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ABSTRACT

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

Despite a vast literature documenting the negative effects of climate change on various socio-economic outcomes, little, if any, evidence exists on the global impacts of hotter temperature on poverty. Analyzing a new global dataset of subnational poverty in 166 countries, we find higher temperature to increase poverty. This finding is robust to various model specifications, data samples, and measures of temperature. Our preferred specification shows that a 1°C increase leads to a 2.1 percent increase in the headcount poverty rate, using the US$ 1.90 daily poverty threshold. Regional heterogeneity exists, with Sub-Saharan African countries being most vulnerable to higher temperature. We find suggestive evidence that reduction in crop yields could be a key channel that explains the effects of rising temperature. Further simulation indicate that global warming can significantly increase poverty, with more pronounced effects occurring in poorer regions and under scenarios of higher greenhouse gas emissions without mitigation policies.

JEL Classification: Q54, I32, O1

Keywords: climate change, global warming, poverty, agriculture

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1. Introduction

Climate change may exacerbate poverty through different channels. Poorer households likely live in areas with higher exposure to climate extremes and have fewer resources to help them recover from disasters such as droughts, hurricanes, and floods. The livelihoods of the poor are also more likely to depend on climate vulnerable sectors, such as agriculture, fishing, and forestry, or on low-income informal jobs with little protection against climate-related employment disruptions. Finally, they have less access to knowledge and information that enables them to have better adaptation to climate change.

The increasingly prominent threats of climate change have inspired a significant body of economic research on its impacts 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), crime and conflict (Burke et al. 2015a; Heilmann et al., 2021), and economic growth (Dell et al., 2012). Yet, to our knowledge, no study currently exists on the relationship between global warming and poverty on a global scale. This lack of evidence poses an important, and perhaps quite urgent, challenge since climate change may push over 130 million people, mostly in poorer countries, into poverty by 2030 (World Bank, 2021a). With the global average temperature predicted to increase by up to 6°C this century (IPCC, 2021), understanding the effects of higher temperature on poverty is vital for formulating anti-poverty policies in general and achieving the Sustainable Development Goal of eradicating extreme poverty by 2030 in particular.[1]

[1] Examples abound for other negative effects of global warming. For example, a study from the United Kingdom's Met Office suggests that recent blistering heat wave affecting millions of people in northwest India and Pakistan was made over 100 times more likely because of human-caused climate change and that high temperatures that used to occur about every 300 years may now happen about every three years (Christidis, 2022). The World Meteorological Organization reports that global oceans reached their hottest and most acidic levels on record in 2021, dramatically increasing the number of species projected to become extinct (WMO, 2022). The same report also observes that record-breaking heatwaves have occurred more frequently in traditionally colder Western North America, killing about 1,000 people in the summer of 2021 alone.

A possible explanation for the lack of empirical evidence on the poverty impacts of global warming is the challenge of obtaining the appropriate measure of poverty. While household surveys—the main source of official poverty statistics—have become increasingly more available, these surveys are still unavailable or infrequently collected in many countries, particularly in poor regions.[2] Another explanation is that poverty can widely vary within countries (as well as across countries). Consequently, ignoring subnational variations in poverty analysis could easily mask its dynamic relationship with climatic conditions, which have long been known to be location specific.

To illustrate, we plot in Figure 1, Panels A and B poverty against temperature at the subnational level for India, a populous country with a major share of the global poor. The figure shows large degrees of subnational variation in both poverty and temperature. Poverty, as measured by the headcount poverty rate at US$ 1.90 a day, ranges from being relatively low in the Northern regions (lowest rate of zero percent) to extremely high in the Central and Eastern regions (highest rate of 41.9 percent) (Panel A).[3] Temperature also strongly varies within the country between 4.3˚C and 28.7˚C (Panel B). Such wide-ranging subnational temporal (poverty) variations are not revealed by simply looking at India's average level of approximately 23˚C (10 percent), suggesting that analyzing data at the subnational level is critical to better understand the relationship between global warming and poverty.

To shed light on this issue, we employ the Global Subnational Atlas of Poverty (GSAP), a newly constructed database by the World Bank that provides headcount poverty estimates for 1,780 subnational areas in 166 economies in 2018 (World Bank, 2021b). The GSAP is generated using household consumption surveys, which underlie country official poverty

[2] 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.

[3] More general, the within-country variance can account for up to 15 percent of the total variance of global poverty (Appendix B, Table B2).

statistics, and offers the most detailed subnational poverty data on a global scale to date. We combine the GSAP with historical climatic data (i.e., temperature and precipitation) during 1979 – 2018 from the European Centre for Medium-Range Weather Forecasts Reanalysis 5 (ERA-5) and various other data sources.

