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

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Abstract

Despite a vast literature documenting the harmful effects of climate change on various socio-economic outcomes, little evidence exists on the global impacts of hotter temperature on poverty and inequality. Analysis of a new global panel dataset of subnational poverty in 134 countries finds that a one-degree Celsius increase in temperature leads to a 9.1 percent increase in poverty, using the US$1.90 daily poverty threshold. A similar increase in temperature causes a 1.4 percent increase in the Gini inequality index. The paper also finds negative effects of colder temperature on poverty and inequality. Yet, while poorer countries—particularly those in South Asia and 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 the responsibilities of richer countries versus poorer countries.

JEL Classification: Q54; I32; O1

Key words: Climate change; temperature; poverty; inequality; subnational data

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1. Introduction

The increasingly prominent threats of climate change have inspired a significant body of economic research on a variety of outcomes, such as agriculture (Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009), labor productivity (Somanathan *et al.*, 2021), human health (Deschênes and Greenstone, 2011), and crime and conflict (Burke *et al.*, 2015a; Heilmann *et al.*, 2021). In particular, since climate change could reduce economic growth (Dell *et al.*, 2012; Newell *et al.*, 2021), this might, in turn, translate into slower progress with poverty reduction. Furthermore, climate change may unevenly affect different countries and population groups with the most harmful consequences of income decline being borne by less affluent groups; these would likely result in increasing inequality both across and within countries (Diffenbaugh and Burke, 2019; Hsiang *et al.*, 2019).

A possible explanation for the lack of empirical evidence on the impacts of global warming is the challenge of obtaining appropriate measures of poverty and inequality. While household surveys—the main source of official poverty statistics—have become increasingly available, these surveys are still unavailable or infrequently collected in many countries, particularly in poorer regions.[1] Another explanation is that poverty and inequality can widely vary within (and across) countries. Consequently, ignoring subnational variations could easily mask the dynamic relationship of these outcomes with climatic conditions, which have long been known to be location specific. Indeed, recent studies suggest that analysis using spatial aggregation of data at the country level may not reveal the true effects of climate change on economic growth, which can be improved with analysis using more disaggregated data at the subnational level (Damania *et al.*, 2020; Kalkuhl and Wenz, 2020).

[1] A recent survey by Beegle *et al.* (2016) indicates that just slightly more than half (i.e., 27) of the 48 countries in Sub-Saharan Africa had two or more comparable household surveys for the period between 1990 and 2012. Dang *et al.* (2019) find that a 10-percent increase in a country's household consumption level is associated with almost one-third (i.e., 0.3) more surveys.

To further illustrate, we plot in Figure 1 poverty and inequality against temperature at the subnational level for Indonesia, a populous country with a major share of the global poor. This figure shows large degrees of subnational variation in both poverty and inequality. Poverty, as measured by the headcount poverty rate at US$1.90 a day, ranges from being relatively low in the Western regions (lowest rate of 0 percent) to quite considerable in the Eastern regions (highest rate of 34 percent) (Panel C). A similar pattern is seen with inequality, as measured by the Gini index, which ranges between 26 percent and 45 percent (Panel D). Within the country, average temperature also widely varies between 21˚C and 30˚C (Panel E). Such wide-ranging subnational variations are not revealed by simply looking at Indonesia's country-level averages of poverty, inequality, and temperature (9 percent, 36 percent, and 25˚C, respectively), suggesting that an accurate assessment of the effects of global warming on poverty and inequality would require data analysis at the subnational level.

In this study, we find strong and statistically significant global effects of both higher and lower temperature on poverty and inequality, employing different identification strategies on a novel global database of subnational poverty and inequality. Our (preferred) subnational fixed effects model shows that a one-degree Celsius (i.e., 1˚C) annual increase in temperature causes headcount poverty increases of 0.9, 1.8, and 2.3 percentage points, respectively, using the daily poverty lines of $1.90, $3.20, and $5.50 (which correspond to 9.1 percent, 9.0 percent, and 6.8 percent increases). The corresponding estimated effects using the long differences model are less pronounced at 0.5, 1.2, and 2.0 percentage point increases in poverty (which correspond to 5.3 percent, 6.1 percent, and 5.9 percent increases), suggesting household adaptation to gradual warmer temperature over time. Analysis of subnational inequality data suggests that a 1˚C rise in temperature leads to 0.8 and 1.4 percent increases in the Gini and Theil indices, respectively.

For both poverty and inequality, we find evidence that points to larger climate change effects at the subnational level than those estimated using more aggregated, country-level data, particularly in regions where temperature change has the largest effects. Our heterogeneity analysis further shows that countries in South Asia and Sub-Saharan Africa are more vulnerable to warmer temperature, but the effects of colder weather are also observed among countries in Europe and Central Asia.

Our study makes several new contributions to the literature. First and most importantly, we offer the first global assessment of warmer temperature on *both* poverty and inequality, exploiting a novel global subnational panel database that we constructed based on the Global Subnational Atlas of Poverty (GSAP) (World Bank, 2021). Several attempts were made to understand the direct effects of global warming on poverty and inequality, but none examines these outcomes together.[2] For example, analyzing cross-sectional household survey data from 24 Sub-Saharan African countries, 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) use data from 150 countries and find that a one percent temperature increase is associated with a 0.5 percentage point increase in the Gini index.[3]

This lack of evidence poses an important, and perhaps quite urgent, challenge given the recent public debate of whether richer countries should take more responsibilities for the costs of climate change that correspond to their shares of the pollutants (Birnbaum *et al.*, 2022; Popovich and Plumer, 2021). As an example, 80 percent of global greenhouse gas emissions are currently produced by G20 economies—the world's largest economies—but these economies can only price 49 percent of CO_2 emissions from energy use (OECD, 2021).

[2] There are also a number of studies investigating the effects of natural disasters on temporary (transient) poverty (e.g., Sawada and Takasaki, 2017). Our study, in contrast, focuses on chronic poverty as a result of climate change.
[3] Other studies mostly focus on a country-specific context. See also Karim and Noy (2016) and Hallegatte *et al.* (2020) for recent reviews of the literatures on climate change, natural disasters, and poverty. Furthermore, since we analyze poverty and inequality using the same source of official household survey data, our estimates are consistent (and more comparable) than estimates that are based on different data sources.

Second, we offer new, disaggregated data on headcount poverty estimates and inequality indices for 1,594 subnational areas in 134 economies from 2003 to 2019, based on the GSAP database which is generated using household income and consumption surveys that underlie countries' official poverty statistics. This helps distinguish our study from the few existing cross-national studies that predominantly focused on country-level datasets, which, although informative, were not able to adequately capture the intricate subnational dynamics of poverty, inequality and temperature change. As part of our analysis, we make this new dataset publicly available for the first time. Our results show that analysis based on subnational data yields more accurate estimates of the impacts of temperature on poverty and inequality; consequently, this new subnational dataset can contribute to further and better research on climate change and poverty and inequality on a global scale.

Finally, we add fresh evidence to the emerging literature on the distributional effects of climate change. While existing studies on other development outcomes mostly focus on areas with hotter temperature, far fewer studies investigate the effects of colder temperature. Yet, no study is currently available on these distributional effects for poverty and inequality. For example, Dell *et al.* (2012) show that both hot and cold deviations from the average temperature have similar effects on economic growth; Deschênes and Greenstone (2011) find more cold days to be associated with higher mortality. Most recently, Cook and Heyes (2020) find that outdoor cold temperature negatively impacts indoor cognitive performance. More evidence on the potentially adverse effects of colder temperature is important since, despite global warming, unusually colder weather has become more common in many countries in the past decades. Overall, our results indicate that the distributional effects across temperature ranges (as well as across subnational regions) should be considered together with longer-term effects of temperature change as inputs for designing more effective policies aiming at fighting climate change, poverty, and inequality.

This paper consists of six sections. We discuss the data in the next section, and the analytical framework in Section 3. In Section 4, we report on the estimation results for poverty (Section 4.1), inequality (Section 4.2), their nonlinear effects (Section 4.3), and further robustness checks and heterogeneity analysis (Section 4.4). We offer further analysis on potential mechanisms, projected impacts under future climate change, and some back-of-the-envelope cost-benefit analysis in Section 5 and finally conclude in Section 6. We provide additional results in Appendix A, describe the data in more detail in Appendix B, offer more robustness checks and heterogeneity results in Appendix C and additional analysis on the potential mechanisms and projected impacts of temperature in Appendix D.

2. Data

The data used for our analysis are derived from multiple sources. We introduce a novel dataset that provides a granular perspective on poverty and inequality at the subnational level. In particular, we draw on the Global Subnational Atlas of Poverty (GSAP) (World Bank, 2021), a collaborative effort among different teams at the World Bank over a period of time. The GSAP is built on countries' official household income (consumption) surveys, covering over 1,594 subnational units across 134 countries, with more than 90 percent of the data ranging from 2010 to 2019. 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.

For the main outcomes, we utilize the (headcount) poverty rate at US$1.90 a day, as estimated by the percentage of the population living on less than $1.90 a day at the 2011 purchasing power parities (PPP) prices.[4] For richer analysis, we also employ other poverty lines of $3.20 and $5.50 a day. As alternative sources of poverty data, we also utilize two other

[4] The data are accessible on the Harvard Dataverse depository at https://doi.org/10.7910/DVN/MLHFAF.

sources: i) country-level poverty data from the World Bank World Development Indicators (WDI), which is a widely used database for global poverty measures, and ii) subnational GDP from Kalkuhl and Wenz (2020) and Kummu *et al.* (2020), which we further convert to poverty data. Panel A of Figure 1 shows that Sub-Saharan Africa currently has the highest poverty rates and the poorest countries include Tanzania (51.3 percent), Mozambique (54.7 percent), and the Democratic Republic of Congo (72.9 percent).

For inequality, we mostly employ the Gini index and Theil index, which are the most commonly used measures of income inequality. 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 2011 PPP dollars. Panel B of Figure 1 provides a global map of income inequality at the subnational level, which shows substantial variation of inequality across regions within a country.

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 (Dell *et al.*, 2014). 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.[5] For robustness tests, we use the global gridded data from Climate Research Unit of the University of East Anglia (CRU) available at 0.5° resolution. We provide a more detailed description of the data sources, including the list of the countries in each dataset and the summary statistics of the main variables in Appendix B.

[5] Auffhammer *et al.* (2013) find high correlations between ERA5 reanalysis data and weather station data for temperature, which further supports our study focus on temperature. However, we appear not to have similar supportive evidence for rainfall, particularly in poorer countries with limited ground station data.

3. Empirical Specifications

Different identification strategies were employed to estimate the effects of climate change on economic outcomes (Burke and Emerick, 2016; Dell *et al.*, 2014; Kolstad and Moore, 2020). Early studies mostly used a cross-sectional approach utilizing spatial variation at a point of time, comparing outcomes between hot and cold areas (Mendelsohn *et al.*, 1994; Schlenker *et al.*, 2005). Yet, a key assumption when estimating the coefficients of the climate-related variable from cross-sectional models is that climate change is not correlated with other unobservable factors. Violation of this assumption could result in an omitted variables problem, causing the estimated coefficient of interest to be biased. Therefore, 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):

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

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 (Auffhammer *et al.*, 2013; Dell *et al.*, 2012), we control for precipitation ($P_{i,t}$), measured in millimeters, 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).

For robustness, we also report Conley standard errors that allow for spatial correlation and arbitrary serial correlation in the error term (Conley, 1999). 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 (see, e.g., Burke and Emerick (2016)):

$$\Delta Y_i = \beta_{LD}\Delta T_i + \gamma_{LD}\Delta P_i + \omega_i \qquad (2)$$

In Equation (2), ΔY_i represents changes in poverty (or inequality) in the same location between two periods, and ΔT_i and ΔP_i are the corresponding changes in temperature and precipitation. 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 2003–2019, we analyze the differences between their averages of the earliest 3-year period 2003–2005 and their averages of the latest 3-year period 2017–2019 (e.g., $\Delta Y_{i,2003-2019} = \frac{\sum_{2017}^{2019} Y_{i,t}}{3} - \frac{\sum_{2003}^{2005} Y_{i,t}}{3}$). 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 (e.g., Chen and Gong, 2021; Mullins and White, 2020) that offers estimates of nonlinear effects:

$$Y_{i,t} = \sum_{j=1}^{12} \beta_{TB,j} T_{i,j,t} + \gamma_{TB} P_{i,t} + \alpha_i + \pi_t + \vartheta_{i,t} \tag{3}$$

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 18–21˚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

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

4. Results

4.1. Effects of temperature on poverty

We start examining the effects of temperature change on poverty using the country-level analysis (Panel A) and subnational level analysis (Panel B) in Table 1. We use the WDI database for the country-level analysis and our newly constructed database for the subnational analysis. We analyze three poverty indicators using the daily poverty lines of \$1.90, \$3.20, and \$5.50. For each outcome, we present the results of the fixed-effects panel model in Columns (1), (3), (5), followed by the results of the long differences model in Columns (2), (4), (6). 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 estimates at the subnational-level analysis (Panel B) have stronger magnitudes than those derived from the country-level analysis (Panel A). The differences between these two sets of estimates are statistically significant, which is confirmed by the t-tests for equality of the estimated coefficients shown at the bottom of Table 1. This suggests that studies using spatial aggregation of data at the country level could mask the impacts of warmer temperature. This finding is also consistent with previous studies showing more pronounced effects of temperature on economic growth at the subnational level (e.g., Damania *et al.*, 2020; Kalkuhl and Wenz, 2020).

We subsequently focus on the subnational analysis for interpreting the estimation results. In particular, Column (1) of Panel B shows that a 1˚C increase in temperature causes a 0.9 percentage point increase in poverty (at the daily \$1.90 poverty line). This equals a 9.1 percent increase in poverty using the mean poverty rate of 10.1 percent. For higher poverty lines, the impact magnitudes are higher in absolute terms (i.e., 1.8 percentage point and 2.3 percentage point increases for the daily poverty lines of \$3.20 and \$5.50, respectively) but are somewhat weaker in relative terms (i.e., the corresponding increases in poverty for these two poverty lines are respectively 9 percent and 6.8 percent).

Using the long differences model on the same data, we show the estimated longer-term effects of temperature on poverty in Columns (2), (4), and (6). The results are qualitatively similar, indicating positive and strongly statistically significant effects of higher temperature on poverty. However, the long differences coefficient estimates are smaller in absolute value than the corresponding panel FE coefficient estimates. Specifically, a 1˚C increase in temperature is estimated to result in a poverty increase of 0.5 percentage points (5.3 percent) (using the daily poverty line \$1.90) (Column 2). As shown by the t-tests at the bottom of Panel

B, the differences between the panel FE estimates and the long differences estimates are statistically significant, implying that longer-run household adaptation appears to have offset the negative short-run impacts of temperature on poverty by 0.4 percentage point (or 3.8 percent).[6] These findings are consistent with previous studies that show the role of household adaptation in mitigating the negative effects of temperature on economic production, agriculture, and human capital (e.g., Chen and Gong, 2021; Graff Zivin *et al.*, 2018; Kalkuhl and Wenz, 2020).

While we focus on the impacts of temperature on poverty, Table 1 also reveals significant, but mixed, effects of precipitation. We find higher rainfall to be associated with 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).[7] This ambiguity is, however, perhaps consistent with previous findings showing both negative impacts (Damania *et al.*, 2020; Kotz *et al.*, 2022) and positive impacts (Burke *et al.*, 2015b; Dell *et al.*, 2012) of rainfall on economic growth.

4.2. Effects of temperature on inequality

We show in Table 2 the estimates on the effects of warmer temperature on income inequality at both the country-level and subnational level, which are strongly statistically significant. In particular, a 1˚C increase in temperature is estimated to result in an increase of 0.29 percentage point (0.8 percent) in the Gini index (Column 1 of Panel B), and an increase of 0.35 percentage point (1.4 percent) in the Theil index (Column 3 of Panel B). Similar to the estimation results for poverty (Table 1), the estimates at the subnational-level analysis (Panel B) are stronger than those obtained at the country-level analysis (Panel A). These results provide supportive

[6] The long differences estimation results are based on a much smaller sample size compared with the panel FE model. To address this issue, we employ the same sample sizes used in the long-differences model and rerun regressions using the panel FE model. The results, presented in Table A1 (Appendix A), are qualitatively similar to those shown in Tables 1 and 2.

[7] In addition, we employ alternative rainfall functions, including the quadratic term and the deviation of rainfall from the long-term mean, but still find similar results.

evidence for our earlier discussion that global warming might exacerbate income inequality because poorer countries or individuals could be more vulnerable to climate change.

Indeed, our findings concur with previous studies, which find negative effects of hotter temperature on various economic outcomes. For example, recent studies by Hsiang (2010), Dell *et al.* (2014), and Deryugina and Hsiang (2014) have discovered that a 1°C increase in temperature are associated with losses in, respectively, industrial output (2.5 percent), average country-level GDP per capita (1.0 percent), and county-average income per capita (1.7 percent). Our results are also qualitatively similar to, but offer slightly smaller estimates than, those found in Paglialunga *et al.* (2022), which show a one percent temperature increase to be associated with 0.5 percentage point increase in the Gini index.

To investigate the potential long-run effects, we estimate Equation (2) and present the results in Columns (2) and (4) of Table 2. We document strong and statistically significant effects of hotter temperature on income inequality for both country-level analysis and subnational-level analysis and both measures of inequality. Again, we also find the effects at the subnational level to be stronger than those at the country level. Specifically, higher temperature by 1°C is found to increase the Gini index and the Theil index by 0.35 (1 percent) and 0.59 (2.3 percent) percentage points (Panel B, Columns 2 and 4). Comparing the panel FE and long differences models, the magnitudes of effects appear larger for the latter. This may suggest inequality could accumulate over the longer term (i.e., intensification of negative effect). But we also note that the t-tests for the differences with the two models are only statistically significant for the Theil index with the subnational analysis, but not for the Gini index (and the country-level analysis).

4.3. Nonlinear effects

The effects of hotter temperature on poverty and income inequality discussed earlier are linear. To allow for a more flexible functional form of temperature, we assess the potential for nonlinear effects by specifying temperature as a series of indicator variables corresponding to 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 2 displays the point estimates and the 95% confidence intervals of these temperature bins, using Equation (3). Again, the results provide strong evidence for temperature effects, suggesting that one additional day of hotter temperature will lead to higher poverty and inequality, and the estimates are statistically significant at the 5 percent level. The magnitudes of the effects are generally consistent across hotter temperature bins. These results are consistent with our earlier findings of negative effects of warmer temperature.

Furthermore, the results in Figure 2 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 (Cook and Heyes, 2020; Dell *et al.*, 2012; Deschênes and Moretti, 2009) and add fresh evidence for the impacts of colder weather on poverty and inequality. Since adaptation to colder weather differs from those to hotter weather, our results imply that the distributional effect of temperature should be considered when designing mitigation policies.

Finally, we consider the model specification that controls for a series of lag of temperature bins (Equation 4). This approach offers insight into the cumulative effects of extreme temperature on income inequality. The estimated cumulative effects of temperature remain negative and slightly increase in magnitude compared to the contemporaneous effects as shown in Figure 2. In summary, our results 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, and such effects are documented in both the short-term and long-term.

