.900	1.300	2.100	3.000	3.800
Gini index	Mean	0.531	0.758	1.137	1.554	1.895
	Upper	0.834	1.099	1.630	2.350	2.805
	Lower	0.341	0.493	0.796	1.137	1.440
Theil index	Mean	1.414	2.020	3.030	4.141	5.050
	Upper	2.222	2.929	4.343	6.262	7.474
	Lower	0.909	1.313	2.121	3.030	3.838

Notes: Data on simulated temperature are from the Coupled Model Intercomparison Project (CMIP6) climate projections. The projection is estimated using the coefficient on the effects of temperature on inequality reported in Columns (1), and (3) (Panel B) of Supplementary Table S3.

Table S7: Alternative specifications of panel model

Panel A: Poverty

Dependent variable: Poverty rate at $2.15	Adding country-specific linear time trend	Adding region-specific linear time trend	Adding temperature change	Adding temperature squared term	Adding temperature cubic term
	(1)	(2)	(3)	(4)	(5)
Temperature	0.312***	1.425***	1.456***	1.401***	1.417***
	(0.093)	(0.284)	(0.272)	(0.261)	(0.257)
ΔTemperature			0.281***		
			(0.106)		
Temperature squared				0.008*	0.015
				(0.005)	(0.010)
Temperature cubic					-0.000
					(0.000)
Other weather controls	Yes	Yes	Yes	Yes	Yes
Subnational/Year FE	Yes	Yes	Yes	Yes	Yes
Mean dependent var.	8.322	8.322	8.322	8.322	8.322
Observations	6,169	6,169	6,169	6,169	6,169

Notes: Robust standard errors in parentheses. Standard errors are clustered at the subnational level. *** p<0.01, ** p<0.05, * p<0.1

Panel B: Inequality

Dependent variable: Gini index	Adding country-specific linear time trend	Adding region-specific linear time trend	Adding temperature change	Adding temperature squared term	Adding temperature cubic term
	(1)	(2)	(3)	(4)	(5)
Temperature	0.341**	0.325**	0.376***	0.379***	0.374***
	(0.136)	(0.135)	(0.136)	(0.136)	(0.136)
ΔTemperature			-0.060		
			(0.072)		
Temperature squared				0.000	-0.026***
				(0.002)	(0.007)
Temperature cubic					0.001***
					(0.000)
Other weather controls	Yes	Yes	Yes	Yes	Yes
Subnational/Year FE	Yes	Yes	Yes	Yes	Yes
Mean dependent var.	35.605	35.605	35.605	35.605	35.605
Observations	5,260	5,260	5,242	5,242	5,242

Notes: Robust standard errors in parentheses. Standard errors are clustered at the subnational level. *** p<0.01, ** p<0.05, * p<0.1

Table S8: Alternative measure of poverty – Multidimensional poverty

	Percentage of population deprived					
	Monetary poverty	Educational attainment	Educational enrolment	Electricity	Sanitation	Drinking water
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature	0.589***	0.017	-0.047	1.017***	1.761***	1.189***
	(0.176)	(0.824)	(0.172)	(0.329)	(0.390)	(0.238)
Other weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Subnational/Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean dependent var.	12.325	17.768	7.720	17.050	25.938	11.661
Observations	2,478	2,464	2,260	2,437	2,315	2,321

Notes: Robust standard errors in parentheses. Standard errors are clustered at the subnational level. Column (1) measures the percentage of the population living on less than $2.15 a day at 2017 international prices, Column (2) measures the percentage of population deprived of primary educational attainment; Column (3) measures the percentage of population deprived of school enrolment; Column (4) measures the percentage of population deprived of electricity; Column (5) measures the percentage of population deprived of sanitation; Column (6) measures the percentage of population deprived of drinking water. *** p<0.01, ** p<0.05, * p<0.1

Table S9: Robustness test – Alternative measures of temperature

Panel A: Poverty

	Dependent variable: Poverty rate at $2.15					
	Log temperature	Temperature (ºF)	Temperature from CRU	Number of days temperature above 28	Dropping subregions with temperature above 28	Temperature shock
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature	1.784***	0.791***	0.032**	0.038***	1.570***	0.305***
	(0.392)	(0.148)	(0.014)	(0.015)	(0.110)	(0.116)
Other weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Subnational/Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,063	6,169	5,754	6,169	5,222	6,169

Notes: Results of panel fixed effects model. Robust standard errors in parentheses. Standard errors are clustered at the subnational level. In Column (6), temperature shock is defined as the difference between actual temperature and long-term temperature being greater (less) than 2 (-2) standard deviation. *** p<0.01, ** p<0.05, * p<0.1