We find strong and statistically significant effects of higher temperature on subnational poverty. This result is robust to various robustness checks including different model specifications, alternative measures of temperature, controlling for additional covariates, and analyzing various data subsamples. Our preferred model shows that a one-degree Celsius (i.e., 1°C) increase in temperature causes headcount poverty increases of 0.21, 0.33, and 0.30 percentage points respectively using the daily poverty lines of $1.90, $3.20, and $5.50 (which correspond to 2.1 percent, 1.7 percent, and 0.9 percent increases).

The adverse effects of rising temperature predominantly occur among regions in Africa and South Asia, which currently have higher poverty. Further analysis suggests that a key channel through which increased temperature can raise poverty is reduction of major crops including rice, maize, and soybean. Our simulation for the rest of the 21st century shows that global warming can significantly increase poverty in the short, medium, and long runs. The effects are more pronounced under scenarios of higher greenhouse gas emissions without mitigation policies and likely concentrate in poorer regions.

To our knowledge, we offer the first global assessment of warmer temperature on poverty using disaggregated subnational data from 166 countries. Notably, previous studies focus on single-country case studies and typically study natural disasters that can suddenly push households into poverty by destruction of assets, loss of financial resources, and personal injury or illness.[4] However, the global, slow-onset effects of rising temperature, which slowly but

[4] For example, Rodriguez-Oreggia et al. (2013) find a poverty increase of 1.5-3.7 percent caused by natural disaster in Mexico, and Arouri et al. (2015) observe positive effects of flood on poverty in Vietnam. See also Karim and Noy (2016) and Hallegatte et al. (2020) for recent review of the literatures on climate change, natural disasters, and poverty.

steadily increase poverty via different mechanisms, have received barely any attention. The only exception is Azzarri and Signorelli (2020), who analyze household survey data from 24 Sub-Saharan African countries and show that temperature shock is associated with a 2.8 percentage point increase in poverty.[5]

Our study is broadly related to other literatures on global warming. For example, some studies, while do not directly investigate climate change and poverty, observe negative climate change effects on household consumption (e.g., Hirvonen, 2016). Earlier studies find negative effects of climate change on economic growth but they typically analyze data at the more aggregated country level (e.g., Barrios et al., 2010; Burke et al., 2015b; Dell et al., 2012; Newell et al., 2021). Recent studies find that temperature increases tend to increase Gross Regional Product (GRP) in cold regions and reduce GRP in hot regions (Kalkuhl and Wenz, 2020), or that day-to-day temperature variability have negative effects on economic growth (Kotz et al., 2021).[6] A general finding from these studies is that weather conditions often vary within country, and thus analysis using spatial aggregation of data at the country level may not reveal any effect. Our study concurs with these studies and shows that while the effects of warming temperature on poverty are observed at the subnational level, such effects are not discernible at the country level.

This paper has five sections. We describe the data in the next section before presenting our analytical framework in Section 3. We discuss the estimation results, robustness checks, potential mechanism of impacts, and projected future impacts in Section 4. We finally conclude in Section 5.

[5] Our study is different from Azzarri and Signorelli (2020) in several aspects. Besides the regional focus, Azzarri and Signorelli (2020) analyze gridded data, which can exclude areas where underlying ground station data are sparse, particularly in middle-income and developing countries (Dell et al., 2014). Furthermore, the global setting allows us to better detect the impacts of global warming, compare different country estimates on a common scale as well as examine heterogeneity of effects across regions. We also provide early empirical evidence for agriculture as a key linkage between global warming and poverty.

[6] Other studies have analyzed subnational data and find negative effects of rainfall shocks on economic growth (e.g., Damania et al., 2020; Kotz et al., 2022).

2. Data

We construct the data from multiple sources. Our main outcomes are (headcount) poverty rates using the daily poverty lines of US \$1.90, \$3.20, and \$5.50, which are provided at the subnational level by the World Bank's Global Subnational Atlas of Poverty (GSAP). Using harmonized household survey data, the GSAP dataset offers global poverty estimates in 2018, which are statistically representative of more than 1,780 subnational units across 166 countries (World Bank, 2021b). In most cases, a subnational unit refers to 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.

We match our poverty 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. 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.

To examine the impacts of future climate change on poverty, we employ the temperature projections from NASA Earth Exchange (NEX) Global Daily Downscaled Projections (GDDP). We also exploit data from different sources including the global gridded data of annual crop yields from Iizumi and Sakai (2020), the broadband internet coverage provided by Collins Bartholomew's Mobile Coverage Explorer, and other country-level characteristics from NASA Socioeconomic Data and Applications Center (SEDAC).