4.4. Robustness tests and heterogeneity analysis

To investigate the robustness of the finding of negative temperature effects on poverty and inequality, we conduct a number of additional analyses. We briefly summarize the main results here and offer more detailed discussion in Appendix C.

First, we use several variants of the panel FE and long differences models, which include adding country-specific linear time trends, controlling for temperature change, adding a quadratic or cubic term of temperature, adding an interaction term between temperature and temperature change, and using difference choices of window. We also use alternative thresholds to define hotter and colder days in the temperature bin approach. Next, we exploit different subsamples and alternative data sources and measures of temperature.[8] Finally, we conduct a placebo test by using within-sample randomization of temperature. Overall, the results of these exercises remain similar to our main findings.

We also offer further heterogeneity analysis across regions. We employ the temperature bin approach to consider the non-linearity of temperature effects and plot the results in Figure 3. It shows that rising temperature causes higher poverty (Panel A) and inequality (Panel B) in poorer regions such as Sub-Saharan Africa, Middle East and North Africa, and South Asia, but the effects are attenuated in the other richer regions. Furthermore, we also document negative effects of colder temperature on both outcomes, particularly in Europe and Central Asia. We further estimate temperature effects for each country. Plotting the results where each country's

[8] These include using (i) log of temperature; (ii) temperature measured in degrees Fahrenheit; (iii) the temperature data from CRU; (iv) the number of days that temperature is above 28°C; (v) dropping regions with temperature being above that level; and (vi) temperature shock, defined as the difference between actual temperature and long-term temperature being greater (less) than 2 (-2) standard deviations (Appendix A, Table A4).

marker is proportional to its real GDP per capital, Figure A5 (Appendix A) shows that countries bearing the largest effect of global warming (e.g., Uganda, Ghana, and Mozambique) also tend to be poorer or located in poorer regions.

Furthermore, we explore different country characteristics that might help mitigate temperature effects. Employing a democracy index that categorizes countries into democracies, authoritarian regimes, and hybrid regimes, we find that countries with democratic regimes appear to be less vulnerable to the impacts of global warming. Additionally, we observe that temperature effects are stronger in countries with higher shares of agriculture and are weaker in countries with higher shares of manufacturing. These findings suggest that institutions could play important roles in mitigating the effects of global warming on different countries and regions.[9]

5. Further analysis

5.1. Potential mechanisms and projected impacts under future climate change

Having demonstrated strong evidence of temperature effects on poverty and inequality at the subnational level, we further explore agriculture as a potential mechanism. Agriculture plays an important role in poverty reduction for various reasons. The majority of the global poor live in rural areas where agriculture is the predominant form of economic activity and agricultural growth is more effective at reducing poverty than non-agricultural growth; moreover, poorer households are more vulnerable to increases in food prices (Hertel and Rosch, 2010; Hallegate *et al.*, 2016). We analyze the global dataset of historical yields from Iizumi and Sakai (2020), which provides actual crop yields at 0.5° resolution for the period 1981-2016. Using the panel FE and long differences models as with Equations (1) and (2), we find negative effects of higher

[9] We also investigate the role of information and communication technologies (ICTs) in poverty reduction by providing access to markets, decreasing transaction costs, and increasing income for a significant proportion of people living in developing countries (World Bank, 2016). Our results show that regions with better access to ICT are less vulnerable to the effects of higher temperature.

temperature on different crop yields including rice, maze, and soybean, as shown in Table A11 (Appendix A). Again, we find the long differences model estimates to be smaller than the panel FE model estimates, which are in line with previous studies showing potential adaptation in the long run (e.g., Chen and Gong, 2021). We also document the heterogenous effects of hotter temperature and discuss the results in Appendix D.[10]

We next provide projections of the effects of future temperature on poverty to better understand potential effects under different scenarios. We focus on two climate change scenarios—the RCP4.5 and RCP8.5—which are two extreme emission pathways that represent opposite ends of the climate spectrum depending on the uptake of renewable energy.[11] Tables A13 and A14 (Appendix A) provide a summary of the projected changes for temperature for these scenarios in the short, medium, and long terms, where temperature can increase by between 2.6˚C and 6.0˚C in 2099. These temperature increases can result in poverty increases between 1.4 and 3.1 percentage points (i.e., 13.6 and 31.1 percent increases) (Appendix A, Table A13). Similarly, the simulated effects on inequality are estimated to be between 0.4 and 2.1 percentage point increases in Gini index (i.e., 1.2 and 5.9 percent increases) (Appendix A, Table A14). In both cases, the largest poverty and inequality increase would occur in the scenario without any countervailing strategies based on renewable energy to address climate change between 2021 and 2099.[12]

[10] As another potential mechanism, we explore subnational migration flow between the period 2005 and 2010. Using a simple OLS regression, we find some suggestive evidence that hotter temperature could lead to more migration (Appendix A, Figure A8). However, since migration could help households obtain better economic opportunities and escape poverty, our estimation results could be considered as the net impacts of hotter temperature (after factoring in the beneficial effects of migration on poverty reduction).
[11] The Representative Concentration Pathway (RCP) model captures future trends in climate change under alternative scenarios of human activities. RCP8.5 tracks emissions consistent with current trends (business as usual scenario in which greenhouse gas emissions go unchecked), while RCP4.5 considers a scenario with increased reliance on renewable energy and less reliance on coal-fired power (IPCC, 2021).
[12] We also note that our projection of future impacts might be influenced by various other factors. For example, changes in ecosystems or global food production and sea level rises may amplify or lessen these effects, rendering the task of projecting the potential consequences of climate change extremely complicated.

5.2. Back-of-the-envelope cost analysis

We next perform some rough calculations to help compare the costs of impeding temperature rise against that of eradicating poverty. Among the various measures for mitigating the effects of global warming, reducing carbon emissions such as carbon dioxide (CO_2), methane, and nitrous oxide, is deemed crucial. The Intergovernmental Panel on Climate Change (IPCC) reports that limiting global warming to 1.5°C by 2030 would require reducing CO_2 emissions by approximately 45 percent compared to 2010 levels and achieving net-zero emissions by 2050 (IPCC, 2018). This ambitious target is estimated to require a $US50 trillion investment in zero-carbon technology (Morgan Stanley, 2019).

Using the estimated effects of temperature on poverty reported in Table 1 Column (2) (i.e., 0.53 percentage point increase in poverty per one-degree increase in temperature), we estimate that the poverty headcount ratio at US$1.90 a day would increase by 0.8 percentage point (an 8 percent increase) by 2030 if the temperature increases by 1.5°C. To counteract this rise in poverty, using Lakner *et al.*'s (2022) estimates, we calculate that the global GDP would have to increase by approximately 1.08 percent, or around $US1.12 trillion (based on the estimated global GDP of $US103.86 trillion in 2022). Although this estimated figure only amounts to 2 percent of the investment cost of $US50 trillion, our analysis does not consider the positive externalities of poverty elimination on other welfare outcomes, such as improved health and subjective well-being, or the beneficial impacts of poverty reduction on growth in the longer term (Thorbecke and Ouyang, 2022).

To further our investigation, we estimate the allocation of costs for each country according to their respective contribution to warmer temperature. To provide a back-of-the-envelope estimate of this allocation, we use the share of CO_2 emissions across countries from 1975 to 2022 (Friedlingstein et al., 2022). Table A15 (Appendix A) indicates a wide range of contribution shares for countries: while low-income countries should contribute less than 1 percent of the total costs, this figure increases to 10 percent, 29.7 percent, and 59.5 percent for lower-middle income, upper-middle income, and high-income countries, respectively. We plot in Figure A11 (Appendix A) more detailed estimates for each country.

6. Conclusions

While there is growing evidence of harmful effects of climate change on macro-economic outcomes, little evidence exists regarding the impacts of warmer temperature on poverty and inequality on a global scale. A notable challenge is the absence of data at a disaggregated level that can allow for more accurate analysis of this relationship both within and across countries. Analyzing a new global panel dataset representative of subnational areas in 134 countries that we constructed, we find both hotter and colder temperature to result in higher poverty rate and inequality. We find stronger effects at the subnational level, which implies that country-level analysis does not reveal the true estimate of the global warming consequences. We also find significant, but smaller, effects of temperature in the long run, which suggests that households likely adapt to permanent changes in weather conditions.

Our findings add to the ongoing discussion of richer countries' responsibilities in mitigating the global effects of climate change. Over the last decades, poorer countries have been calling for compensation for the costs of climate change (also known as "climate reparations") from wealthier nations, who are generally considered to be more responsible for global climate change. Our study contributes to this discussion by offering new global evidence that poorer regions are bearing the heaviest burden of global warming, and thus richer countries could provide further support in order to reduce the effects of climate change.

The availability of subnational poverty data opens other avenues for future research. While our study provides supportive evidence that agriculture is an important factor influencing climate-induced poverty and inequality, alternative channels, such as civil conflicts and labor productivity, could offer another direction. Further research on these topics would help provide policy inputs for more effective actions by different countries to address the challenge of global warming.

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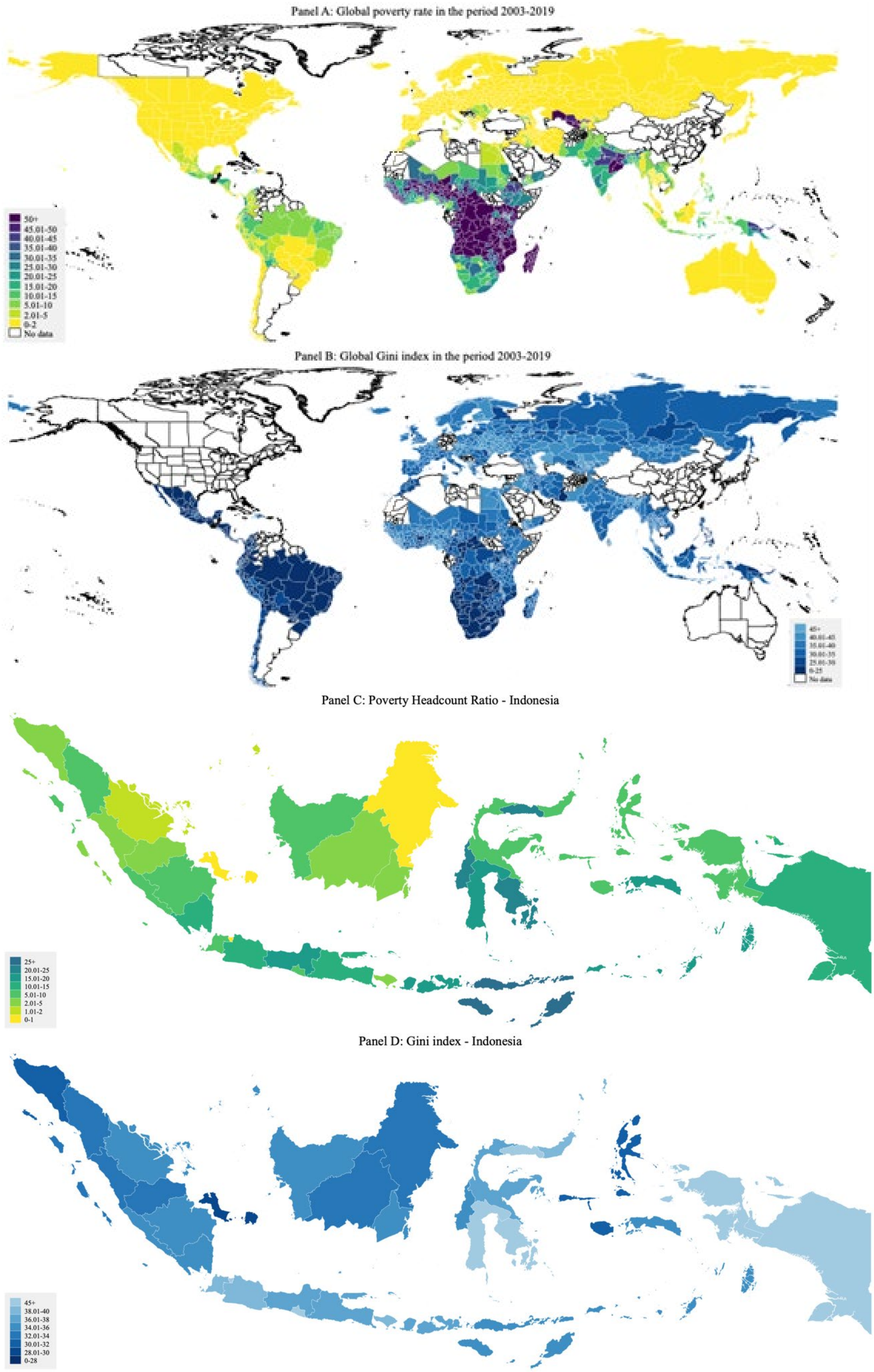
Figure 1: Global and subnational poverty and temperature

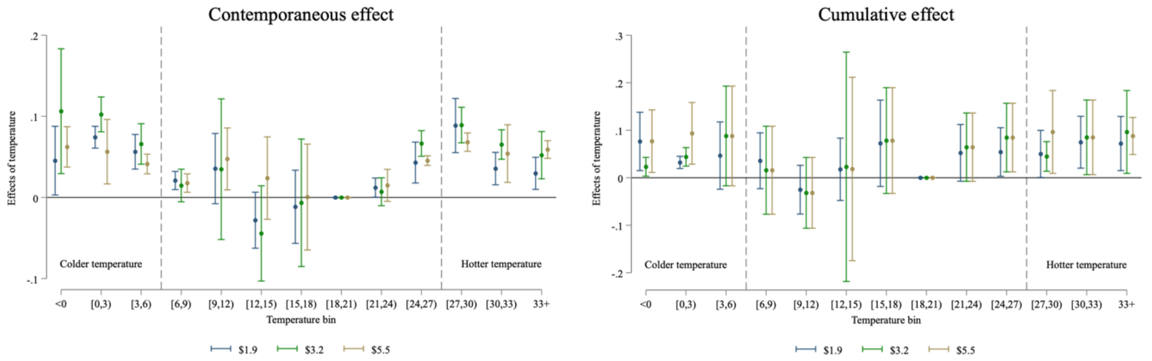


Panel E: Average temperature - Indonesia

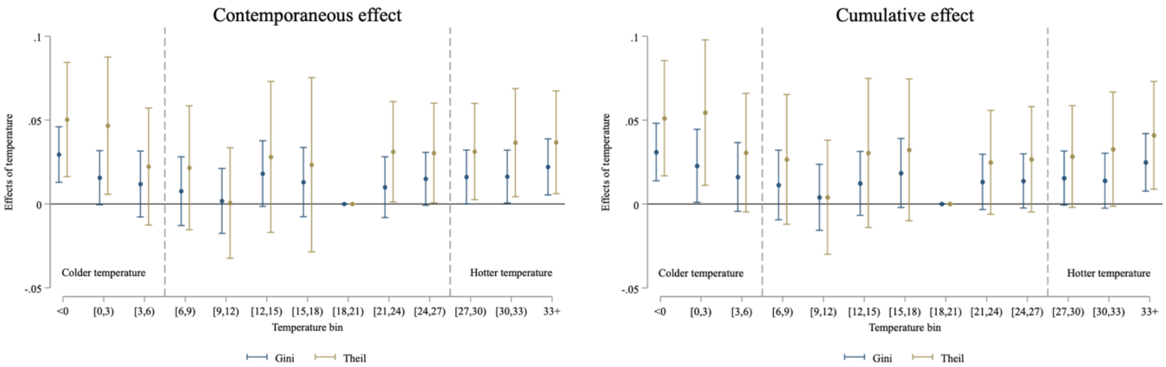
Notes: Poverty is measured by Global Subnational Poverty Headcount Ratio using the daily threshold of US$ 1.90. Inequality is measured by the Gini index. Temperature data is taken from the European Centre for Medium-Range Weather Forecasts Reanalysis 5 (ERA-5). Data on simulated weather conditions at the subnational level are from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP). Poverty rate, inequality and temperature data are measured in the period 2003 – 2019.