Panel B: Inequality

	Dependent variable: Gini index					
	Log temperature	Temperature (ºF)	Temperature from CRU	Number of days temperature above 28	Dropping subregions with temperature above 28	Temperature shock
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature	1.655**	0.210***	0.047**	0.012***	0.209***	0.504***
	(0.838)	(0.075)	(0.019)	(0.005)	(0.034)	(0.144)
Other weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Subnational/Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,222	5,260	4,845	5,260	5,160	5,260

Notes: Results of panel fixed effects model. Robust standard errors in parentheses. Standard errors are clustered at the subnational level. In Column (6), temperature shock is defined as the difference between actual temperature and long-term temperature being greater (less) than 2 (-2) standard deviation. *** p<0.01, ** p<0.05, * p<0.1

Table S10: Robustness test – Alternative samples

Panel A: Poverty

	Dependent variable: Poverty rate at $2.15							
	Balanced panel	Dropping countries with few subregions	Excluding USA	Excluding India	Excluding 10% cold countries	Excluding 10% hot countries	Weighted regression	Spatially-corrected Conley S.E.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Temperature	1.423***	1.493***	1.698***	1.504***	2.553***	2.030***	0.551***	2.127***
	(0.267)	(0.299)	(0.340)	(0.275)	(0.117)	(0.094)	(0.126)	(0.098)
Other weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Subnational/Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,881	4,979	5,608	5,740	5,553	6,169	5,260	6,169

Notes: Results of panel fixed effects model. Robust standard errors in parentheses. Standard errors are clustered at the subnational level. In column (8), we use the Conley standard error to adjust for spatial correlation based on a radius of 200 km. *** p<0.01, ** p<0.05, * p<0.1

Panel B: Inequality

	Dependent variable: Gini index							
	Balanced panel	Dropping countries with few subregions	Excluding USA	Excluding India	Excluding 10% cold countries	Excluding 10% hot countries	Weighted regression	Spatially-corrected Conley S.E.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Temperature	0.379***	0.623***	0.379***	0.418***	0.197***	0.277***	0.236***	0.209***
	(0.136)	(0.169)	(0.136)	(0.140)	(0.038)	(0.039)	(0.050)	(0.031)
Other weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Subnational/Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,972	4,084	5,260	4,831	4,976	4,643	5,260	5,260

Notes: Results of panel fixed effects model. Robust standard errors in parentheses. Standard errors are clustered at the subnational level. In column (8), we use the Conley standard error to adjust for spatial correlation based on a radius of 200 km. *** p<0.01, ** p<0.05, * p<0.1

Table S11: The effects of temperature on poverty – Subnational GDP analysis

	Poverty rate $2.15		Poverty rate $3.65		Poverty rate $6.85	
	FE	LD	FE	LD	FE	LD
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature	0.148**	0.057***	0.206**	0.120**	0.224**	0.105*
	(0.064)	(0.021)	(0.084)	(0.057)	(0.095)	(0.060)
Other weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Subnational/Year FE	Yes	No	Yes	No	Yes	No
Observations	138,060	1,306	138,060	1,306	138,060	1,306

Notes: Robust standard errors in parentheses. Standard errors are clustered at the subnational level. Poverty rate is calculated using subnational GDP and the poverty lines of $2.15, $3.65, and $6.85. Poverty and weather variables in the long-differences model are measured by the difference between the earliest year and the latest year. The long differences estimation is based on cross-sectional data with a smaller sample size compared with panel data. *** p<0.01, ** p<0.05, * p<0.1

Table S12: The effects of temperature on poverty – Grid-level analysis

Dependent variable:	FE		LD	
Poverty rate at $2.15	Baseline	Extension	Baseline	Extension
	(1)	(2)	(3)	(4)
Temperature	0.102***	-2.046***		-0.0006***
	(0.022)	(0.060)		(0.0001)
ΔTempearture		0.870***	0.009***	0.005***
		(0.033)	(0.001)	(0.001)
Temperature squared		0.092***		0.0001***
		(0.002)		(0.00004)
Other weather controls	Yes	Yes	Yes	Yes
Country/Year FE	Yes	Yes	No	No
Observations	1,115,478	1,072,575	42,903	42,903

Notes: Robust standard errors in parentheses. Standard errors are clustered at the country level. Poverty incidence is calculated using subnational GDP and the poverty line from WDI. The long differences estimation is based on cross-sectional data with a smaller sample size compared with panel data. *** p<0.01, ** p<0.05, * p<0.1

Table S13: The effects of temperature on poverty and inequality – Country level analysis using alternative data from WDI and SWIID

Panel A: Poverty data from WDI

Poverty:	$2.15/day		$3.65/day		$6.85/day	
	FE	LD	FE	LD	FE	LD
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature	0.629***	0.217***	1.020***	0.381***	1.344***	0.501***
	(0.098)	(0.028)	(0.153)	(0.042)	(0.220)	(0.055)
Other weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Country/Year FE	Yes	No	No	No	Yes	No
Observations	1,717	95	1,717	95	1,716	95

Notes: Robust standard errors in parentheses. Standard errors are clustered at the country level. Poverty data are taken from the WDI. The long differences estimation is based on cross-sectional data with a smaller sample size compared with panel data. *** p<0.01, ** p<0.05, * p<0.1.