The GSAP offers high-quality subnational poverty data and is our preferred data for analysis, but it is only available for a single year. To address this limitation, we also examine for robustness checks and richer analysis two alternative sources of subnational poverty provided by Kalkuhl and Wenz (2020) and Kummu et al. (2020). Kalkuhl and Wenz's (2020) Gross Regional Product (GRP) data is annually available from 1981 to 2016 for more than 1,500 regions in 77 countries. This dataset, however, includes only few countries in Africa. Kummu et al.'s (2020) annual gridded datasets for GDP per capita (PPP) covers a shorter period from 1990 to 2015 for 82 countries and records each grid cell at 5 arc-min resolution. For both datasets, we calculate poverty rates by imposing the poverty lines of $1.90, $3.20, and $5.50 for all the regions after converting the nominal GRP to real values.[7] Since these two datasets are built from macro-economic indicators (rather than household consumption surveys) and cover significantly fewer countries than the GSAP, they are not our preferred data for analysis.[8] But their longitudinal data allows us to employ richer panel data models with region fixed effects.

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.

3. Empirical Specifications

We employ three types of econometric models for analysis: (i) panel model; (ii) long differences model; and (iii) cross-sectional model. We start first with estimating the following panel model with location and year fixed effects (FE)

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

[7] Since regional GRP deflators are unavailable, we convert the nominal GRP to real values using the national GDP deflators from World Development Indicators. We subsequently 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. We present the list of countries in the different datasets in Appendix B, Table B3.

[8] Estimated growth rate of consumption based on the national account was long found to be different from and tends to be larger than that based on the household survey, both across countries and over time (Dang and Serajuddin, 2020; Deaton, 2005; Ravallion, 2003).

where $Y_{i,t}$ represents the poverty rate 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-level analysis. We employ three different poverty indicators for the three different poverty lines (i.e., \$1.90, \$3.20, and \$5.50 a day).

Our variable of interest $T_{i,t}$ represents the average temperature in degrees Celsius, and β_{FE} is expected to be positive (i.e., global warming likely increases poverty). 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 ($P_{i,t}$), the average precipitation measured in millimeters in all the regressions. α_i is the country (or sub-national) fixed effects that controls for unobserved time-invariant location-specific factors (i.e., institutions or culture) that may be correlated with climate or local economic patterns; π_t is the year fixed effects that controls for unobserved temporal changes affecting poverty each year. ϵ_{it} is an idiosyncratic error term. We cluster our errors at the country level to allow for potential serial correlation over time within 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).

Our model specification in Equation (1) follows Dell et al. (2012), who assume linear effects of climate change. To compare this approach with other specifications recently employed in the literature (e.g., Kalkuhl and Wenz, 2020), we also consider several variants of Equation (1) including (i) capturing the non-linear effects of temperature by adding a quadratic term ($T_{i,t}^2$); (ii) controlling for the effects of temperature changes ($\Delta T_{i,t} = T_{i,t} - T_{i,t-1}$); and (iii) controlling for the interactive effects between temperature levels and changes ($T_{i,t} \times \Delta T_{i,t}$).

Causal interpretation of β_{FE} requires the assumption that, conditional on the location and year fixed effects, any remaining variation in temperature and precipitation is random. Since climatic variables are exogenously determined, at least in the short run, this assumption is reasonable and Equation (1) can identify the effects of temperature changes on poverty in the short run. Yet, Equation (1) does not capture the long-run effects if these effects are mediated through adaption, or are compounded and intensified over time (Burke and Emerick, 2016). To complement Equation (1), we estimate the following long differences regression for the long-run temperature effects on poverty

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

In Equation (2), ΔY_i represents changes in poverty 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 not affected by data fluctuations in any single year, we use 10-year difference averages. That is, for all the variables in Equation (2) in our study period of 1979–2018, we analyze the differences between their averages of the earliest 10-year period 1979–1988 (i.e., $\overline{Y_{\iota,1979-1988}} = (\sum_{1979}^{1988} Y_{i,t})/10$) and their averages of the latest 10-year period 2009–2018 (i.e., $\overline{Y_{\iota,2009-2018}} = (\sum_{2009}^{2018} Y_{i,t})/10$).

Under the long differences approach, any time-invariant location-specific factors are differenced out. But unbiased estimates of β_{LD} requires the assumption that, conditional on the location fixed effects, long-term changes in temperature are exogenous with respect to the outcomes. As with Equation (1), the coefficients of interest, β_{LD}, is expected to be positive. To provide robustness checks for this approach, we conduct a number of alternative specifications including (i) constructing alternative period-average definitions such as 5-year and 15-year periods; (ii) controlling for covariates with respect to geography and resource endowments that might influence poverty; and (iii) applying additional model specifications as with the panel model in Equation (1).