Figure 2: Nonlinear effects of temperature on poverty and inequality

Panel A: Poverty



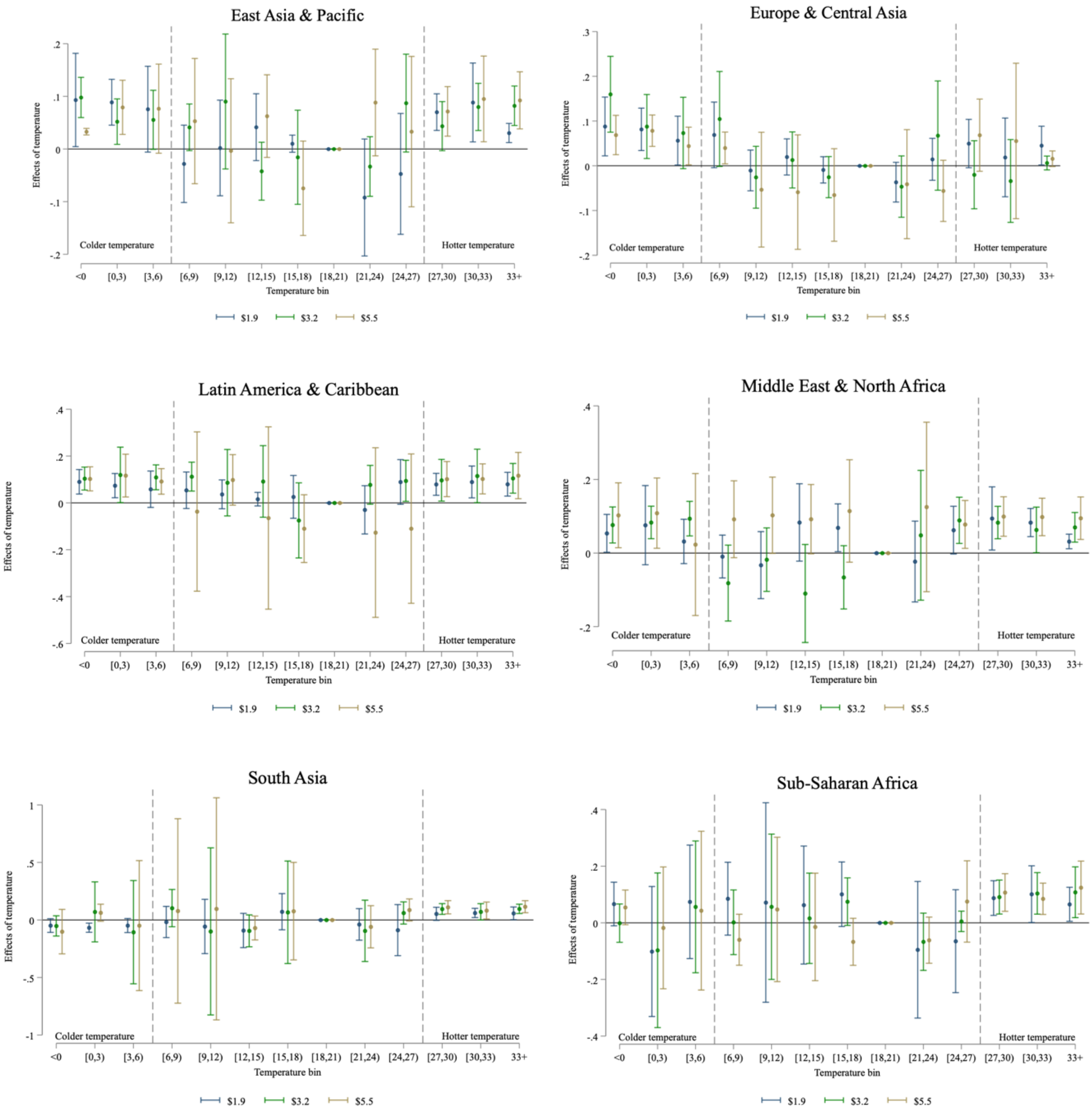
Panel B: Inequality



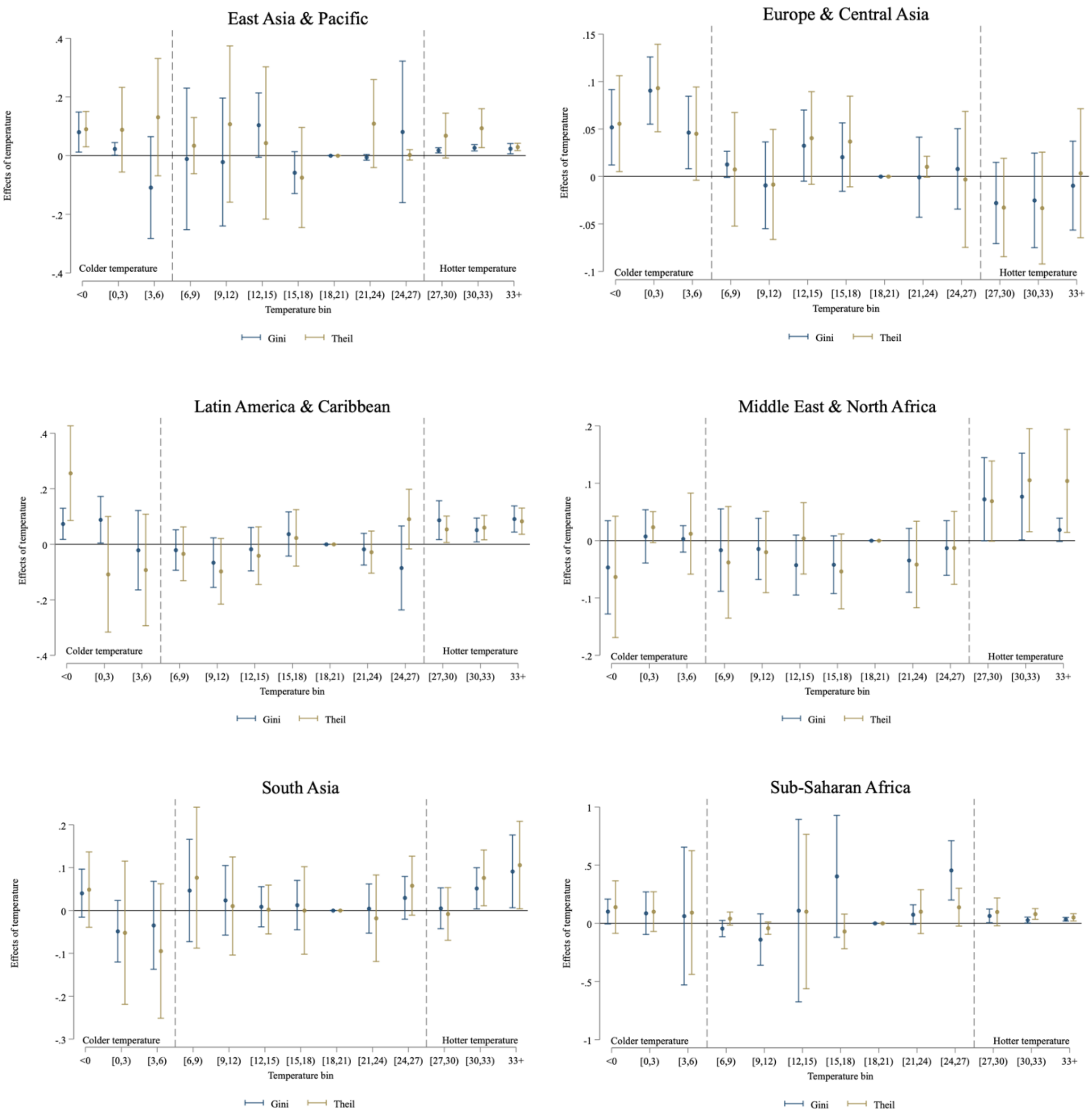
Notes: The figures show the point estimates and their 95 percent confidence intervals of temperature bins using regression with rainfall and subnational fixed effects. Robust standard errors are clustered at the subnational level. Regressions are weighted by region population. The reference temperature bin is [18,21). The cumulative effects are obtained by estimating the model with four 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 3: Heterogeneity analysis

Panel A: Effects of temperature on poverty by region



Panel B: Effects of temperature on inequality by region



Notes: The figures show the point estimates and their 95 percent confidence intervals of temperature bins using regression with rainfall and subnational fixed effects. Robust standard errors are clustered at the subnational level. Regressions are weighted by region population. 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., greater than 27°C) and bottom decile (i.e., less than 6°C) of the temperature range, respectively.

Table 1: The effects of temperature on subnational poverty

Poverty:	$1.90/day		$3.20/day		$5.50/day	
	Panel FE – all countries	Long differences	Panel FE – all countries	Long differences	Panel FE – all countries	Long differences
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Country-level analysis						
Temperature	0.681***	0.235***	1.085***	0.409***	1.397***	0.528***
	(0.107)	(0.029)	(0.165)	(0.044)	(0.233)	(0.058)
Precipitation	-0.023	0.117	-0.021	-0.011	-0.011	-0.054
	(0.018)	(0.279)	(0.031)	(0.400)	(0.039)	(0.441)
Country FE	Yes	No	No	No	Yes	No
Year FE	Yes	No	No	No	Yes	No
Mean dependent var.	7.288	7.288	15.399	15.399	26.593	26.593
Observations	464	95	464	95	464	95
Equality test (Panel vs. long differences)	p = 0.000		p = 0.000		p = 0.000	
Panel B: Subnation-level analysis						
Temperature	0.920***	0.535***	1.834***	1.240***	2.298***	2.008***
	(0.160)	(0.039)	(0.214)	(0.070)	(0.308)	(0.108)
Precipitation	0.236***	-0.365***	0.373**	-0.486***	-0.072	-0.177
	(0.069)	(0.092)	(0.166)	(0.142)	(0.160)	(0.248)
Subnational FE	Yes	No	Yes	No	Yes	No
Year FE	Yes	No	Yes	No	Yes	No
Mean dependent var.	10.061	10.061	20.327	20.327	34.009	34.009
Observations	4,972	1,109	4,972	1,109	4,972	1,109
Equality test (Panel vs. long differences)	p = 0.000		p = 0.000		p = 0.016	
Equality test (country vs. subnational)	p = 0.014	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Number of countries	134	95	134	95	134	95
Number of regions	1,594	1,109	1,594	1,109	1,594	1,109

Notes: Robust standard errors in parentheses. Standard errors are clustered at the subnational level. Regressions are weighted by region population. Poverty data are taken from the WDI (Panel A) and GSAP (Panel B). 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 data for the country-level analysis and the subnational-level analysis comes from our newly constructed database. The equality test p-values show the t-test between the panel FE results vs. the long differences results, and the country analysis results vs. the subnational analysis results. *** p<0.01, ** p<0.05, * p<0.1.

Table 2: The effects of temperature on subnational inequality

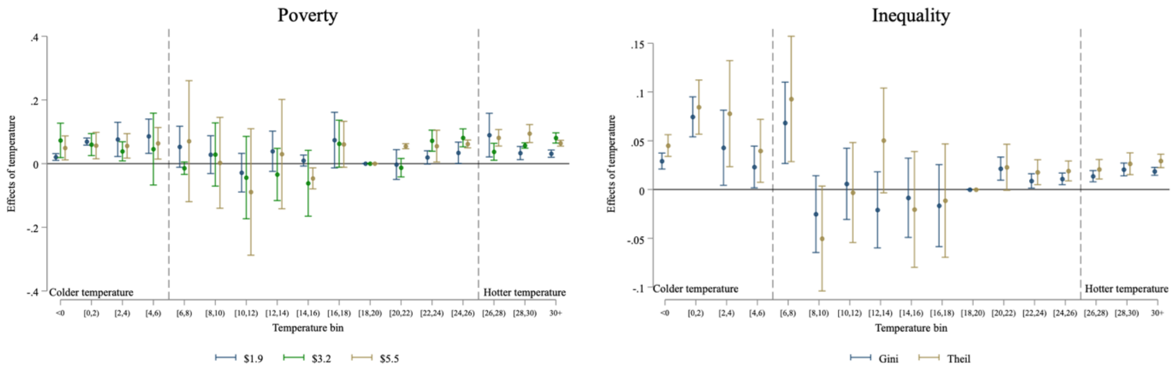
Inequality:	Gini		Theil	
	Panel FE – all countries (1)	Long differences (2)	Panel FE – all countries (3)	Long differences (4)
Panel A: Country-level analysis				
Temperature	0.154***	0.171***	0.253***	0.275***
	(0.029)	(0.040)	(0.049)	(0.063)
Precipitation	0.002	0.025**	-0.002	0.031
	(0.007)	(0.012)	(0.012)	(0.021)
Country FE	Yes	No	Yes	No
Year FE	Yes	No	Yes	No
Mean dependent var.	34.406	34.406	23.417	23.417
Observations	423	90	423	90
Equality test (Panel vs. long differences)	p = 0.726		p = 0.604	
Panel B: Subnation-level analysis				
Temperature	0.285***	0.349***	0.350***	0.592***
	(0.086)	(0.049)	(0.032)	(0.082)
Precipitation	-0.156**	0.474***	0.267**	0.699***
	(0.072)	(0.100)	(0.110)	(0.170)
Subnational FE	Yes	No	Yes	No
Year FE	Yes	No	Yes	No
Mean dependent var.	35.605	35.605	25.383	25.383
Observations	4,129	1,019	4,129	1,019
Equality test (Panel vs. long differences)	p = 0.383		p = 0.029	
Equality test (country vs. subnational)	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Number of countries	128	90	128	90
Number of regions	1,484	1,019	1,484	1,019

Notes: Robust standard errors in parentheses. Standard errors are clustered at the subnational level. Regressions are weighted by region population. Inequality data are taken from the GSAP. 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 data for the country-level analysis and the subnational-level analysis comes from our newly constructed database. The equality test p-values show the t-test between the panel FE results vs. the long differences results, and the country analysis results vs. the subnational analysis results. *** p<0.01, ** p<0.05, * p<0.1.

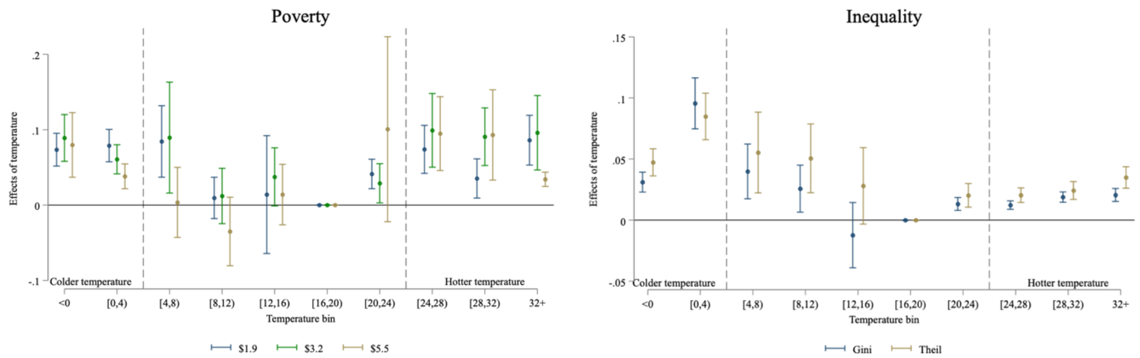
Appendix A: Additional Tables and Figures

Figure A1: Alternative temperature bin

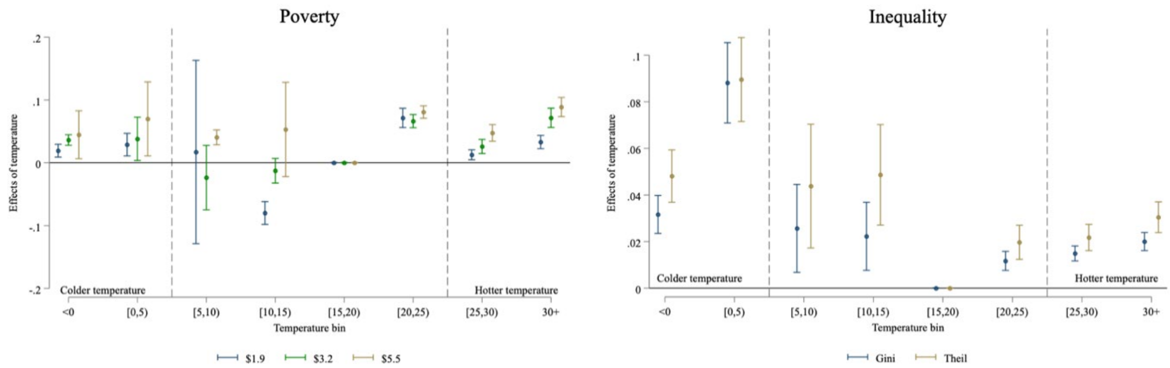
Panel A: 2-degree bin



Panel B: 4-degree bin



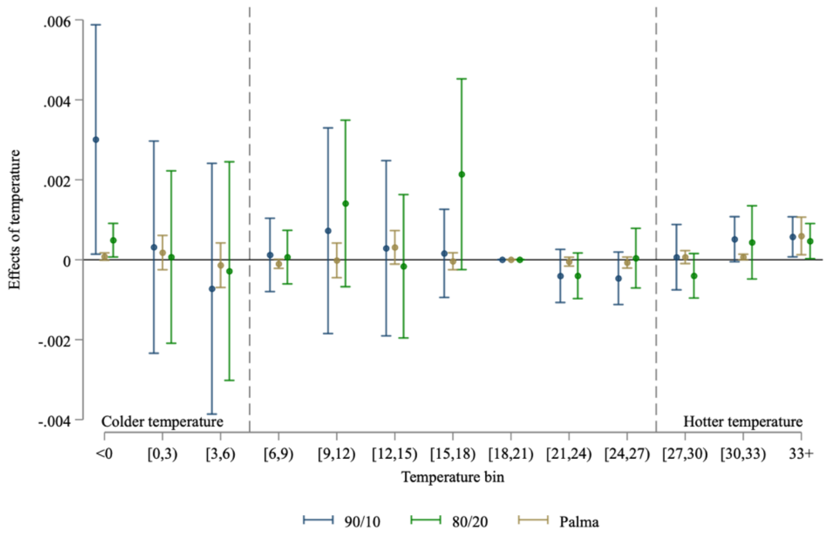
Panel C: 5-degree bin



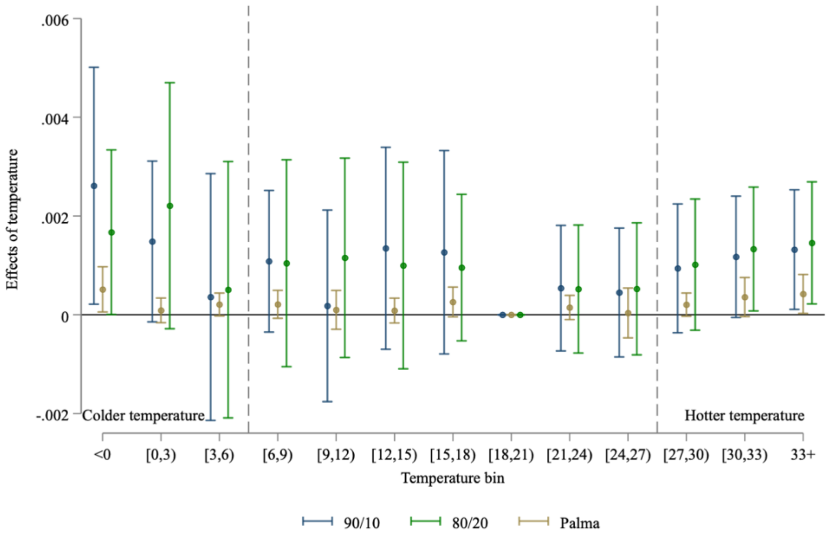
Notes: The figures show the point estimates and their 95 percent confidence intervals of temperature bins using regression with rainfall and subnational fixed effects. Robust standard errors are clustered at the subnational level. Regressions are weighted by region population. Hotter temperature and 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 A2: Alternative measures of inequality

Panel A: Contemporaneous effect



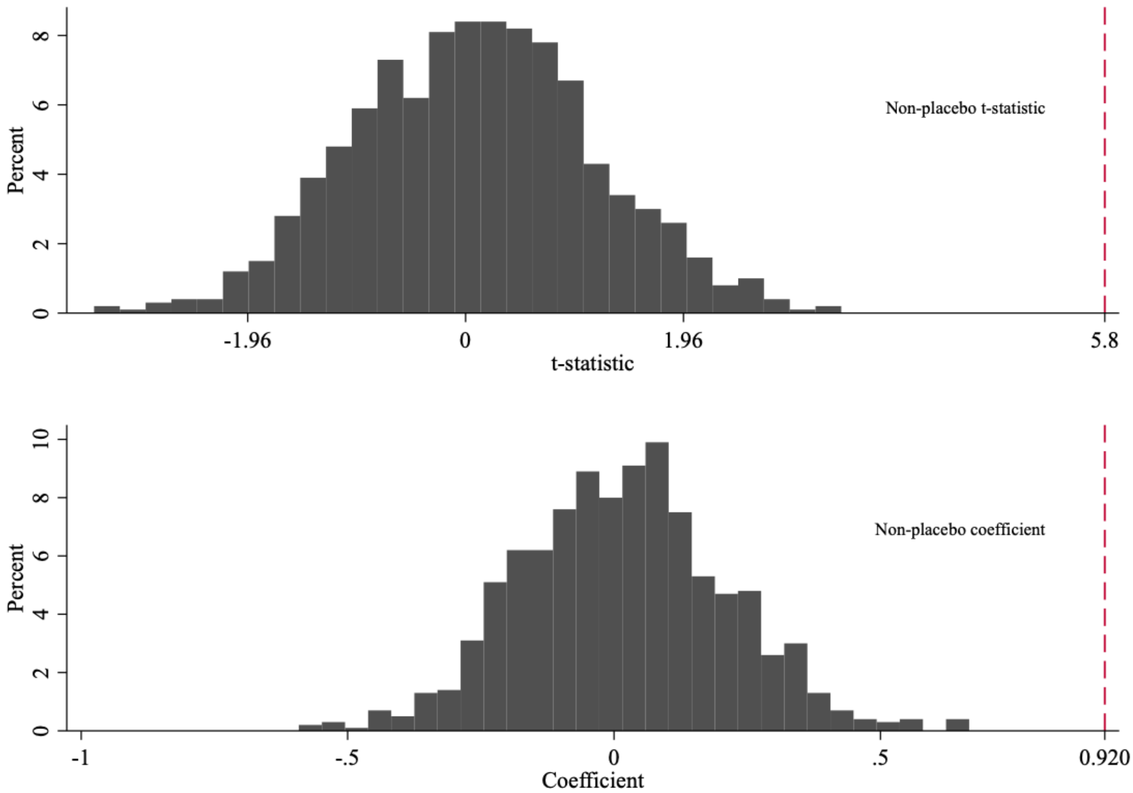
Panel B: Cumulative effect



Notes: The figure shows the point estimates and their 95 percent confidence intervals of temperature bins using regression with rainfall and subnational fixed effects. Robust standard errors are clustered at the subnational level. Regressions are weighted by region population. The reference temperature bin is [18,21). The cumulative effects in Panel B are obtained by estimating the model with four 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.