Panel B: Inequality data from WDI and SWIID

Inequality:	Gini – WDI		Gini – SWIID	
	FE	LD	FE	LD
	(1)	(2)	(3)	(4)
Temperature	0.171***	0.194***	0.165***	0.255***
	(0.023)	(0.033)	(0.037)	(0.040)
Precipitation	0.013**	0.022*	0.006*	0.018*
	(0.005)	(0.013)	(0.003)	(0.010)
Other weather controls	Yes	Yes	Yes	Yes
Country/Year FE	Yes	No	Yes	No
Observations	1,505	90	3,781	90

Notes: Robust standard errors in parentheses. Standard errors are clustered at the country level. Inequality data in Columns (1)-(2) are taken from the World Development Indicators (WDI). Inequality data in Columns (3)-(4) are taken from the Standardized World Income Inequality Database (SWIID). The long differences estimation is based on cross-sectional data with a smaller sample size compared with panel data. *** p<0.01, ** p<0.05, * p<0.1

Table S14: The effects of temperature on poverty and inequality – 10-year analysis

Panel A: Poverty

	2003 – 2013			2014 – 2022		
Poverty:	$2.15/day (1)	$3.65/day (2)	$6.85/day (3)	$2.15/day (4)	$3.65/day (5)	$6.85/day (6)
Temperature	0.180**	0.244***	0.203*	0.626***	0.569***	0.178
	(0.080)	(0.091)	(0.111)	(0.176)	(0.175)	(0.261)
Rainfall	0.062	0.069	0.086	0.006	0.002	-0.036
	(0.044)	(0.053)	(0.055)	(0.030)	(0.033)	(0.057)
Humidity	-0.040***	-0.043***	-0.030	-0.051***	-0.050***	-0.068***
	(0.015)	(0.016)	(0.023)	(0.011)	(0.011)	(0.015)
Subnational/Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,169	1,402	6,169	1,402	6,169	1,402

Notes: Results of fixed-effects model using subnational data. Robust standard errors in parentheses. Standard errors are clustered at the subnational level. Poverty data are taken from SPID. *** p<0.01, ** p<0.05, * p<0.1.

Panel B: Inequality

	2003 – 2013		2014 – 2022	
Inequality:	Gini (1)	Theil (2)	Gini (3)	Theil (4)
Temperature	0.246***	0.899**	0.299**	0.952***
	(0.075)	(0.433)	(0.123)	(0.271)
Rainfall	-0.238	-0.401	-0.024	-0.062
	(0.171)	(0.398)	(0.040)	(0.093)
Humidity	-0.012	-0.308	0.009	0.024
	(0.064)	(0.211)	(0.012)	(0.031)
Subnational/Year FE	Yes	Yes	Yes	Yes
Observations	804	804	4,456	4,456

Notes: Results of fixed-effects model using subnational data. Robust standard errors in parentheses. Standard errors are clustered at the subnational level. Inequality data are taken from SPID. *** p<0.01, ** p<0.05, * p<0.1.

Table S15: The effects of temperature on poverty gap

Poverty gap power of:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Poverty line of $2.15/day										
Temperature	0.704***	0.429***	0.281***	0.195***	0.141***	0.105***	0.081***	0.063***	0.050***	0.040***
	(0.141)	(0.088)	(0.061)	(0.044)	(0.034)	(0.026)	(0.021)	(0.017)	(0.014)	(0.012)
Panel B: Poverty line of $3.65/day										
Temperature	0.649***	0.393***	0.258***	0.180***	0.130***	0.098***	0.075***	0.059***	0.047***	0.038***
	(0.139)	(0.085)	(0.058)	(0.042)	(0.032)	(0.025)	(0.020)	(0.016)	(0.014)	(0.011)
Panel C: Poverty line of $6.85/day										
Temperature	0.785***	0.637***	0.494***	0.386***	0.306***	0.246***	0.200***	0.165***	0.138***	0.116***
	(0.189)	(0.138)	(0.106)	(0.083)	(0.067)	(0.055)	(0.046)	(0.038)	(0.033)	(0.028)
Other weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Subnational/Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,739	5,739	5,739	5,739	5,739	5,739	5,739	5,739	5,739	5,739

Notes: Results of fixed-effects model using subnational data. Robust standard errors in parentheses. Standard errors are clustered at the subnational level. Inequality data are taken from SPID. *** p<0.01, ** p<0.05, * p<0.1.