The results from the panel model and long differences model provide useful analysis, but employing these models requires longitudinal, subnational poverty data. This data requirement is not satisfied by the GSAP, which offers subnational poverty for 2018 alone. We thus run the following cross-sectional model at the subnational level using the GSAP data

$$Y_{i,j} = \beta_{CS}\bar{T}_{i,j} + \gamma_{CS}\bar{P}_{i,j} + \sigma_j + \varphi_{i,j} \quad (3)$$

where $Y_{i,j}$ is poverty for region i in country j, and $\bar{T}_{i,j}$ and $\bar{P}_{i,j}$ are the average temperature and precipitation over the last 10 years (i.e., 2009 – 2018).[9] Since the GSAP is our preferred data (with more country coverage and high-quality poverty data), Equation (3) is our preferred model for analysis. The estimates using the panel and long-differences models, albeit constrained by samples of fewer countries and poverty estimates based on macro-economic data, can further offer qualitative supporting evidence for the effects of temperature on poverty.

The cross-sectional poverty data can, however, result in biased estimates for β_{CS} in Equation (3). One challenge is the potential omitted variable bias. For example, the unobserved correlation between temperature and other factors, such as technological change or labor productivity, may influence poverty. Another issue is potential misspecification of the functional form of temperature if non-linear effects of temperature on poverty exist. To address these challenges, we include the country fixed effects (σ_j), which account for unobserved time-invariant characteristics that are specific to country j, such as geographic features or institution characteristics. This feature is not available for previous studies that employ cross sectional analysis at the country level. We also analyze temperature and precipitation averaged over longer and different periods of time to ensure stability of these climatic variables, which reduces to some extent the concern regarding their correlation with other unobserved variables.[10]

Furthermore, we conduct various analysis to provide further support to our main finding. First, as discussed in Section 4.2 on robustness checks, our estimation results for Equation (3)

[9] We offer robustness checks using different time intervals in Section 4.2.
[10] We provide a summary of econometric models used in recent studies on global warming in Table B4 (Appendix B).

are not sensitive to a number of checks including adding covariates at the subnational level and using alternative samples. Second, we conduct a placebo exercise based on repeated within-sample randomization. Third, we more generally allow for temperature to have non-linear effects on poverty by adding a quadratic term for temperature to Equation (3) for robustness checks.

Finally, we conduct additional analysis of the non-linear effects using a temperature-bin approach that allows for a more flexible function of temperature (e.g., Chen and Gong, 2021; Mullins and White, 2020)

$$Y_{i,j} = \sum_{j=1}^{10} \beta_{TB} T_{i,j} + \gamma_{TB} P_{i,j} + \theta_j + \vartheta_{i,j} \tag{4}$$

Specifically, we divide temperature into ten five-degrees Celsius bins, where extreme low temperature is captured as temperature less than 0ºC and extreme high temperature is captured as temperature greater than 32ºC. The temperature shock variable reflects the number of days when the daily average temperature in a region is within a specific bin in 2018. Since the number of days falling into these ten bins sums to 365, we drop one bin in the regression as the reference category. We use the most thermally comfortable temperature bin as the reference group, which is 16ºC–20ºC, as the baseline group. The coefficient on temperature variable is thus interpreted as the effect of exchanging a day in the 16ºC–20ºC range with a day in other bins.

4. Results

4.1. Main findings

We start examining the effects of higher temperature on poverty using the country-level analysis in Table 1. We first use an unbalanced country-level panel for 161 countries over the period 1979 – 2018 and analyze three poverty indicators at the daily poverty lines of $1.90, $3.20, and $5.5. For each outcome, we start with the location and year FE panel approach

(Equation 1), followed by the long differences model (Equation 2) and the cross-sectional model (Equation 3). In all the regressions, we control for precipitation given that changes in rainfall can be an important aspect of long-run climate trends affecting poverty rate. Two main results emerge from Table 1, which are rather robust across different specifications. First, we find little evidence of the effects of higher temperature on poverty at the country level, except for the results using cross-sectional model. This is in line with our earlier discussion that poverty varies considerably within a country, and thus using data aggregated at larger spatial scales may mask the harmful effects of hotter temperature. Second, we find no significant effect for precipitation, which is consistent with previous studies that find small or non-significant effects of rainfall on different outcomes (e.g., Burke et al., 2015b; Dell et al., 2012).