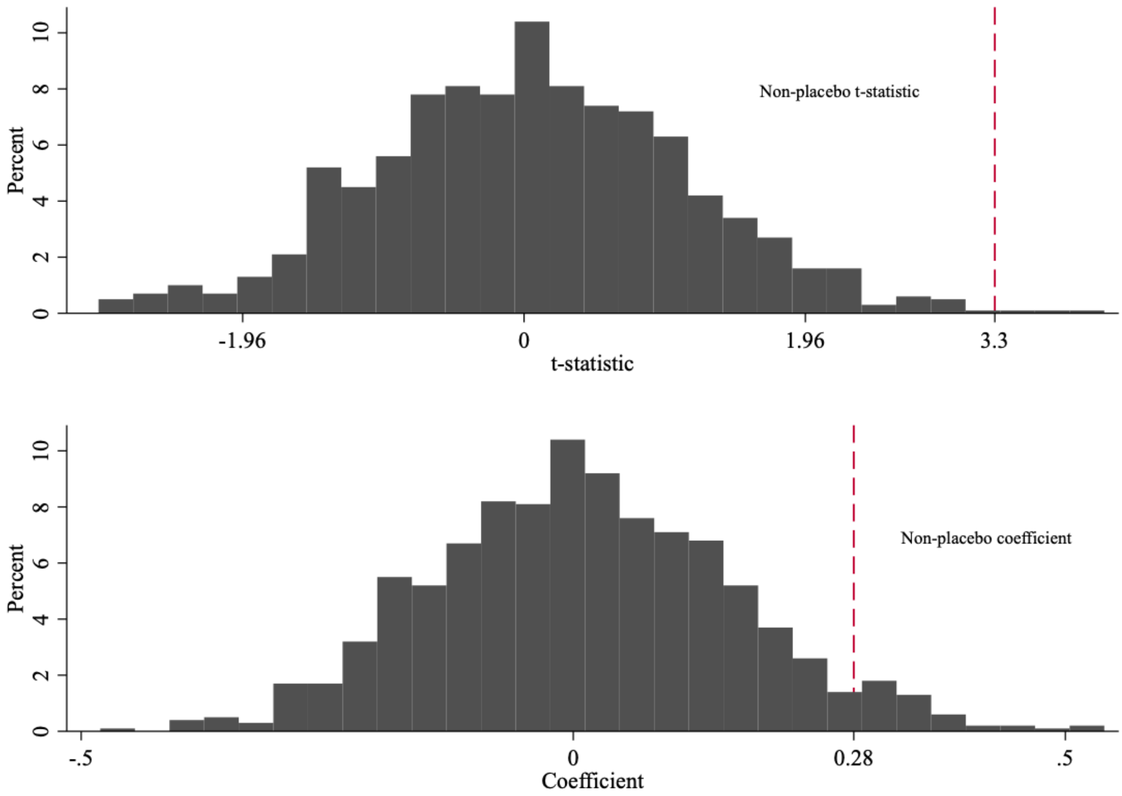
Figure A3: Placebo test

Panel A: Poverty



Notes: Results of placebo exercise using 1,000 randomizations of regions. The outcome is poverty headcount ratio at $1.90. All regressions include precipitation and subnational fixed effects. Regressions are weighted by region population.

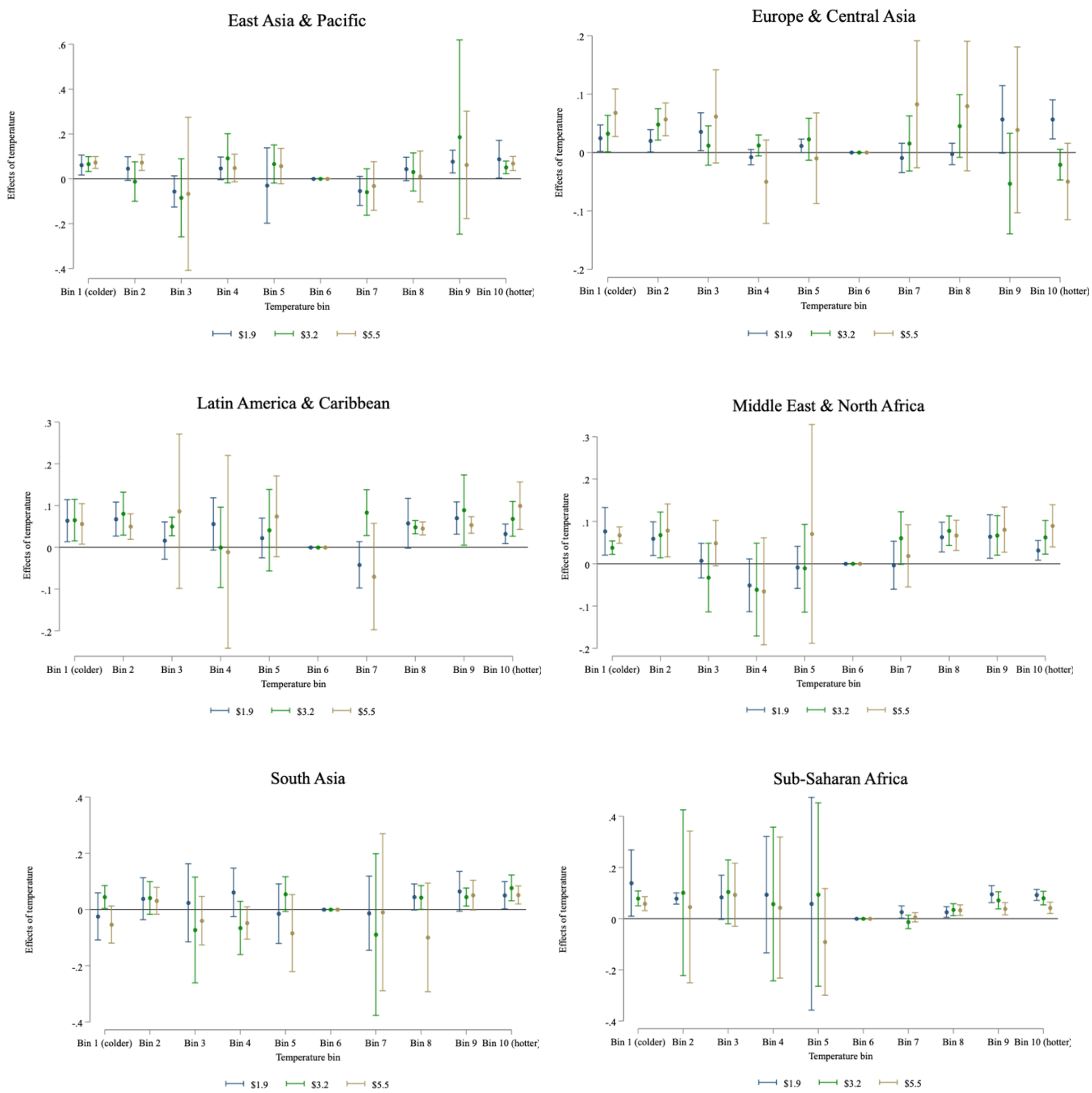
Panel B: Inequality



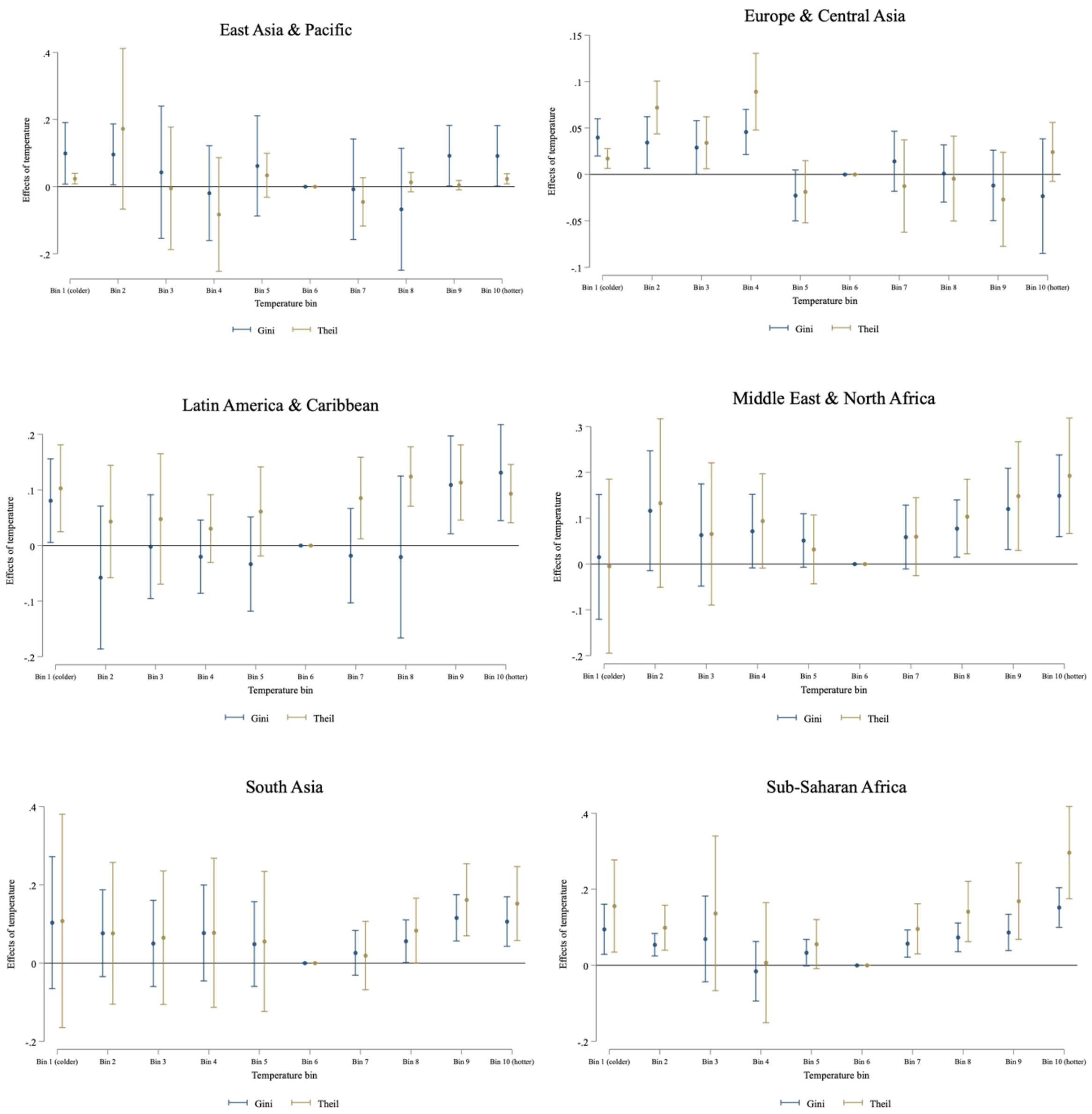
Notes: Results of placebo exercise using 1,000 randomizations of regions. The outcome is Gini index. All regressions include precipitation and subnational fixed effects. Regressions are weighted by region population.

Figure A4: Heterogeneity analysis using regional temperature

Panel A: Poverty



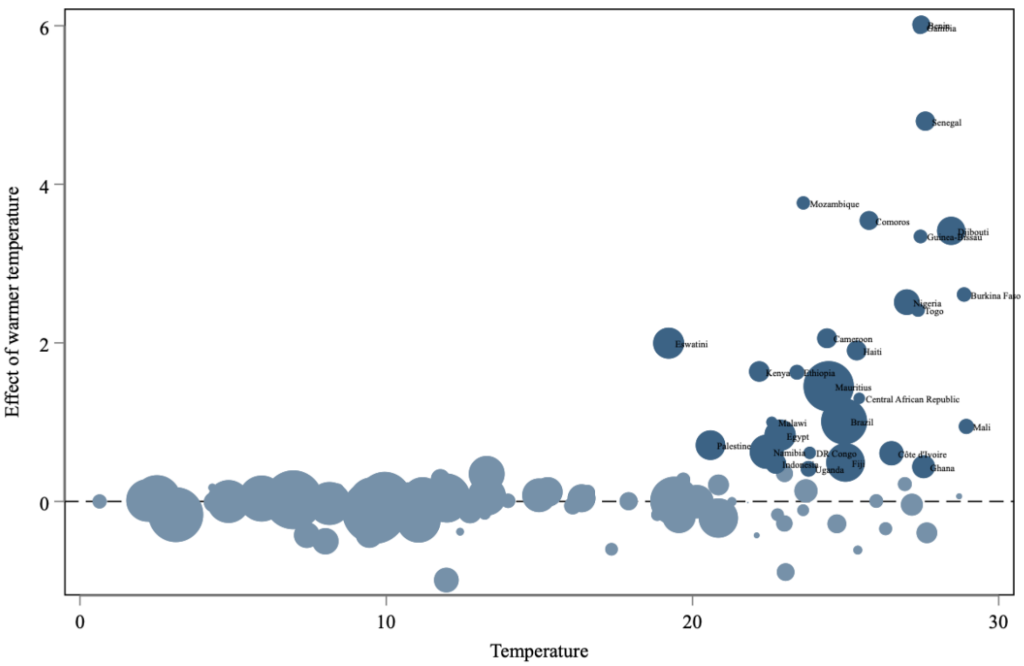
Panel B: Inequality



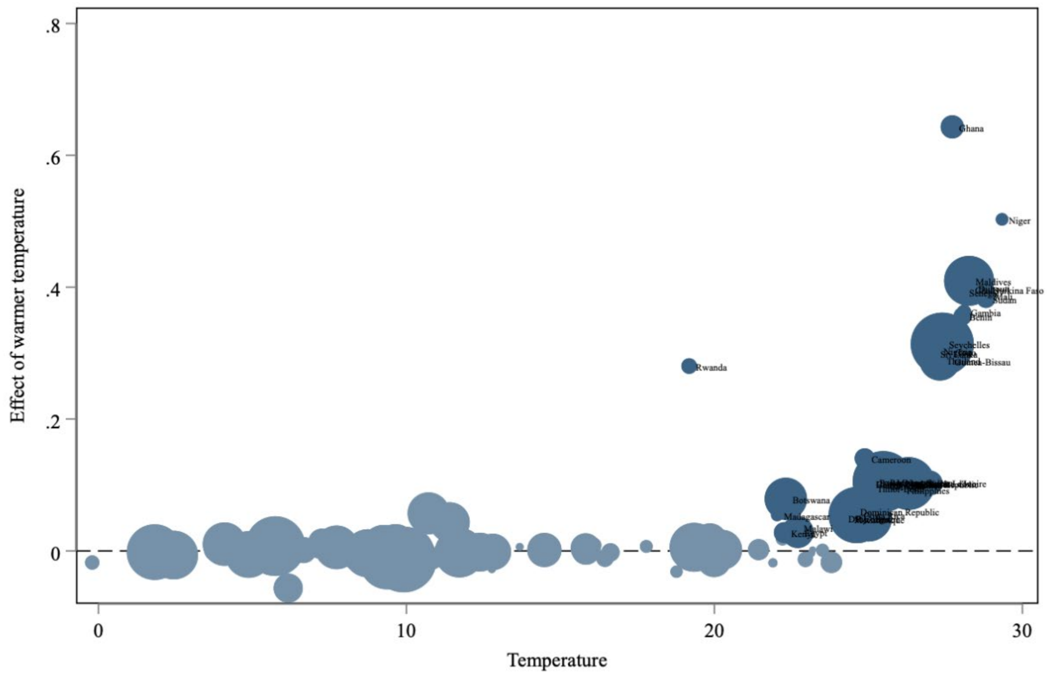
Notes: The figure shows the point estimates and their 95 percent confidence intervals of temperature bins using regression with rainfall and subnational fixed effects. Robust standard errors are clustered at the subnational level. Regressions are weighted by region population. Temperature bins are identified 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.

Figure A5: The effects of temperature on poverty and inequality across countries adjusted by real GDP

Panel A: Poverty



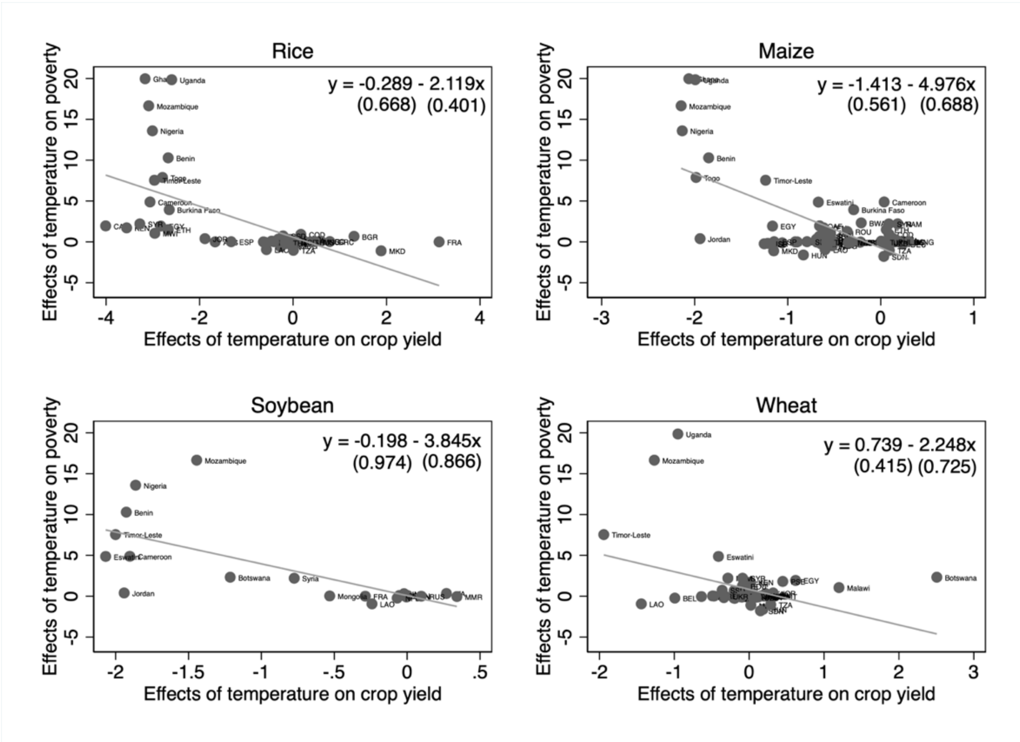
Panel B: Inequality



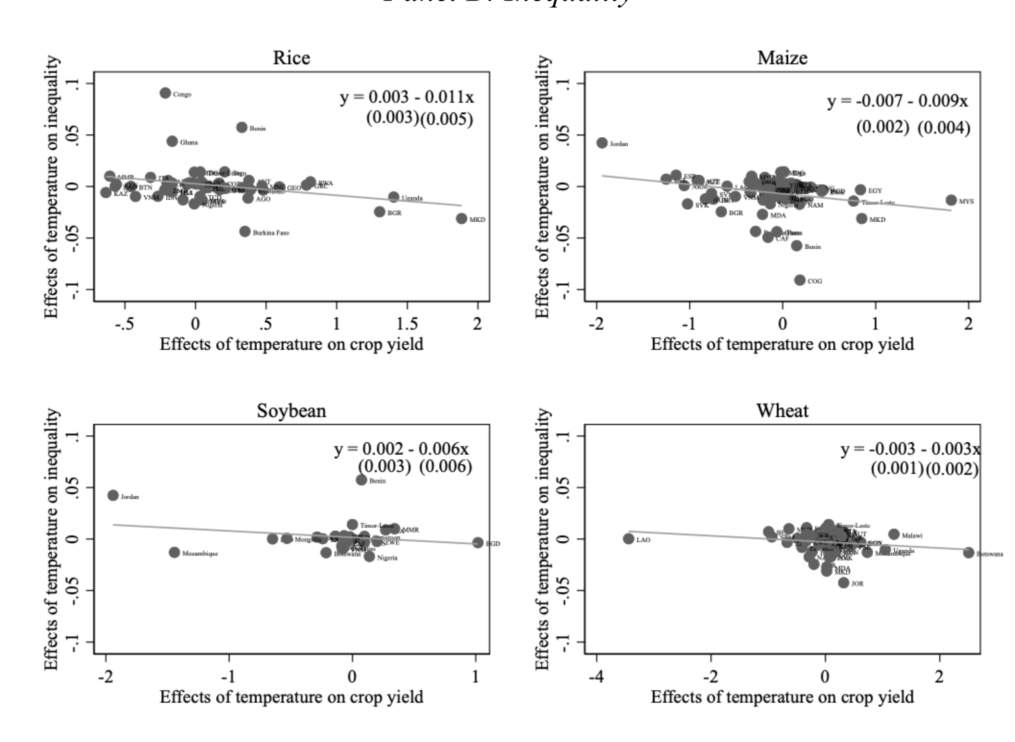
Notes: Poverty rate is measured by the Subnational Poverty Headcount Ratio at $1.90 a day. Inequality is measured by the Gini index. The figure shows the point estimates of temperature and the country dummies using regression with control variable and subnational fixed effects. Each country's marker is proportional to its real GDP per capital using the WDI database (i.e., a larger size indicates a higher GDP per capita level).