Appendix B. Robustness tests

We explore the robustness of our results in a number of different ways. We start with the results of panel model presented in Supplementary Table S2 and show that our results are broadly consistent when using alternative model specifications. First, we estimate several alternate specifications to assuage the reader of misspecification concerns. These are presented in Supplementary Table S7. Our panel model with fixed effects represents a substantial improvement over the standard cross-sectional regression, but it may also be subject to bias if there are unobservable, time-varying differences across countries or regions. We show that our estimates are insensitive to the inclusion of country (region) specific time trends (Columns 1 and 2). Another concern is related to misspecification of the functional form of temperature. Therefore, from Columns (3) to (5), we employ different functional forms of temperature including controlling for temperature change, quadratic term and cubic term of temperature. Results of these exercises strengthen our main findings.

Second, we replicate the results in Figure 4 but using alternative thresholds to define hot and cold days. In Panel A of Supplementary Figure S4, we present the results of the temperature bin approach using the 4-degree bin, while Panels B and C show the results using the 2-degree bin and decile bin, respectively. We find that when our definition of hot and cold days is less (or more) demanding, the implied effects on income inequality remain consistent.

Third, we present the results using alternative measures of poverty and income inequality at the subnational level. In Supplementary Table S8, we employ the multidimensional poverty indicators, which complement the traditional measure by capturing the acute deprivations in different aspects including monetary, education, electricity, sanitation, and drinking water. Similarly, we plot in Supplementary Figure S5 the effects of temperature using alternative measures of income including (i) the 90/10 ratio, (ii) the 80/20 ratio, and (iii) the Palma ratio. This helps address potential concern of using Gini and Theil indices as they are more sensitive to changes in the middle-income group. In overall, the results reaffirm the negative effects of higher temperature on poverty and income inequality.

Fourth, we provide further tests in Supplementary Table S9 to ensure that our results are not sensitive to the choice of temperature measures. We do so by using (i) log of temperature (Column 1); (ii) temperature measured in degrees Fahrenheit (Column 2); (iii) the temperature data at 0.5◦ resolution from the Climate Research Unit of the University of East Anglia (CRU) (Column 3); (iv) the number of days that temperature is above 28°C (Column 4); (v) dropping regions with temperature being above that level (Column 5); and (vi) temperature shock, defined as the difference between actual temperature and long-term temperature being greater (less) than 2 (-2) standard deviations (Column 6). The results show little change from the baseline specification.

Fifth, we replicate our main analysis to different subsamples to investigate the sensitivity of our finding, as shown in Supplementary Table S10. First, we show that our findings remain consistent when using a balanced sample in Column (2). Second, there are countries in our samples that contain only a small number of regions. We show in Column (2) that our results remain consistent when excluding these countries. The same finding is found when we exclude large countries that may drive our results such as United States and India (Columns 3 and 4). We also employ subsamples of countries without extremely cold weather (Column 5) and extremely hot weather (Column 6) using the 10% threshold. In Column (7), we use weighted regression taking into account regional population, while in Column (8) we use Conley standard errors that allow for spatial correlation in the error term. In overall, we find the estimated coefficients and significance levels are largely unchanged compared to our main finding.

Sixth, we exploit poverty and inequality data from alternative sources to check the robustness of our results. We exploit the annual (subnational/grid level) GDP data coming from previous studies to construct poverty measures[1,2]. An advantage of these datasets is that we are able to use a longer period-average (10-year) in the long differences model compared to our analysis using GSAP data. Using both panel and long differences models, Supplementary Tables S11 and S12 show that our findings are not sensitive to the alternative datasets, and the results are consistent across different specifications. We then conduct a similar exercise using country-level data from the World Development Indicators (WDI) and the Standardized World Income Inequality Database (SWIID). The results presented in Supplementary Table S13 confirm our expectation.

Finally, we conduct a placebo test of our study design. It is motivated by the fact that if estimating our chosen specification, but replacing the true value of the regressor of interest with an alternative we know should be irrelevant, we should expect to see no evidence of the effects on poverty. We do this exercise by using a within-sample randomization. First, the 'true' temperature of a region is replaced by temperature from another, randomly chosen in our sample without replacement. Second, the specification from Column (1) of Supplementary Tables 2 and 3 was estimated using the resulting placebo temperature series and the resulting coefficient and t-statistic on the temperature variable collected. This process is repeated with 1,000 randomizations and we present in Supplementary Figure S6 the coefficients and t-statistics harvested. Panel A shows that none of the placebo runs generate values anywhere close to those derived under true assignment, denoted by the dashed vertical lines. In Panel B, we find that only 5% of these estimates are larger in magnitude than the actual coefficient. It thus provides further support to our main estimates of the effects of temperature on poverty and inequality.

Additional references

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2. Kummu, M., Taka, M., & Guillaume, J. H. (2018). Gridded global datasets for gross domestic product and Human Development Index over 1990–2015. *Scientific Data*, *5*(1), 1–15.