We subsequently present in Table 2 the estimation results obtained from the analysis at the subnational level. Columns (1), (4), and (7) show the estimates using the panel model with the region, country, and year fixed effects (using Equation (1)) for the three poverty lines. For these regressions, we employ the poverty estimates that we generate based on the subnational GDP data in Kalkuhl and Wenz (2020). The results are strongly statistically significant at the 5 percent level and confirm the negative effects of higher temperature on poverty for all the three different poverty lines. For example, Column (1) shows that a 1°C increase in temperature leads to a 0.15 percentage points (or 0.72 percent) increase in poverty, using the poverty line \$1.90 a day.

Using the same data, we show the estimated long-term effects of temperature on poverty in Table 2, Columns (2), (5), and (8) (using Equation (2)). The results of the long differences model are qualitatively similar, indicating positive and strongly statistically significant effects of higher temperature on poverty. In addition, the long differences coefficient estimates are much larger in absolute value than the corresponding panel coefficient estimates. For instance, the estimated coefficient for the regression for poverty using the \$1.9 daily poverty line jumps to 5.7 percentage points (27.8 percent) under the long differences specification (Column 2). This suggests that higher temperature may have intensifying effects on poverty in the longer run.

However, as discussed earlier, the results with the panel model and the long differences model can be biased since they are based on a data sample which excludes many countries in Africa—the poorest region in the world. Furthermore, the poverty outcomes for these data are based on macro-economic indicators (i.e., GDP), which can be different from the official poverty estimates based on household survey data. Given these limitations, we next turn to analyzing the preferred GSAP data with more country coverage and better poverty data constructed from harmonized household surveys.

Since the GSAP data is available only in 2018, we present the results using the cross-sectional model (Equation (3)) in Table 2, Columns (3), (6), and (9). Overall, we document positive, statistically significant effects of hotter temperature on poverty. Column (1) shows that a 1°C increase in temperature causes a 0.210 percentage points increase in poverty (at the daily $1.90 poverty line). This equals a 2.12 percent increase in poverty using the mean poverty rate of 9.9 percent. Furthermore, the impact magnitudes are higher for higher poverty lines (0.33 percentage points and 0.30 percentage points increases for the daily poverty lines of $3.20 and $5.50, respectively). At the same time, we find no effect of precipitation on poverty using the cross-sectional model.[11]

4.2. Robustness tests and heterogeneity analysis

[11] Applying the cross-sectional model to the GRP data from Kalkuhl and Wenz (2020), but keeping the poverty outcomes in 2016 alone (the latest year in this data set), yields qualitatively similar results for the negative effects of hotter temperature on poverty (Appendix A, Table A13). This provides further support to this preferred specification using GSAP data.

To investigate the robustness of the finding of negative temperature effects on poverty, 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 and long differences model as employed in recent studies (e.g., Kalkuhl and Wenz, 2020; Kotz et al., 2021). They include controlling for temperature change, adding a quadratic term of temperature, adding an interaction term between temperature and temperature change, and using difference choices of window length. We also exploit alternative sources of temperature and subnational GDP data as well as controlling for additional covariates. The results, shown in Tables A1 and A2 (Appendix A), indicate that our findings remain robust, and the results are consistent across different specifications.

We also provide a battery of robustness tests on our preferred specification using the GSAP data. They include (i) making use of alternative measures of temperature; (ii) accounting for the non-linear effect of temperature on poverty; (iii) controlling for additional covariates; (iv) using weighted regression; and (v) using different subsamples. Again, the results of these tests deliver qualitatively similar findings (Appendix A, Tables A3-A7). Finally, we conduct a placebo test by using within-sample randomization, where we replace the actual temperature of a region with the temperature from a randomly chosen region in our sample. We find that none of the estimated coefficient and *t*-statistic obtained from 1,000 placebo runs generates any value close to those derived under true assignment (Appendix A, Figure A3). It thus provides further support to our main estimate of the effect of temperature on poverty.

We offer further heterogeneity analysis across regions. We plot the results in Figure 2, which shows that rising temperature causes higher poverty in poorer regions such as Sub-Saharan Africa, Middle East and North Africa, and South Asia, but the effects are attenuated in other richer regions. We also plot the estimated effects for each country, adjusted by their real GDP per capital in 2018, and find that countries bearing the largest effects of global warming are those currently with the lowest income (Appendix A, Figure A4). Futhermore, we examine whether the impacts of temperature differ by country characteristics. Estimation results, shown in Table A9 (Appendix A), suggest that countries with a democratic regime appear to be less vulnearable to the impacts of global warming, while the opposite holds for countries near the equator. In addition, the effects of hotter temperature are stronger for those with a higher share of agriculture, but are less pronounced in areas with a higher share of manufacturing. Finally, we show that regions with better access to information and communication technologies (ICTs) are less vulnerable to the effects of higher termperature (Table A10, Appendix A).