Figure A6: The effects of temperature on poverty/inequality and agriculture

Panel A: Poverty



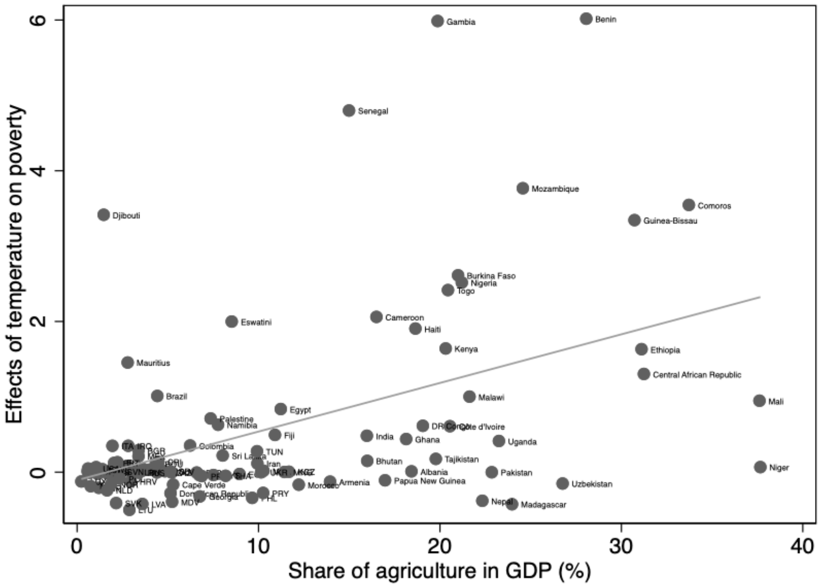
Panel B: Inequality



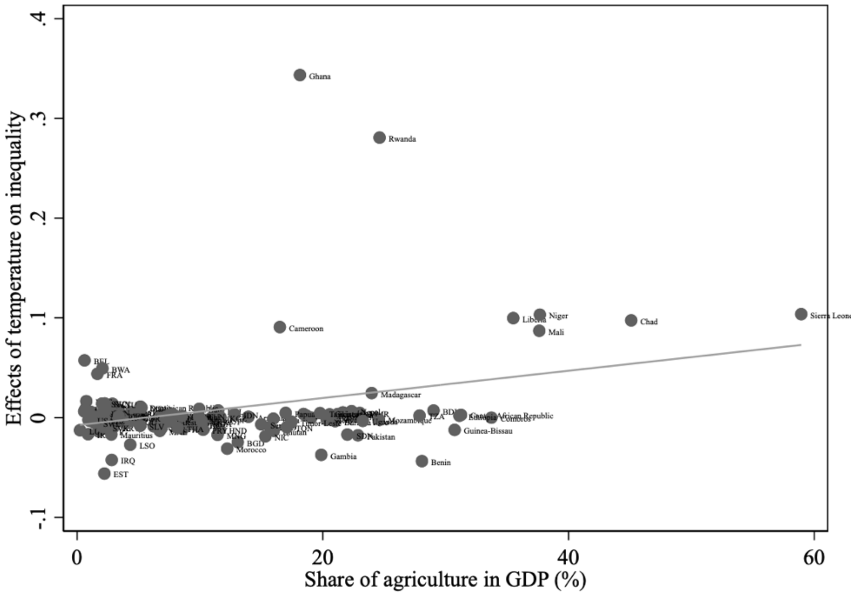
Notes: The figure shows the point estimates of temperature effects on poverty and inequality (y-axis) and crop yield (x-axis) using regressions with control variable and subnational fixed effects. We then use an OLS regression of the poverty (inequality) effects on crop yield effects. Standard errors are in parentheses. Poverty is measured by the headcount ratio at $1.90 a day. Inequality is measured by the Gini index. Crop yield data is provided by Iizumi and Sakai (2020).

Figure A7: The effects of temperature on poverty and inequality by share of agriculture

Panel A: Poverty

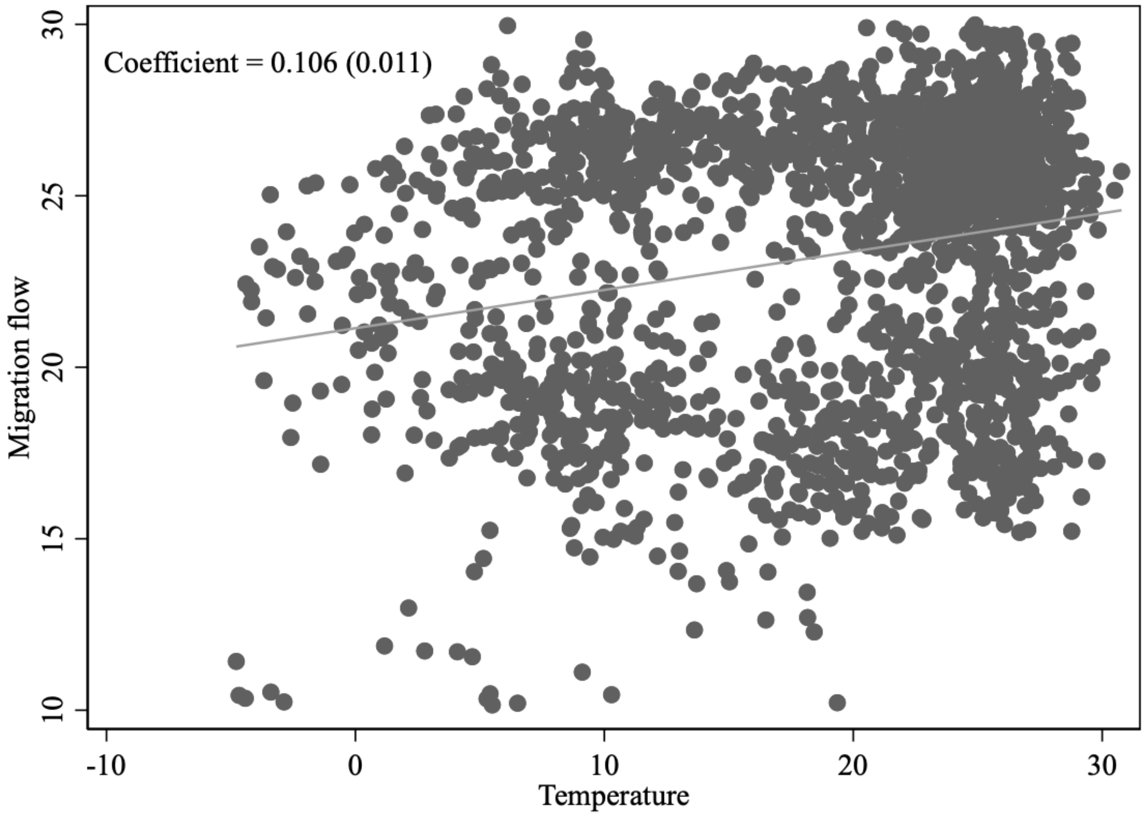


Panel B: Inequality



Notes: The figure shows the point estimates of temperature effects on poverty and inequality (y-axis) and share of agriculture in GDP (x-axis) using regressions with control variable and subnational fixed effects. Poverty rate is measured by the Subnational Poverty Headcount Ratio at $1.90 a day. Inequality is measured by the Gini index. Share of agriculture in GDP is taken from WDI database.

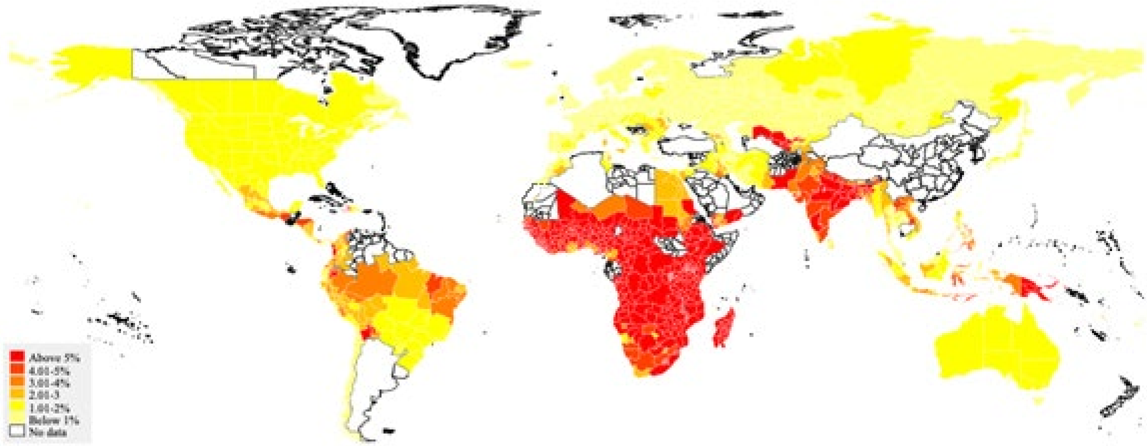
Figure A8: The effects of temperature on migration



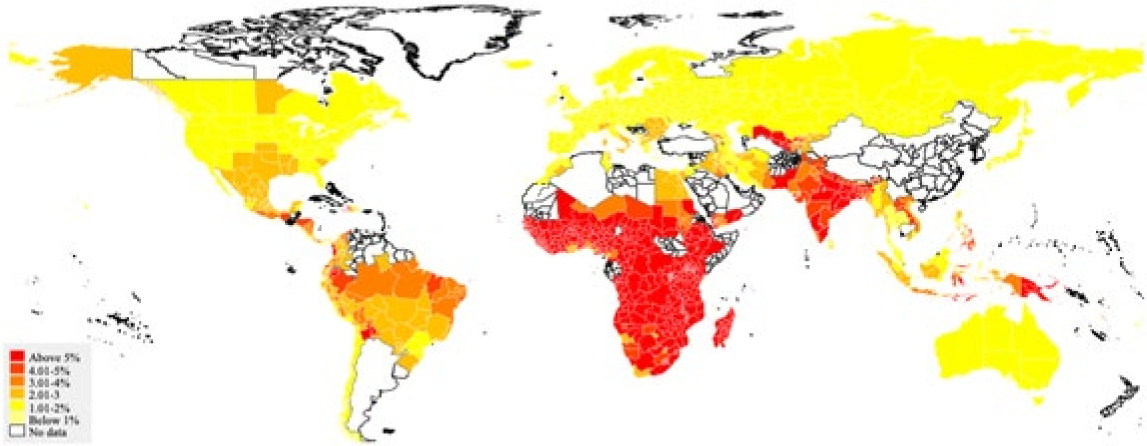
Notes: The figure shows the relationship between temperature (x-axis) and migration (y-axis) using OLS regressions with rainfall as control variable and country fixed effects. Standard errors are in parentheses. Migration is measured by the internal migration flows between 2005 and 2010 (in log). Migration data is available at https://hub.worldpop.org/.

Figure A9: Projected impacts of temperature on poverty

Panel A: RCP 4.5



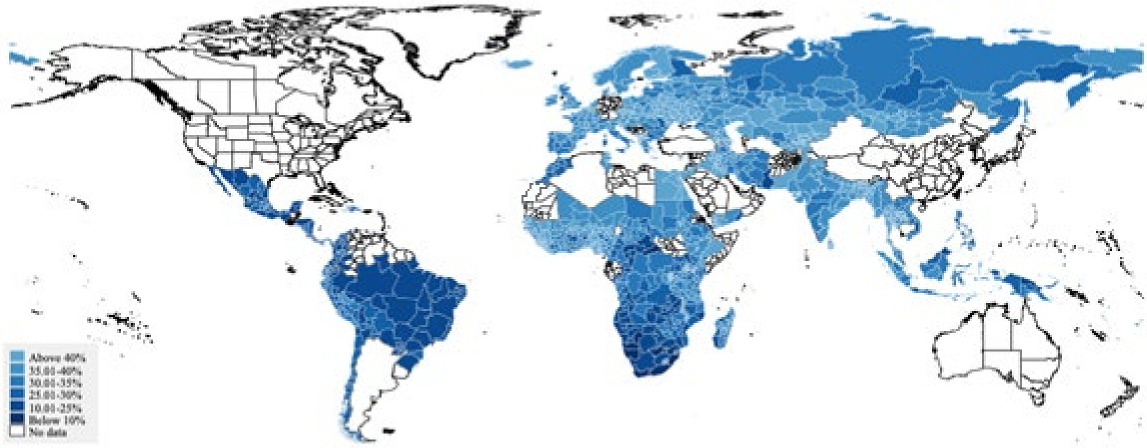
Panel B: RCP 8.5



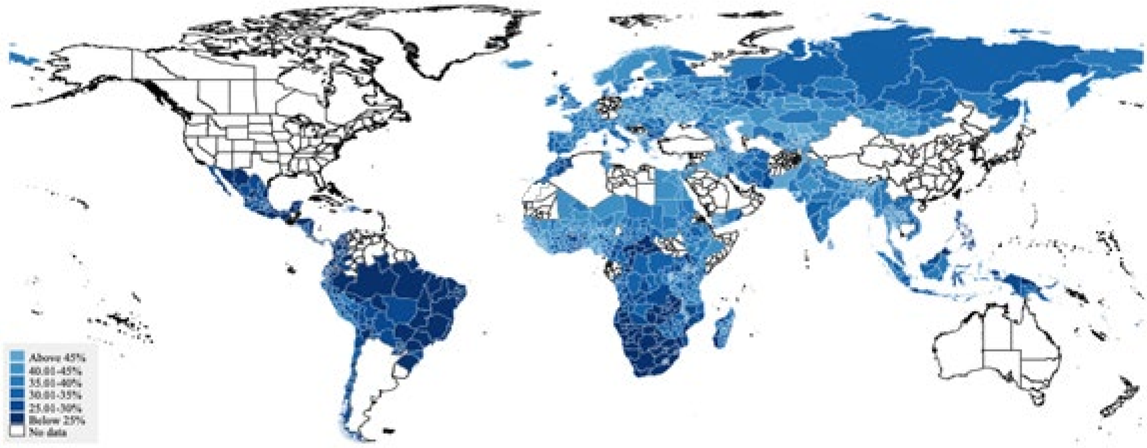
Notes: Poverty is measured by Global Subnational Poverty Headcount Ratio using the daily threshold of US$ 1.90. Temperature data is taken from the European Centre for Medium-Range Weather Forecasts Reanalysis 5 (ERA-5). Data on simulated weather conditions at the subnational level are from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP). The projection is estimated using the coefficient on the effects of temperature on poverty reported in Column (2) of Table 1 and the average temperature of during the period 1979 – 2019.

Figure A10: Projected impacts of temperature on inequality

Panel A: RCP 4.5

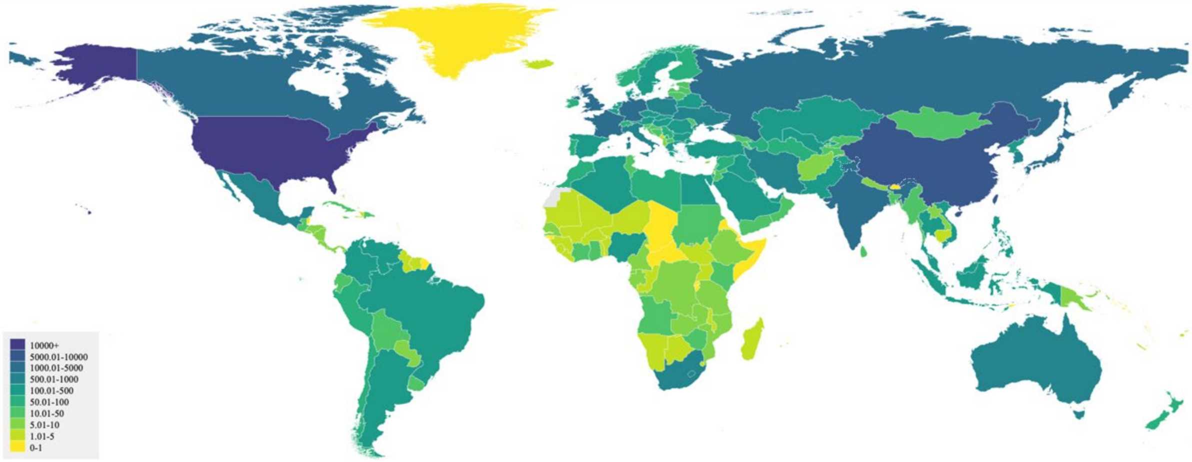


Panel B: RCP 8.5



Notes: Inequality is measured by Gini index. Temperature data is taken from the European Centre for Medium-Range Weather Forecasts Reanalysis 5 (ERA-5). Data on simulated weather conditions at the subnational level are from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP). The projection is estimated using the coefficient on the effects of temperature on inequality reported in Column (2) of Table 2 and the average temperature of during the period 1979 – 2019.

Figure A11: Carbon emission cost allocation



Notes: The cost allocation ($US million) is calculated by using each country's share of carbon emissions from 1975 to 2022 and the estimated cost of achieving net-zero emissions by 2050, based on data from Morgan Stanley (2019).