4.3. Potential mechanism

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 a panel fixed effects model as in Equation (1), we find consistent and negative effects of higher temperature on different crop yields including rice, maze, and soybean, as shown in Table 3. Similarly, we also find the effects of global warming to be more pronounced among regions with a higher share of agriculture (Appendix A, Table A11).

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 our preferred specification in Table 2 on the *y*-axis, and the effects of temperature on agriculture in Table 3 on the *x*-axis in Figure A5 (Appendix A). Since the unit of analysis is different across two samples, we aggregate the data at the country level for comparison purpose. For all the panels, we find a negative and strongly statistically significant correlation between crop yield and poverty. Overall, these findings suggest that by reducing crop yield, warmer temperature may directly contribute to more poverty.

4.4. Projected impacts under future climate change

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 cross-sectional model estimates in Table 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.[12] 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 – 2018. We then calculate 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 by multiplying with the baseline estimates in columns (3), (6), and (9) of Table 2.

[12] 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.

Table A12 (Appendix A) provides a summary of the projected changes for temperature and in 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 2.631°C and 5.999°C in 2099. These temperature increases can result in poverty increases between 0.552 and 1.95 percentage points (which correspond to 3.3 and 6.5 percent changes). The largest poverty increase would occur in the scenario without any countervailing strategies to address climate change between 2021 and 2099 in the form of investment in renewable energy.

In particular, Figure 1 shows that Sub-Saharan Africa currently has the highest poverty rates, particularly for countries including Tanzania (51.3 percent), Mozambique (54.7 percent), and Congo DRC (72.9 percent) (Panel C). In Panel D of Figure 1, we present projections of the effects of temperature across regions in our sample under the RCP8.5 emission pathways.[13] It reaffirms our previous findings that poor countries in Africa continue to be most vulnerable to hotter temperature. Consequently, climate change will add to the burdens of those who are already poor and vulnerable.

5. Conclusions

While there is growing evidence of harmful effects of climate change on macro-economic outcomes, little evidence exists regarding the relationship between global warming and poverty on a global scale. We analyze the GSAP data, a new global poverty dataset representative of subnational areas in 166 countries and we find that higher temperature results in higher poverty rate. This result is robust to various robustness checks including different model specifications, alternative measures of temperature, controlling for additional covariates, and analyzing various other datasets.

[13] We present the projected effects under RCP4.5 emission pathways in Figure A6 (Appendix A).

Our preferred specification shows that a 1°C increase in temperature leads to 0.21 percentage points (2.12 percent) increases in the headcount poverty ratio using the daily poverty line of $1.90. At the same time, we do not find strong evidence of such effects when using the country-level analysis, which can be possibly explained by large variation of temperature and poverty within a country. Sub-Saharan Africa and South Asia are most susceptible to higher temperature. We also offer suggestive evidence of agriculture as a key channel in which higher temperature leads to higher poverty. Finally, our projection shows alarming effects on increased poverty of up to 6.5 percent as a result of global warming. This finding is especially relevant from a policy perspective, considering that nearly 10 percent of the world are living in extreme poverty (as measured against the daily poverty line of US$1.90) and around 30 percent remain in poverty (as measured against the daily poverty line of US$5.50).

The availability of subnational poverty data opens other avenues of future research. The effects of global warming can be different for population groups at different income levels. As such, one promising direction is to improve our understanding of the distributional effects of global warming on inequality. Another direction is to investigate the role of other mechanisms, such as civil conflicts, in explaining how rising temperature increases poverty. Further (global) evidence on these topics would help provide better, and more coordinated policy inputs for more effective actions by different countries to address the challenge of global warming.

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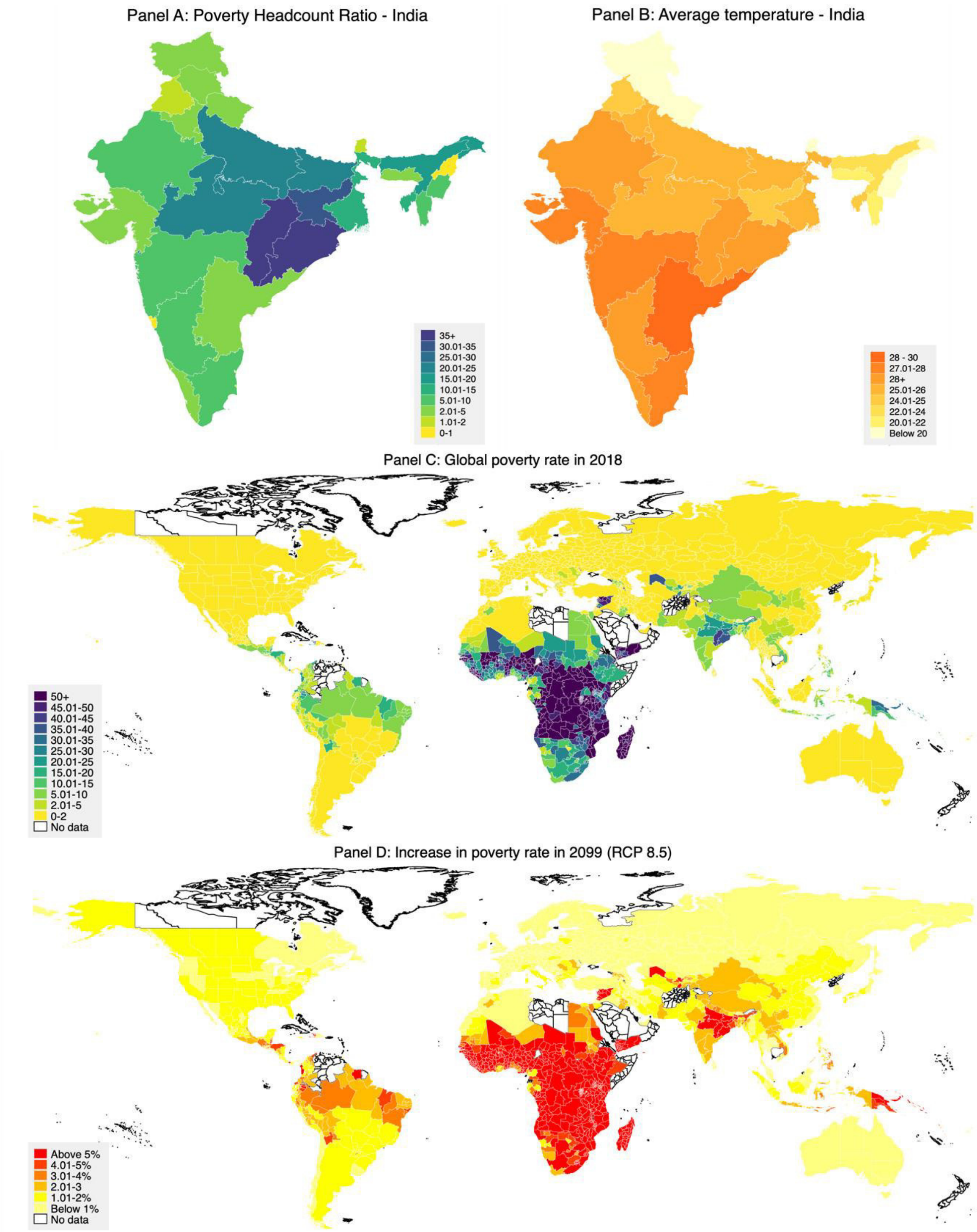
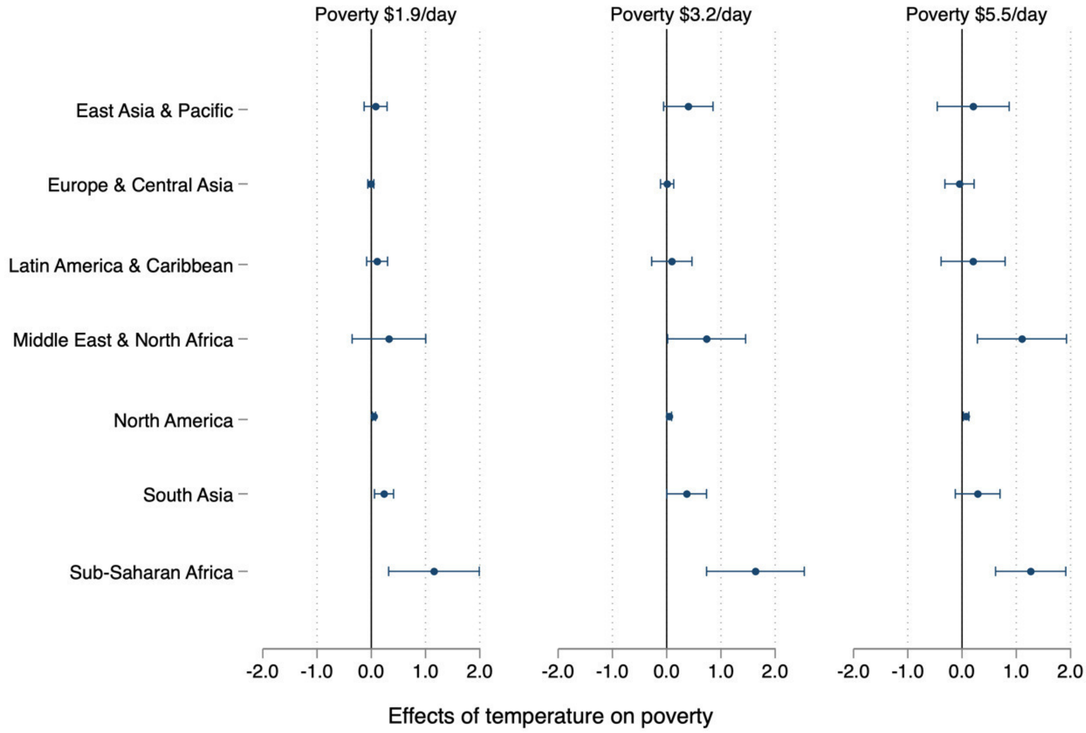
Figure 1: Subnational poverty and temperature in India and projected global poverty