Table A1: Results of Panel fixed effects model using the same sample sizes as in long differences model

	Poverty measures			Inequality measures	
	$1.90/day	$3.20/day	$5.50/day	Gini	Theil
	(1)	(2)	(3)	(4)	(5)
Panel A: Country-level analysis					
Temperature	0.498**	0.797***	0.614**	0.137***	0.220***
	(0.200)	(0.276)	(0.238)	(0.027)	(0.043)
Precipitation	-0.004	0.005	-0.001	0.003	0.000
	(0.011)	(0.015)	(0.012)	(0.006)	(0.014)
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Mean dependent var.	7.288	15.399	26.593	34.406	23.417
Observations	403	403	403	364	364
Panel B: Subnation-level analysis					
Temperature	0.846***	1.807***	2.293***	0.264***	0.261***
	(0.144)	(0.232)	(0.308)	(0.071)	(0.029)
Precipitation	0.213***	0.200	-0.143	-0.119*	0.524***
	(0.066)	(0.150)	(0.159)	(0.069)	(0.111)
Subnational FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Mean dependent var.	10.061	20.327	34.009	35.605	25.383
Observations	4,225	4,225	4,225	3,400	3,400
Number of countries	95	95	95	90	90
Number of regions	1,109	1,109	1,109	1,109	1,109

Notes: Robust standard errors in parentheses. Standard errors are clustered at the subnational level. Regressions are weighted by region population. Poverty and inequality data are taken from the GSAP. The data for the country-level analysis and the subnational-level analysis comes from our newly constructed database. *** p<0.01, ** p<0.05, * p<0.1.

Table A2: Alternative specifications of panel model and long-difference model

Panel A: Poverty

Dependent variable:	Panel model						Long differences model			
Poverty rate at $1.90	Adding country-specific linear time trend	Adding temperature change	Adding temperature squared term	Adding temperature cubic term	Adding temperature squared term and temperature change	Adding temperature interaction term	4-year average	5-year average	Adding time-invariant covariates	Adding temperature interaction term
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Temperature	0.867***	0.879***	0.873***	0.719*	0.523***	0.524***				-0.045
	(0.129)	(0.211)	(0.321)	(0.370)	(0.129)	(0.129)				(0.127)
ΔTemperature		-0.046			0.044*	0.074	0.510***	0.601***	0.708***	0.266***
		(0.030)			(0.024)	(0.047)	(0.037)	(0.040)	(0.054)	(0.077)
Temperature squared			-0.007	-0.003	-0.002	-0.002				0.011**
			(0.006)	(0.012)	(0.002)	(0.002)				(0.005)
Temperature cubic				0.000						
				(0.001)						
Temperature*ΔTempearture						-0.003				0.155
						(0.005)				(0.115)
Controlling for rainfall	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Subnational FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Number of countries	134	134	134	134	134	134	95	95	95	95
Number of regions	1,594	1,594	1,594	1,594	1,594	1,594	1,109	1,109	1,109	1,109
Observations	4,972	4,972	4,972	4,972	4,972	4,972	1,109	1,109	1,109	1,109

Notes: Robust standard errors in parentheses. Standard errors are clustered at the subnational level. Regressions are weighted by region population. Poverty rate is measured by the Subnational Poverty Headcount Ratio at $1.90 a day. Control variables in Column (9) are taken from Kalkuhl and Wenz (2020) which include cumulative oil gas, distance to coast, distance to river, and altitude. 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

Dependent variable:	Panel model						Long differences model			
Gini index	Adding country-specific linear time trend	Adding temperature change	Adding temperature squared term	Adding temperature cubic term	Adding temperature squared term and temperature change	Adding temperature interaction term	4-year average	5-year average	Adding time-invariant covariates	Adding temperature interaction term
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Temperature	0.290***	0.537***	0.283***	0.282***	0.533***	0.512***				0.333
	(0.103)	(0.099)	(0.087)	(0.086)	(0.101)	(0.104)				(0.388)
ΔTemperature		0.209**			0.249*	0.099	0.309***	0.339***	0.421***	0.977**
		(0.092)			(0.135)	(0.164)	(0.045)	(0.042)	(0.052)	(0.455)
Temperature squared			-0.001	-0.003	-0.003	-0.005				-0.027***
			(0.004)	(0.013)	(0.007)	(0.007)				(0.007)
Temperature cubic				0.000						
				(0.000)						
Temperature*ΔTempearture						0.012				-0.464***
						(0.013)				(0.070)
Controlling for rainfall	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Subnational FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Number of countries	128	128	128	128	128	128	90	90	90	90
Number of regions	1,484	1,484	1,484	1,484	1,484	1,484	1,019	1,019	1,019	1,019
Observations	4,129	4,129	4,129	4,129	4,129	4,129	1,019	1,019	1,019	1,019

Notes: Robust standard errors in parentheses. Standard errors are clustered at the subnational level. Regressions are weighted by region population. Inequality is measured by Gini index. Control variables in Column (9) are taken from Kalkuhl and Wenz (2020) which include cumulative oil gas, distance to coast, distance to river, and altitude. 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 A3: Alternative measure of poverty – Multidimensional poverty

	Percentage of population deprived						
	Monetary poverty	Educational attainment	Educational enrolment	Electricity	Sanitation	Drinking water	Headcount ratio
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Temperature	0.737***	0.726**	0.119	1.137***	0.682*	0.097	1.374***
	(0.203)	(0.282)	(0.172)	(0.355)	(0.373)	(0.199)	(0.395)
Precipitation	-0.011	-0.192***	0.049	0.509**	0.461**	-0.133	-0.155
	(0.097)	(0.064)	(0.044)	(0.210)	(0.200)	(0.117)	(0.120)
Subnational FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,478	2,464	2,260	2,437	2,315	2,321	2,478
R-squared	0.419	0.089	0.232	0.259	0.146	0.047	0.412
Number of regions	1,179	1,179	1,109	1,172	1,163	1,169	1,179
Mean headcount poverty rate (percent)	7.651	10.51	3.516	7.311	21.83	7.909	11.31

Notes: Robust standard errors in parentheses. Standard errors are clustered at the subnational level. Regressions are weighted by region population. 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; Column (7) is the share of people who are considered multidimensionally deprived. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A4: Robustness test – Alternative measures of temperature

Panel A: Poverty

	Dependent variable: Poverty rate at $1.90					
	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	2.218***	0.434***	0.760***	0.070***	0.666***	0.337***
	(0.481)	(0.064)	(0.118)	(0.025)	(0.111)	(0.114)
Controlling for rainfall	Yes	Yes	Yes	Yes	Yes	Yes
Subnational FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of countries	134	134	134	134	134	134
Number of regions	1,594	1,594	1,594	1,594	1,594	1,594
Observations	5,090	5,090	5,059	4,209	4,856	5,090

Notes: Results of panel fixed effects model. Robust standard errors in parentheses. Standard errors are clustered at the subnational level. Regressions are weighted by region population. In Column (5), 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	1.018***	0.158***	0.248***	0.064***	0.302***	2.594***
	(0.346)	(0.048)	(0.086)	(0.013)	(0.086)	(0.472)
Controlling for rainfall	Yes	Yes	Yes	Yes	Yes	Yes
Subnational FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of countries	134	134	134	134	134	134
Number of regions	1,594	1,594	1,594	1,594	1,594	1,594
Observations	5,090	5,090	5,059	4,209	4,856	5,090

Notes: Results of panel fixed effects model. Robust standard errors in parentheses. Standard errors are clustered at the subnational level. Regressions are weighted by region population. In Column (5), 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 A5: Robustness test – Alternative samples

Panel A: Poverty

	Dependent variable: Poverty rate at $1.90					
	Dropping countries with few subregions	Excluding USA	Excluding India	Excluding 10 percent cold countries	Excluding 10 percent hot countries	Spatially-corrected Conley S.E.
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature	0.922***	0.781***	0.786***	1.033***	0.521***	0.639***
	(0.178)	(0.116)	(0.114)	(0.158)	(0.100)	(0.089)
Controlling for rainfall	Yes	Yes	Yes	Yes	Yes	Yes
Subnational FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of countries	134	134	134	134	134	134
Number of regions	1,594	1,594	1,594	1,594	1,594	1,594
Observations	4,055	4,580	5,020	4,679	4,806	5,089

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

Panel B: Inequality

	Dependent variable: Gini index					
	Dropping countries with few subregions	Excluding India	Excluding Brazil	Excluding 10 percent cold countries	Excluding 10 percent hot countries	Spatially-corrected Conley S.E.
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature	0.363**	0.288***	0.386***	0.274**	0.258***	0.213**
	(0.142)	(0.086)	(0.086)	(0.111)	(0.085)	(0.087)
Controlling for rainfall	Yes	Yes	Yes	Yes	Yes	Yes
Subnational FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of countries	128	128	128	128	128	128
Number of regions	1,157	1,449	1,457	1,329	1,352	1,484
Observations	3,175	4,059	3,994	3,789	3,865	4,149

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

Table A6: The effects of temperature on poverty – Subnational GDP analysis

	Poverty rate $1.90		Poverty rate $3.20		Poverty rate $5.50	
	Panel FE	Long differences	Panel FE	Long differences	Panel FE	Long differences
	(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)
Controlling for rainfall	Yes	Yes	Yes	Yes	Yes	Yes
Subnational FE	Yes	No	Yes	No	Yes	No
Year FE	Yes	No	Yes	No	Yes	No
Number of countries	74	61	74	61	74	61
Number of regions	3,394	1,306	3,394	1,306	3,394	1,306
Observations	138,060	1,306	138,060	1,306	138,060	1,306
Adjusted R-squared	0.334	0.204	0.350	0.369	0.385	0.254
Mean headcount poverty rate (percent)	16.847	16.847	30.152	30.152	45.559	45.559

Notes: Robust standard errors in parentheses. Standard errors are clustered at the subnational level. Poverty rate is calculated using subnational GDP from Kalkuhl and Wenz (2020) and the poverty lines of $1.90, $3.20, and $5.50. Poverty rates and weather variables in the long-differences model are measured by the difference between averages of the earliest 10-year period (1979–1988) and averages of the latest 10-year period (2009–2018). 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 A7: The effects of temperature on poverty – Grid-level analysis

Dependent variable:	Panel model		Long differences model	
Poverty rate at $1.90	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)
Controlling for rainfall	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	No	No
Year FE	Yes	Yes	No	No
Number of countries	82	82	82	82
Observations	1,115,478	1,072,575	42,903	42,903
R-squared	0.929	0.555	0.001	0.007

Notes: Robust standard errors in parentheses. Standard errors are clustered at the country level. Poverty incidence is calculated using subnational GDP from Kummu *et al.* (2018) 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 A8: The effects of temperature on inequality – Country level analysis using alternative data from WDI and SWIID

	Gini – WDI		Gini – SWIID	
	Panel FE	Long differences	Panel FE	Long differences
	(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)
Country FE	Yes	No	Yes	No
Year FE	Yes	No	Yes	No
Mean dependent var.	38.295	38.295	38.445	38.445
Number of countries	128	90	128	90
Observations	1,505	90	3,781	90

Notes: Robust standard errors in parentheses. Standard errors are clustered at the subnational level. Regressions are weighted by region population. 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). 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. *** p<0.01, ** p<0.05, * p<0.1

Table A9: The effects of temperature on poverty and inequality – Heterogeneity analysis

	Poverty $1.90	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	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. Regressions are weighted by region population. *** p<0.01, ** p<0.05, * p<0.1

Table A10: Role of information and communication technologies (ICTs) as mediator

	Poverty \$1.90	Gini index
	(1)	(2)
Panel A: ICT Development index		
Temperature* ICT Index	-0.178***	-0.003***
	(0.031)	(0.001)
Panel B: Internet 2G		
Temperature*Internet coverage	-2.980***	-0.034***
	(0.997)	(0.013)
Panel C: Internet 3G		
Temperature*Internet coverage	-1.594***	-0.012***
	(0.428)	(0.004)
Panel D: Internet 4G		
Temperature*Internet coverage	-0.762**	-0.019***
	(0.297)	(0.006)
Controlling for rainfall	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. Regressions are weighted by region population. *** p<0.01, ** p<0.05, * p<0.1

Table A11: Effects of temperature on agriculture

Crop yield	Rice		Maize		Soybean		Wheat	
	Panel FE	Long differences	Panel FE	Long differences	Panel FE	Long differences	Panel FE	Long differences
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Temperature	-0.197***	-0.111***	-0.183***	-0.115***	-0.042***	-0.041***	0.010	-0.000
	(0.021)	(0.014)	(0.013)	(0.008)	(0.011)	(0.011)	(0.014)	(0.010)
Controlling for rainfall	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Subnational FE	Yes	No	Yes	No	Yes	No	Yes	No
Year FE	Yes	No	Yes	No	Yes	No	Yes	No
Mean crop yield (tonnes/hectare)	3.215	3.215	2.412	2.412	1.719	1.719	3.350	3.350
Number of countries	74	74	101	100	33	33	90	90
Number of regions	660	660	955	955	189	189	670	670
Observations	8,566	660	12,392	955	2,452	189	8,663	670
Equality test (Panel vs. long differences)	p = 0.000		p = 0.000		p = 0.000		p = 0.628	

Notes: Robust standard errors in parentheses. Standard errors are clustered at the subnational level. Regressions are weighted by region population. Crop yield data is provided by Iizumi and Sakai (2020). *** p<0.01, ** p<0.05, * p<0.1

Table A12: Effects of temperature on agriculture

Crop yield	Rice	Maize	Soybean	Wheat
	(1)	(2)	(3)	(4)
Share of agriculture in GDP (Reference group: Low share)				
Temperature*High share	-0.127***	-0.005	-0.119***	-0.035***
	(0.015)	(0.016)	(0.012)	(0.012)
Controlling for rainfall	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Number of countries	42	70	16	68
Number of regions	641	915	178	634
Observations	9,967	14,259	2,778	9,635
R-squared	0.648	0.619	0.682	0.726

Notes: Robust standard errors in parentheses. Standard errors are clustered at the country level. Crop yield data is provided by Iizumi and Sakai (2020). *** p<0.01, ** p<0.05, * p<0.1

Table A13: Simulated effect of temperature on poverty

	Representative Concentration Pathway (RCP) 4.5			Representative Concentration Pathway (RCP) 8.5		
	2030	2050	2099	2030	2050	2099
Increase in temperature	1.388	1.984	2.631	1.235	2.114	5.999
Increase in poverty rate $1.90	0.743	1.061	1.408	0.661	1.131	3.209
Increase in poverty rate $3.20	1.721	2.460	3.262	1.531	2.621	7.439
Increase in poverty rate $5.50	2.787	3.984	5.283	2.480	4.245	12.046

Notes: Data on simulated weather conditions at the postcode level are from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP). The projection is estimated using the coefficient on the effects of temperature on poverty reported in Columns (2), (4), and (6) (Panel B) of Table 1.

Table A14: Simulated effect of temperature on inequality

	Representative Concentration Pathway (RCP) 4.5			Representative Concentration Pathway (RCP) 8.5		
	2030	2050	2099	2030	2050	2099
Increase in temperature	1.388	1.984	2.631	1.235	2.114	5.999
Increase in Gini index	0.484	0.692	0.918	0.431	0.738	2.094
Increase in Theil index	0.822	1.175	1.558	0.731	1.251	3.551

Notes: Data on simulated weather conditions at the postcode level are from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP). The projection is estimated using the coefficient on the effects of temperature on inequality reported in Columns (2), and (4) (Panel B) of Table 2.

Table A15: Cost allocation by income group

Income group	Contribution (%)	Contribution ($US billion)
High income	59.53%	29,762.56
Upper-middle income	29.72%	14,862.37
Lower-middle income	10.14%	5,070.30
Low income	0.61%	304.77
Total	100%	50,000

Notes: The income group is identified using the World Bank country classifications 2022-2023, available at: https://blogs.worldbank.org/opendata/new-world-bank-country-classifications-income-level-2022-2023

Appendix B: Data Description

B1. Poverty data

To implement the analysis, we assemble the most comprehensive data on poverty taken from the Global Subnational Atlas of Poverty (GSAP), produced by the Poverty and Equity Global Practice, coordinated by the Data for Goals (D4G) team, and supported by the six regional statistics teams in the Poverty and Equity Global Practice, and Global Poverty & Inequality Data Team (GPID) in the Development Economics Data Group (DECDG). All the teams are at the World Bank.

For each survey data, the geographical area choice is based on the survey representativeness based on the sampling and sample design and survey documentation when available. For most of the database, surveys are representative at the first administrative level (ADM1) or statistical regions (areas) for the purpose of survey. On average, there are 14 subnational areas for a given country and year observation. For 18 small countries (13 percent), there is no subnational data available from the surveys, thus the national level data is used.

Subnational poverty rates are calculated using official household or income surveys for the purpose of global poverty monitoring. Poverty rates are provided at the subnational level that is representative for the associated household or income survey used. Overall, cross-sectional poverty statistics are shown for about 5,500 subnational areas based on survey representativeness and availability of matched spatial geographic boundaries.

Geographic boundaries must match the subnational regions in these surveys. In many cases, there is a one-to-one association between the regions in a household survey and the areas defined at an administrative level in the country. In cases where there is not a one-to-one association, geographic boundaries are altered to fit the representativeness of the surveys. In some cases, the geographic representation is at the level of "urban", or "rural". In these cases, subnational areas in the household survey are aggregated to levels that can be appropriately represented by boundaries. Several sources of geospatial files were leveraged to construct the GSAP: GADM, GAUL, NUTS, and customized spatial files. The choice of spatial files is based on more disaggregated availability and geographic alignment with household surveys. For example, NUTS spatial files are used prominently for the European countries in GSAP, since these files are developed and regulated by the EU.

Building on the cross-sectional GSAP database, we construct a new database on poverty statistics based on almost 500 available household income/expenditure survey data in the Global Monitoring Database (GMD)[14] for 139 economies, with more than 90 percent of the survey data ranging from 2010 to 2019. This database consists of panel data that are representative at 1,650 subnational areas. The number of countries across regions and over time are presented in Figures B1 and B2.

As both country boundary and survey representativeness can change over time, constructing a panel data of poverty at area-level is not a simple task. When there is a change

[14] The Global Monitoring Database (GMD) is the World Bank's repository of multitopic income and expenditure household surveys used to monitor global poverty and shared prosperity. The household survey data are typically collected by national statistical offices in each country, and then compiled, processed, and harmonized. The process is coordinated by the Data for Goals (D4G) team and supported by the six regional statistics teams in the Poverty and Equity Global Practice. Global Poverty & Inequality Data Team (GPID) in Development Economics Data Group (DECDG) also contributed historical data from before 1990, and recent survey data from Luxemburg Income Studies (LIS). Selected variables have been harmonized to the extent possible such that levels and trends in poverty and other key sociodemographic attributes can be reasonably compared across and within countries over time. The GMD's harmonized microdata are currently used in Poverty and Inequality Platform (PIP), World Bank's Multidimensional Poverty Measures (WB MPM), the Global Database of Shared Prosperity (GDSP), and Poverty and Shared Prosperity Reports.

in the boundary over time or survey representativeness is different, efforts are needed to maintain a long panel of data to have comparable statistics spatially and over time. Such efforts could be (1) regroup areas to a new area that matches the previous definition of areas, or (2) a higher level of geographical disaggregation over time. In this version of the panel data, on average a country has data for 14 geographical areas over the period of 3 years.

We also employ poverty data from different sources available at the country level and subnational level. The first is taken from the World Development Indicator (WDI) which provides different measures including the poverty headcount ratio, poverty gap, and number of poor at both international and national poverty lines. Our measures of interest are poverty headcount ratio at US$1.90 a day. It is calculated by the percentage of the population living on less than $1.90 a day at 2011 international prices. For richer analysis, we also use other poverty lines including the poverty headcount ratio at $3.20 and $5.50 a day.

As an alternative source of subnational poverty, we exploit the annual GRP data provided by Kalkuhl and Wenz (2020), which is available from 1981 to 2016 for more than 1,500 regions in 77 countries worldwide. The dataset, however, includes only a few countries in Africa. We calculate the incidence of poverty by assuming the poverty line of $1.90, $3.20, and $5.50 for all countries in our sample.[15] We also exploit annual gridded datasets for GDP per capita (PPP) from Kummu *et al.* (2020) which covers 26-year period from 1990 to 2015 for 82 countries. In this dataset, each grid cell is recorded at 5 arc-min resolution. We then apply a similar exercise as in the dataset of Kalkuhl and Wenz (2020) and measure the incidence of poverty at different thresholds. We present the list of countries in our datasets in Table B2.

B2. Inequality data

The GSAP dataset is unique in terms of country-time coverage and in the breadth of the measures of inequality covered. As the main outcomes, we use the most widely accepted measures of income distribution including the Gini index and Theil index. 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. The Gini index measures the extent to which the distribution of income (or, in some cases, consumption expenditure) among individuals or households within an economy deviates from a perfectly equal distribution. A Lorenz curve plots the cumulative percentages of total income received against the cumulative number of recipients, starting with the poorest individual or household. The Gini index measures the area between the Lorenz curve and a hypothetical line of absolute equality, expressed as a percentage of the maximum area under the line. Thus, a Gini index of zero represents perfect equality, while an index of 100 implies perfect inequality. Similarly, the Theil index measures an entropic 'distance' the population is away from the 'ideal' egalitarian state of everyone having the same income. The Theil index ranges between zero and infinity, with zero representing an equal distribution and higher values representing a higher level of inequality. As alternative measures of income inequality, we use the distribution of income share held by each decile and calculate different percentile ratios, namely the 90/10 ratio, the 80/20 ratio, and the Palma ratio (90/40 ratio). All income measures are converted to real terms using 2011 Purchasing Power Parity (PPP) dollars for comparison across survey years.

We also employ Gini data from different sources available at the country level. The first is taken from the World Bank Poverty and Inequality Platform (PIP). The data are based on primary household surveys obtained from government statistical agencies and World Bank country departments. In the case of high-income economies, they are mostly derived from the

[15] To illustrate, we fix the poverty line for all regions in our sample and identify a region as poor if its gross income (per day) is below the poverty line.

Luxembourg Income Study database. As an alternative source of country-level inequality, we exploit the Standardized World Income Inequality Database (SWIID). SWIID provides standardized Gini income inequality measures for market and net outcomes based on the same concept, and thus allows the comparison of income inequality before and after redistribution by taxation and transfers over time.

B3. Weather data

We match our poverty and inequality data with the ERA5 satellite reanalysis data, which is taken from 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 (Dell *et al.*, 2014). We use air temperature and precipitation, both measured as annual averages, and map the grid spacings in ERA5 to the country/region in our poverty datasets. We follow previous studies and aggregate the gridded data to the region level by computing area-weighted averages (i.e., averaging all grid cells that fall into a region) (e.g., Heyes and Saberian, 2022; Kalkuhl and Wenz, 2020). Figure B3 provides a distribution of average temperature in our sample. It shows that most regions in our sample belong to the temperature range of between 24°C and 28°C. Another dataset that we use in the paper is the global gridded CRU data which provides monthly estimates at 0.5° resolution. The CRU data, however, is subject to absence of data in regions with less coverage of weather stations. Therefore, our main analysis exploits the ERA5 data which combines information from ground stations, satellites, weather balloons and other inputs with a climate model, and therefore is less prone to station weather bias (Auffhammer *et al.*, 2013).

To examine the impacts of future climate change on poverty and inequality, we obtain climate change prediction data from the NASA Earth Exchange (NEX) Global Daily Downscaled Projections (GDDP). The NEX data provides average temperature projections for the short term (2020–2040), the medium term (2041–2060) and the long term (2061–2099). We select the representative carbon pathway RCP8.5 as a benchmark scenario of unmitigated future warming (van Vuuren *et al.*, 2011). It represents the ensemble average of all global climate models contributing to CMIP5, the Coupled Model Intercomparison Project phase 2010–2014 that informed the fifth assessment report of the Intergovernmental Panel on Climate Change. RCP8.5 corresponds to an expected increase of 4.3°C in global mean surface temperature by 2100 relative to pre-industrial levels (Stocker *et al.*, 2013). For comparison purpose, we also consider the RCP4.5 scenario with increased reliance on renewable energy and less reliance on coal-fired power.

B4. Other data

To examine the role of agriculture as the mechanism, we utilize annual production of four major crops (maize, wheat, soybean, rice) available from Iizumi and Sakai (2020). The dataset records global gridded data of annual crop yields, measured in tonnes/hectare, at 0.5° resolution and covers the period 1982–2015. The dataset was created by combining agricultural census data, satellite remote sensing and information on crop calendar and crop harvested area. Although the data include only four main crops, thereby partly limiting our analysis, the trade-off permits us to assemble consistent long panel data. Finally, in some specifications, we exploit data from different sources including type of regime from The Economist Intelligence, broadband internet coverage provided by Collins Bartholomew's Mobile Coverage Explorer, and other country-level characteristics (i.e., population density, elevation, distance to the nearest coast, and concentration of Particulate matter of 2.5 micrometers or smaller – $PM_{2.5}$) from the NASA Socioeconomic Data and Applications Center (SEDAC). We provide descriptions and summary statistics of all variables in Table B1.

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Figure B1: Number of economies across World Bank regions

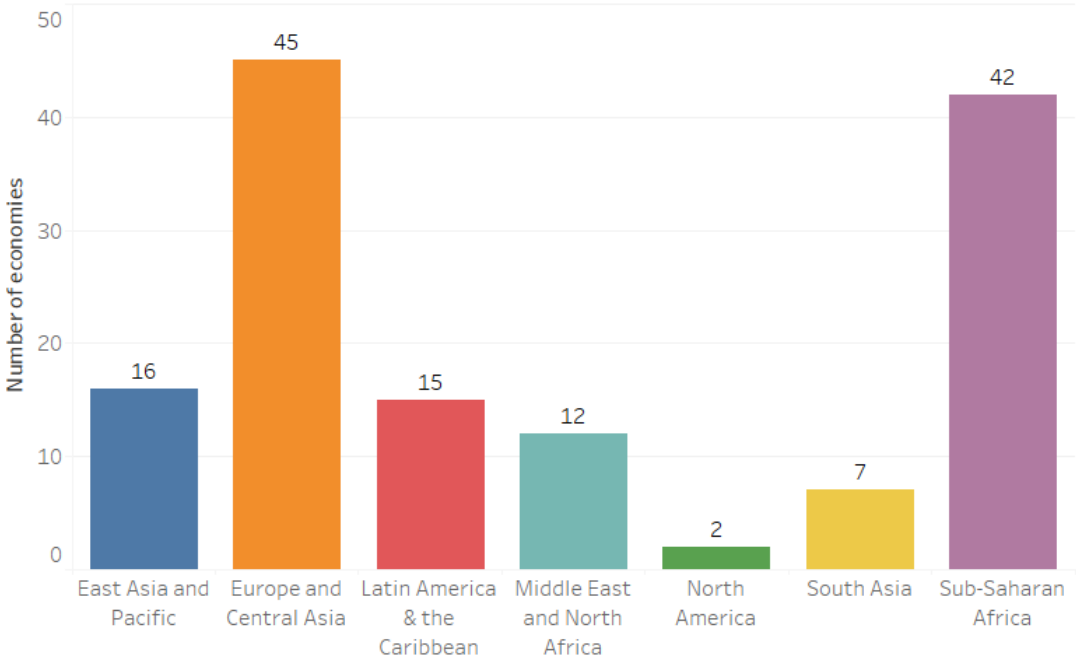


Figure B2: Number of areas over time

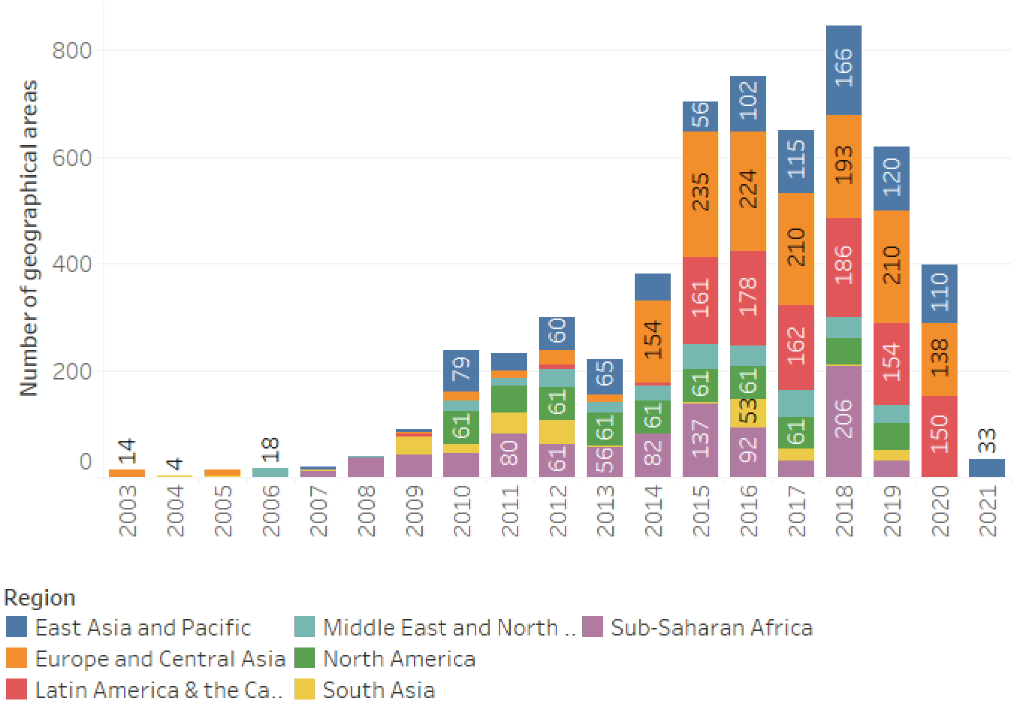
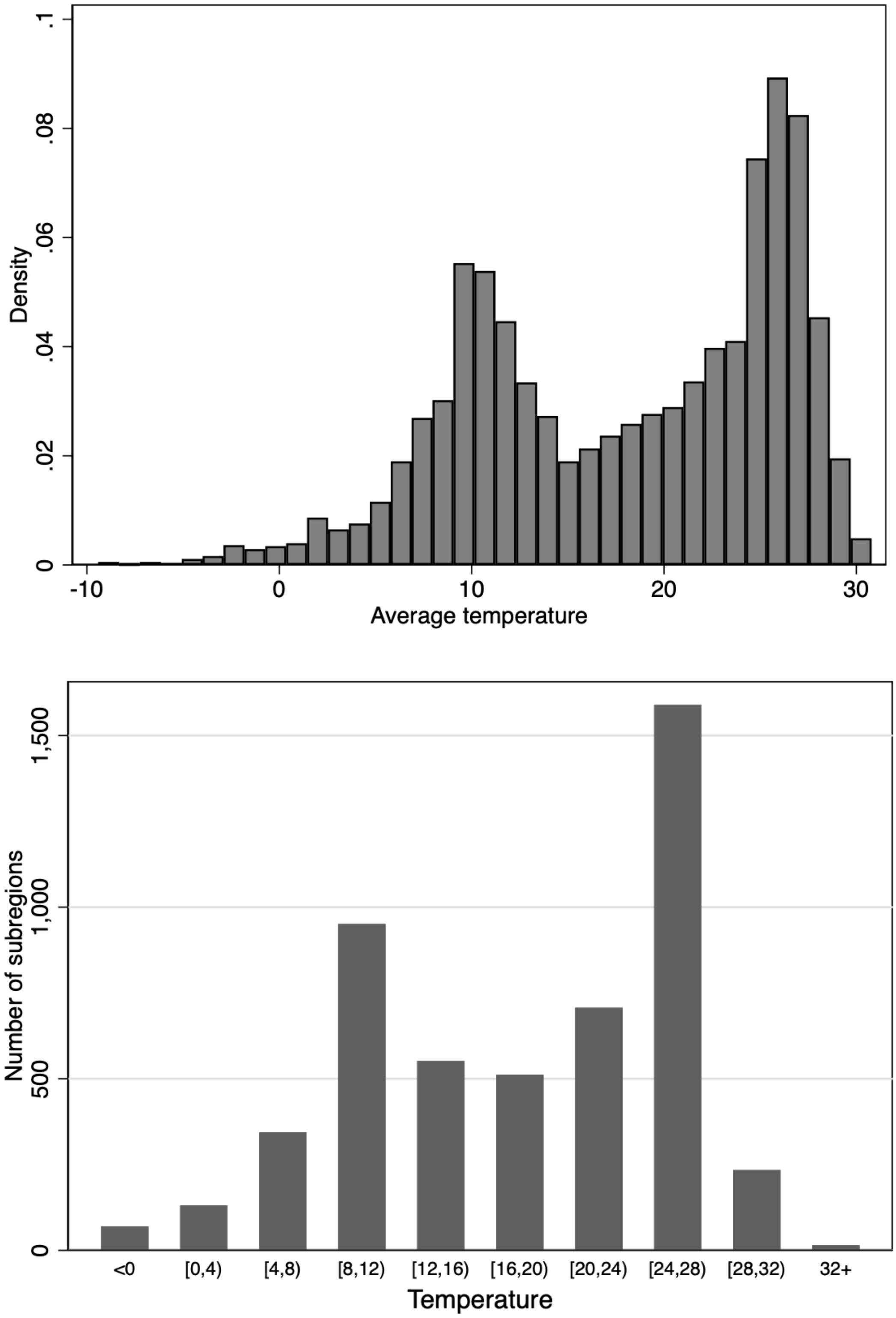


Figure B3: The effects of temperature on poverty by region



Notes: Temperature data is taken from the European Centre for Medium-Range Weather Forecasts Reanalysis 5 (ERA-5).

Table B1: Data sources and summary statistics

Variable	Descriptions	Country No.	Obs. No.	Mean	S.D.	Min	Max
National poverty rate (1979–2019) (percent)							
Source: The World Bank (https://datacatalog.worldbank.org/home)							
Poverty rate $1.90	Poverty Headcount Ratio at US$ 1.90 a day	134	464	7.288	14.814	0.000	78.841
Poverty rate $3.20	Poverty Headcount Ratio at US$ 3.20 a day	134	464	15.399	23.975	0.000	91.518
Poverty rate $5.50	Poverty Headcount Ratio at US$ 5.50 a day	134	464	26.593	32.088	0.051	97.485
Subnational poverty rate (Global Subnational Atlas of Poverty – GSAP) (percent)							
Source: The World Bank (https://datacatalog.worldbank.org/home)							
Poverty rate $1.90	Poverty Headcount Ratio at US$ 1.90 a day	134	4,972	10.061	19.389	0.000	98.010
Poverty rate $3.20	Poverty Headcount Ratio at US$ 3.20 a day	134	4,972	20.327	28.482	0.000	99.724
Poverty rate $5.50	Poverty Headcount Ratio at US$ 5.50 a day	134	4,972	34.009	34.700	0.000	100.000
Subnational poverty rate *(Source: Kalkuhl and Wenz, 2020)*							
Poverty at $1.90	Poverty rate using average gross daily income being below US$ 1.90 a day	77	3,394	20.443	37.990	0.000	100.000
Poverty at $3.20	Poverty rate using average gross daily income being below US$ 3.20 a day	77	3,394	34.075	44.185	0.000	100.000
Poverty at $5.50	Poverty rate using if average gross daily income being below US$ 5.50 a day	77	3,394	57.450	46.434	0.000	100.000
Subnational poverty rate *(Source: Kummu et al., 2018)*							
Poverty at $1.90	Poverty rate using average gross daily income being below US$ 1.90 a day	82	1,811,394	24.245	42.857	0.000	100.000
Poverty at $3.20	Poverty rate using average gross daily income being below US$ 3.20 a day	82	1,811,394	32.000	46.648	0.000	100.000
Poverty at $5.50	Poverty rate using average gross daily income being below US$ 5.50 a day	82	1,811,394	55.000	49.749	0.000	100.000
National inequality							
WDI (Source: The World Bank - https://datacatalog.worldbank.org/home*)*							

Gini	Gini index (%)	128	423	34.406	6.980	22.968	59.777
Theil	Theil index (%)	128	423	23.417	10.882	8.824	70.786
WDI (Source: The World Bank - https://datacatalog.worldbank.org/home)							
Gini	Gini index (%)	128	423	38.295	9.062	20.700	65.800
SWIID (Source: Standardized World Income Inequality Database - https://fsolt.org/swiid/)							
Gini	Gini index (%)	128	423	38.445	8.637	17.900	65.400
Subnational inequality (GSAP)							
Source: The World Bank (https://datacatalog.worldbank.org/home)							
Gini	Gini index	128	4,129	35.627	8.045	13.371	66.448
Theil	Theil index	128	4,129	25.421	13.966	3.359	192.672
90/10 ratio	Ratio of the income of the 10% richest to that of the 10% poorest.	128	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.	128	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.	128	4,150	0.434	1.933	0.000	64.359
Satellite weather data (1979–2019)							
Source: European Union's Copernicus programme (https://sentinels.copernicus.eu/web/sentinel/missions/sentinel-5p)							
Temperature	Average temperature (C)	134	5,090	18.185	7.996	-9.417	30.790
Rainfall	Average rainfall (mm)	134	5,090	3.880	3.178	0.006	34.882
Source: Climatic Research Unit (https://crudata.uea.ac.uk/cru/data/hrg/)							
Temperature	Average temperature (C)	134	5,090	18.328	8.030	-11.082	30.426
Crop yield data							
Source: Izumi and Sakai (2020)							
Rice	Average crop yield (1981–2016)	45	10,257	3.215	3.041	0.000	22.314
Maize	Average crop yield (1981–2016)	76	14,870	2.412	2.480	0.000	27.743
Soybean	Average crop yield (1981–2016)	19	2,953	1.719	1.494	0.000	9.518
Wheat	Average crop yield (1981–2016)	66	10,178	3.350	3.142	0.000	15.636
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 percent	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 percent	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 percent	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 percent	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 percent	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 percent	132	3,924	0.368	0.482	0.000	1.000
Broadband internet (*Source*: https://www.collinsbartholomew.com/)							
ICT	ICT Development Index	118	3,828	5.045	1.833	1.040	8.980
2G	Internet coverage at subnational level	130	3,955	0.913	0.161	0.000	1.000
3G	Internet coverage at subnational level	123	3,337	0.809	0.264	0.000	1.000
4G	Internet coverage at subnational level	94	1,861	0.781	0.331	0.000	1.000

Table B2: List of economies

No.	Region	GSAP	Kalkuhl and Wenz (2020)	Kummu *et al.* (2018)
1	East Asia & Pacific	Australia	Australia	Australia
2	East Asia & Pacific		China	China
3	East Asia & Pacific	Fiji		
4	East Asia & Pacific	Indonesia	Indonesia	Indonesia
5	East Asia & Pacific	Japan	Japan	Japan
6	East Asia & Pacific			Korea, Rep.
7	East Asia & Pacific	Lao PDR		Lao PDR
8	East Asia & Pacific	Malaysia	Malaysia	Malaysia
9	East Asia & Pacific	Mongolia	Mongolia	Mongolia
10	East Asia & Pacific	Myanmar		
11	East Asia & Pacific	Papua New Guinea		
12	East Asia & Pacific	Philippines	Philippines	Philippines
13	East Asia & Pacific	Thailand	Thailand	Thailand
14	East Asia & Pacific	Timor-Leste		
15	East Asia & Pacific	Tonga		
16	East Asia & Pacific	Taiwan, China		
17	East Asia & Pacific	Vanuatu		
18	East Asia & Pacific	Vietnam	Vietnam	Vietnam
19	Europe & Central Asia	Albania	Albania	Albania
20	Europe & Central Asia	Armenia		
21	Europe & Central Asia	Austria	Austria	Austria
22	Europe & Central Asia	Azerbaijan	Azerbaijan	
23	Europe & Central Asia	Belarus	Belarus	
24	Europe & Central Asia	Belgium	Belgium	Belgium
25	Europe & Central Asia		Bosnia and Herzegovina	Bosnia and Herzegovina
26	Europe & Central Asia	Bulgaria	Bulgaria	Bulgaria
27	Europe & Central Asia	Croatia	Croatia	Croatia
28	Europe & Central Asia	Cyprus		
29	Europe & Central Asia	Czechia	Czechia	Czechia
30	Europe & Central Asia	Denmark	Denmark	Denmark
31	Europe & Central Asia	Estonia	Estonia	Estonia
32	Europe & Central Asia	Finland	Finland	Finland
33	Europe & Central Asia	France	France	France
34	Europe & Central Asia	Georgia	Georgia	Georgia
35	Europe & Central Asia	Germany	Germany	Germany
36	Europe & Central Asia	Greece	Greece	Greece
37	Europe & Central Asia	Hungary	Hungary	Hungary
38	Europe & Central Asia	Iceland		
39	Europe & Central Asia	Ireland	Ireland	Ireland

40	Europe & Central Asia	Italy	Italy	Italy
41	Europe & Central Asia	Kazakhstan	Kazakhstan	Kazakhstan
42	Europe & Central Asia	Kosovo		
43	Europe & Central Asia	Kyrgyz Republic		
44	Europe & Central Asia	Latvia	Latvia	Latvia
45	Europe & Central Asia	Lithuania	Lithuania	Lithuania
46	Europe & Central Asia	Luxembourg		
47	Europe & Central Asia	Moldova		
48	Europe & Central Asia	Montenegro		
49	Europe & Central Asia	Netherlands	Netherlands	Netherlands
50	Europe & Central Asia	North Macedonia		
51	Europe & Central Asia	Norway	Norway	Norway
52	Europe & Central Asia	Poland	Poland	Poland
53	Europe & Central Asia	Portugal	Portugal	Portugal
54	Europe & Central Asia	Romania	Romania	Romania
55	Europe & Central Asia	Russian Federation		
56	Europe & Central Asia		Serbia	Serbia
57	Europe & Central Asia	Slovak Republic		
58	Europe & Central Asia	Slovenia	Slovenia	Slovenia
59	Europe & Central Asia	Spain	Spain	Spain
60	Europe & Central Asia	Sweden	Sweden	Sweden
61	Europe & Central Asia	Switzerland	Switzerland	Switzerland
62	Europe & Central Asia	Tajikistan		
63	Europe & Central Asia		Türkiye	Türkiye
64	Europe & Central Asia	Ukraine	Ukraine	Ukraine
65	Europe & Central Asia	United Kingdom		United Kingdom
66	Europe & Central Asia	Uzbekistan	Uzbekistan	Uzbekistan
67	Latin America & Caribbean		Argentina	Argentina
68	Latin America & Caribbean	Bolivia	Bolivia	Bolivia
69	Latin America & Caribbean	Brazil	Brazil	Brazil
70	Latin America & Caribbean	Chile	Chile	Chile
71	Latin America & Caribbean	Colombia	Colombia	Colombia
72	Latin America & Caribbean	Costa Rica		Costa Rica
73	Latin America & Caribbean	Dominican Republic		Dominican Republic
74	Latin America & Caribbean	Ecuador	Ecuador	Ecuador
75	Latin America & Caribbean	El Salvador		
76	Latin America & Caribbean		Guatemala	Guatemala
77	Latin America & Caribbean	Haiti		

78	Latin America & Caribbean	Honduras	Honduras	Honduras
79	Latin America & Caribbean	Mexico	Mexico	Mexico
80	Latin America & Caribbean	Nicaragua		
81	Latin America & Caribbean	Panama	Panama	Panama
82	Latin America & Caribbean	Paraguay	Paraguay	Paraguay
83	Latin America & Caribbean	Peru	Peru	Peru
84	Latin America & Caribbean		Uruguay	Uruguay
85	Middle East & North Africa	Djibouti		
86	Middle East & North Africa	Egypt, Arab Rep.		
87	Middle East & North Africa	Iran, Islamic Rep.		
88	Middle East & North Africa	Iraq		
89	Middle East & North Africa	Israel		Israel
90	Middle East & North Africa	Jordan		Jordan
91	Middle East & North Africa	Lebanon		Lebanon
92	Middle East & North Africa	Malta		
93	Middle East & North Africa	Morocco	Morocco	Morocco
94	Middle East & North Africa	Tunisia		
95	Middle East & North Africa			United Arab Emirates
96	Middle East & North Africa	West Bank and Gaza		
97	Middle East & North Africa	Yemen, Rep.		
98	North America	Canada	Canada	Canada
99	North America	United States		United States
100	South Asia	Bangladesh		Bangladesh
101	South Asia	Bhutan		
102	South Asia	India	India	India
103	South Asia	Maldives		
104	South Asia	Nepal		
105	South Asia	Pakistan	Pakistan	Pakistan
106	South Asia	Sri Lanka		
107	Sub-Saharan Africa	Angola		
108	Sub-Saharan Africa	Benin		Benin

109	Sub-Saharan Africa	Botswana		
110	Sub-Saharan Africa	Burkina Faso		
111	Sub-Saharan Africa	Burundi		
112	Sub-Saharan Africa	Cabo Verde		
113	Sub-Saharan Africa	Cameroon		Cameroon
114	Sub-Saharan Africa	Central African Republic		
115	Sub-Saharan Africa	Chad		
116	Sub-Saharan Africa	Comoros		
117	Sub-Saharan Africa	Congo, Dem. Rep.		
118	Sub-Saharan Africa	Congo, Rep.		
119	Sub-Saharan Africa	Côte d'Ivoire		
120	Sub-Saharan Africa	Eswatini		
121	Sub-Saharan Africa	Ethiopia	Ethiopia	
122	Sub-Saharan Africa			Gabon
123	Sub-Saharan Africa	Gambia, The		
124	Sub-Saharan Africa	Ghana		Ghana
125	Sub-Saharan Africa	Guinea		
126	Sub-Saharan Africa	Guinea-Bissau		
127	Sub-Saharan Africa	Kenya	Kenya	Kenya
128	Sub-Saharan Africa	Lesotho		
129	Sub-Saharan Africa	Liberia		
130	Sub-Saharan Africa	Madagascar		
131	Sub-Saharan Africa	Malawi		Malawi
132	Sub-Saharan Africa	Mali		
133	Sub-Saharan Africa	Mauritius		
134	Sub-Saharan Africa	Mozambique	Mozambique	Mozambique
135	Sub-Saharan Africa	Namibia		Namibia
136	Sub-Saharan Africa	Niger		
137	Sub-Saharan Africa	Nigeria		
138	Sub-Saharan Africa	Rwanda		
139	Sub-Saharan Africa	São Tomé and Principe		
140	Sub-Saharan Africa	Senegal		Senegal
141	Sub-Saharan Africa	Seychelles		
142	Sub-Saharan Africa	Sierra Leone		
143	Sub-Saharan Africa	South Africa	South Africa	South Africa
144	Sub-Saharan Africa	Sudan		
145	Sub-Saharan Africa	Tanzania	Tanzania	Tanzania
146	Sub-Saharan Africa	Togo		
147	Sub-Saharan Africa	Uganda		Uganda
148	Sub-Saharan Africa	Zambia		Zambia
149	Sub-Saharan Africa	Zimbabwe		

Appendix C: Further robustness checks and heterogeneity analysis

C1. Robustness checks

In this section, we explore the robustness of our results in a number of different ways. We start with the results of panel model and long difference model presented in Tables 1 and 2 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 Panels A and B of Table A2 (Appendix A). 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. We show that our estimates are insensitive to the inclusion of country specific time trends (Column 1). Another concern is related to misspecification of the functional form of temperature. Therefore, from Columns (2) to (6), we employ different functional forms of temperature including controlling for temperature change, quadratic term and cubic term of temperature, and an interaction term between temperature and temperature change. Results of these exercises strengthen our main findings.

Similarly, we also apply different variants of the long differences model and present the results in Columns (7)-(10) of Table A2 (Panels A and B). We first check whether our results remain robust when using different choices of window length (i.e., 4-year and 5-year period). The results in Columns (7) and (8) show that our findings are not sensitive to the alternative windows. In Column (9), we add a number of time-invariant covariates at the regional level including cumulative oil gas, distance to coast, distance to river, and altitude. Finally, we include an interaction term between temperature and temperature change in Column (10). In overall, the results are qualitatively similar to our main finding.

Second, we replicate the results in Figure 2 but using alternative thresholds to define hot and cold days. In Panel A of Figure A1 (Appendix A), we present the results of the temperature bin approach using the 2-degree bin, while Panels B and C show the results using the 4-degree bin and 5-degree 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 Table A3 (Appendix A), 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 Figure A2 (Appendix A) 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 Table A4 (Appendix A) 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);[16] (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.

[16] We choose the temperature at 28°C as this is the most common temperature in our sample (see Figure B3, Appendix B).

Fifth, we replicate our main analysis to different subsamples to investigate the sensitivity of our finding, as shown in Panels A and B of Table A5 (Appendix A). First, there are countries in our samples that contain only a small number of regions. We show in Column (1) 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, India, and Brazil (Columns 2 and 3). We also employ subsamples of countries without extremely cold weather (Column 4) and extremely hot weather (Column 5) using the 10 percent threshold. In Column (6), 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 Kalkuhl and Wenz (2020) and Kummu *et al.* (2018) to construct poverty measures. 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, Tables A6 and A7 (Appendix A) 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 for the inequality analysis using country-level data from the World Development Indicators (WDI) and the Standardized World Income Inequality Database (SWIID). The results presented in Table A8 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 Table 1 and Table 2 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 Figure A3 (Appendix A) 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 percent 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.

C2. Heterogeneity analysis

Consistent with the idea that warmer temperature leads to higher poverty rate and inequality, we also expect the impacts to be heterogenous across regions. We expect that countries bearing the largest effects of global warming tend to be poorer (i.e., low-income countries) or located in poor regions. This is explained by the fact that poor countries are less prepared for the effects of climate change. They are also more likely to suffer more damages, have proportionately higher material losses, and face greater obstacles during the phases of response, recovery, and reconstruction. To explore this, we split our sample into six regions and plot the coefficient estimates of temperature in Figure 3 (Panels A and B) using the temperature bin approach. As expected, hot temperatures are found to increase poverty and income inequality in most regions relative to temperature in the reference group, particularly poorer regions such as Sub-Saharan Africa, Middle East and North Africa, and South Asia. Furthermore, we also observe the negative effects of cold temperature among countries in East Asia and Pacific and Europe and Central Asia. Given that the range of temperature varies across countries, we split the temperature distribution within each country into deciles and choose the 60th percentile as the baseline group. Figure A4 (Appendix A) shows that the effects of extreme weather are similar to what we observed in Figure 3.

We also provide further support to the regional heterogeneity by estimating the effect of temperature on poverty and inequality by country, adjusted by their real GDP per capital in 2018. Figure A5 (Appendix A) shows that countries bearing the largest effect of global warming are also those with the lowest income such as Uganda, Ghana, and Mozambique.

Next, 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 Panel A of Table A9 (Appendix A) show evidence that countries with democracy regime appear to be less vulnerable to the impacts of global warming. 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, Table A9 in Appendix A). In addition, the effect of temperature is more pronounced in those with higher share of agriculture, while the opposite is found in countries with higher share of manufacturing (Panels C and D, Table A9 in Appendix A). Finally, we find a stronger effect among countries with lower share of trade, but our estimates are not statistically significant (Panel E, Table A9 in Appendix A).

In this paper, we are also interested in examining the role of information and communication technologies (ICTs). It is reasonable to argue that ICTs, particularly the Internet, may contribute to poverty reduction by providing access to markets, decreasing transaction costs, and increasing income for a significant proportion of people living in developing countries. Therefore, we expect that regions with better internet coverage will be less vulnerable to the effects of higher temperatures. To do this exercise, we exploit the ICT Development index from the International Telecommunication Union as well as the global expansion of mobile network (2G, 3G, and 4G) from Collins Bartholomew with the latter being available at the grid level which allows us to construct a regional index. We then present coefficients on the interaction between our ICT measures and temperature in Table A10 (Appendix A). Across all panels, we find strong and consistent evidence of the role of ICT as the mediator. Specifically, areas with better access to ICT/internet broadband are less vulnerable to the effects of higher temperature.

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Appendix D: Mechanism analysis and projected impacts under future climate change

D1. Potential mechanisms

Having demonstrated strong evidence of the effects of warming temperature on poverty at the subnational level, we further explore why impact heterogeneity exists across regions. A possible explanation is that poor countries are often located in tropical areas, where climate change occurs faster and is more intense, and their livelihoods are more dependent on the climate vulnerable agriculture sector. In fact, a growing body of evidence suggests that extreme temperature has negative effects on crop yields, particularly in poor countries (e.g., Jacoby *et al.*, 2015; Knox *et al.*, 2012; Schlenker and Lobell, 2010). We analyze the global dataset of historical yields from Iizumi and Sakai (2020), which provides actual crop yields for years from 1981 to 2016 at 0.5° resolution. Using the panel fixed effects model and long differences model as in Equations (1) and (2), we find consistent and negative effects of higher temperature on different crop yields including rice, maze, and soybean, as shown in Table A11 (Appendix A). Again, we find the long differences model estimates to be smaller than the panel model estimates, which are in line with previous studies showing potential adaptation in the long run (e.g., Chen and Gong, 2021). Similarly, we also find the effects of global warming to be more pronounced among regions with a higher share of agriculture (Appendix A, Table A12).

Given the adverse impacts of temperature on agricultural production, we further examine whether there exists any correlation between poverty and agriculture. Specifically, we plot the effects of temperature on poverty taken from the panel model specification on the *y*-axis, and the effects of temperature on agriculture in Table A11 on the *x*-axis in Figure A6 (Appendix A). Since the unit of analysis is different across two samples, we aggregate the data at the country level for better comparison. For all the panels, we find a negative and strongly statistically significant correlation between crop yield and poverty. Consistent with our previous findings, African countries are found to be most vulnerable to the effects of global warming. In Figure A7 (Appendix A), we further plot the effects of temperature on poverty against a country's share of agriculture in GDP and also find the effects to be stronger among countries which rely on agriculture as the main source of income. Overall, these findings suggest that by reducing crop yield, warmer temperature may directly contribute to more poverty.[17]

Another potential mechanism that may explain the effects of temperature is migration. Since poverty is a major driver of people's vulnerability to climate-related shocks, it is reasonable to expect that the flow of people escaping poverty is also affected by climate change. In fact, an emerging body of literature has shown that higher temperature increases both internal and international immigration rates (e.g., Cattaneo and Peri, 2016; Missirian and Schlenker, 2017). We reaffirm findings from the literature by using migration data available at the subnational level. The data is provided by WorldPop Open Data Repository which captures internal migration flows between 2005 and 2010.[18] Using a simple OLS regression, we find suggestive evidence that hotter temperature results in higher migration flow (see Figure A8, Appendix A).

D2. Projected impacts under future climate change

[17] For simplicity, we assume land degradation to be constant, but it could play a role in the poverty and environment nexus (Barbier and Hochard, 2018). Temperature may also affect poverty via different channels such as civil conflicts and labor productivity (for a review, see Burke *et al.*, 2015 and Somanathan *et al.*, 2021).

[18] The data is available at https://hub.worldpop.org/.

We next provide projections of the effects of future temperature on poverty to better understand potential effects under different scenarios. To do this, we combine the model estimates in Tables 1 and 2 with data on simulated weather conditions at the subnational level from 2030 to 2099. We focus on RCP4.5 and RCP8.5 scenarios, which are two extreme emission pathways that represent opposite ends of the climate spectrum depending on the uptake of renewable energy.[19] Following Burke and Emerick (2016) and Kalkuhl and Wenz (2020), we generate temperature projections as follows. First, we use annual temperature from ERA-5 to construct historical average temperature and probability distribution functions for the period 1979 – 2019. We then calculate the projected changes in temperature as the difference between the projected temperature, taken from NEX, and the historical average temperature. Finally, the temperature changes are used to calculate poverty rates (inequality) by multiplying with the baseline estimates in Columns (2), (4), and (6) of Table 1 (Columns (2) and (4) of Table 2). We select the estimates from the long differences model since it embodies any adaptations that farmers have undertaken to short-run change in climate, and thus projections of future climate change impacts would appear more trustworthy than those based on either panel or cross-sectional methods (Burke and Emerick, 2016).

Table A13 (Appendix A) provides a summary of the projected changes for temperature and poverty for the RCP4.5 and RCP8.5 emission pathways in the short, medium, and long terms. Under the RCP4.5 and RCP8.5 pathways, temperature will increase by 2.6˚C and 6.0˚C in 2099. These temperature increases can result in poverty increases between 1.4 and 3.1 percentage points (which correspond to 13.6 and 31.1 percent changes). Similarly, the simulated effects on inequality are estimated to be between 0.4 and 2.1 percentage point increases in Gini index (which correspond to 1.2 and 5.9 percent increases) (Table A14, Appendix A). The largest increase in poverty and inequality would occur in the scenario without any countervailing strategies based on renewable energy to address climate change between 2021 and 2099. Finally, Figures A8 and A9 (Appendix A) present the projected temperature effects across regions in our sample under both emission pathways and reaffirm our previous findings that poor countries in Africa continue to be most vulnerable to hotter temperature.

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[19] RCP is the Representative Concentration Pathway, which captures future trends in climate change under alternative scenarios of human activities. RCP8.5 tracks emissions consistent with current trends (business as usual scenario in which greenhouse gas emissions go unchecked), while RCP4.5 considers a scenario with increased reliance on renewable energy and less reliance on coal-fired power (IPCC, 2021).

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