Notes: Poverty is measured by Global Subnational Poverty Headcount Ratio at US$ 1.90 a day. 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). In panels A and B, poverty rate and temperature data are measured in 2015. The projection in Panel D is estimated using the coefficient on the effects of temperature on poverty reported in Columns (3) of Table 2 and the average temperature of during the period 1979 – 2018.

Figure 2: The effects of temperature on poverty by region



Notes: Reported are estimates and their 95 percent confidence intervals by region. Each estimate comes from a separate regression of poverty on temperature and rainfall, and country fixed effects. Robust standard errors are clustered at the country level.

Table 1: The effects of temperature on poverty – Country-level analysis

	Poverty rate $1.90			Poverty rate $3.20			Poverty rate $5.50		
	Panel FE	Long differences	Cross-sectional	Panel FE	Long differences	Cross-sectional	Panel FE	Long differences	Cross-sectional
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Temperature	0.544	-3.263	1.134***	0.510	-3.621	1.991***	-0.211	-5.975	2.606***
	(0.337)	(3.773)	(0.148)	(0.483)	(4.052)	(0.221)	(0.652)	(4.371)	(0.291)
Precipitation	-0.008	-0.201	-0.018	-0.023	-0.199	-0.022	-0.034**	-0.040	-0.020
	(0.011)	(0.169)	(0.019)	(0.015)	(0.166)	(0.030)	(0.016)	(0.158)	(0.037)
Country FE	Yes	No	No	Yes	No	No	Yes	No	No
Year FE	Yes	No	No	Yes	No	No	Yes	No	No
Number of countries	161	133	133	161	133	133	161	133	133
Observations	1,717	133	133	1,717	133	133	1,716	133	133
Adjusted R-squared	0.283	0.009	0.217	0.372	0.006	0.312	0.410	-0.001	0.369

Notes: Robust standard errors in parentheses. Standard errors are clustered at the country level. Poverty rate is taken from the WDI dataset. Poverty rates and weather variables in the long-difference 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). *** p<0.01, ** p<0.05, * p<0.1

Table 2: The effects of temperature on poverty – Subnational level analysis

	Poverty rate \$1.90			Poverty rate \$3.20			Poverty rate \$5.50		
	Panel FE	Long differences	Cross-sectional	Panel FE	Long differences	Cross-sectional	Panel FE	Long differences	Cross-sectional
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Temperature	0.148**	5.677**	0.210**	0.206**	6.486**	0.325***	0.224**	6.154*	0.297*
	(0.064)	(2.756)	(0.090)	(0.084)	(3.232)	(0.124)	(0.095)	(3.329)	(0.176)
Precipitation	0.919***	14.251	-0.273	1.045***	21.608**	0.015	0.479	34.568*	0.130
	(0.176)	(9.462)	(0.319)	(0.246)	(10.312)	(0.293)	(0.311)	(18.262)	(0.288)
Region FE	Yes	No	No	Yes	No	Yes	Yes	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	Yes	No	No	Yes	No	No
Number of countries	74	61	164	74	61	163	74	61	163
Number of regions	3,394	1,306	1,780	3,394	1,306	1,749	3,394	1,306	1,749
Observations	138,060	1,306	1,780	138,060	1,306	1,749	138,060	1,306	1,749
Adjusted R-squared	0.334	0.507	0.858	0.350	0.637	0.905	0.385	0.583	0.932

Notes: Robust standard errors in parentheses. Standard errors are clustered at the country level. In the Panel FE and long difference regressions, poverty rate is calculated using subnational GDP from Kalkuhl and Wenz (2020) and the poverty lines of \$1.90, \$3.20, and \$5.50. In the cross-sectional model, poverty rate is taken from the GSAP dataset. 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). *** p<0.01, ** p<0.05, * p<0.1

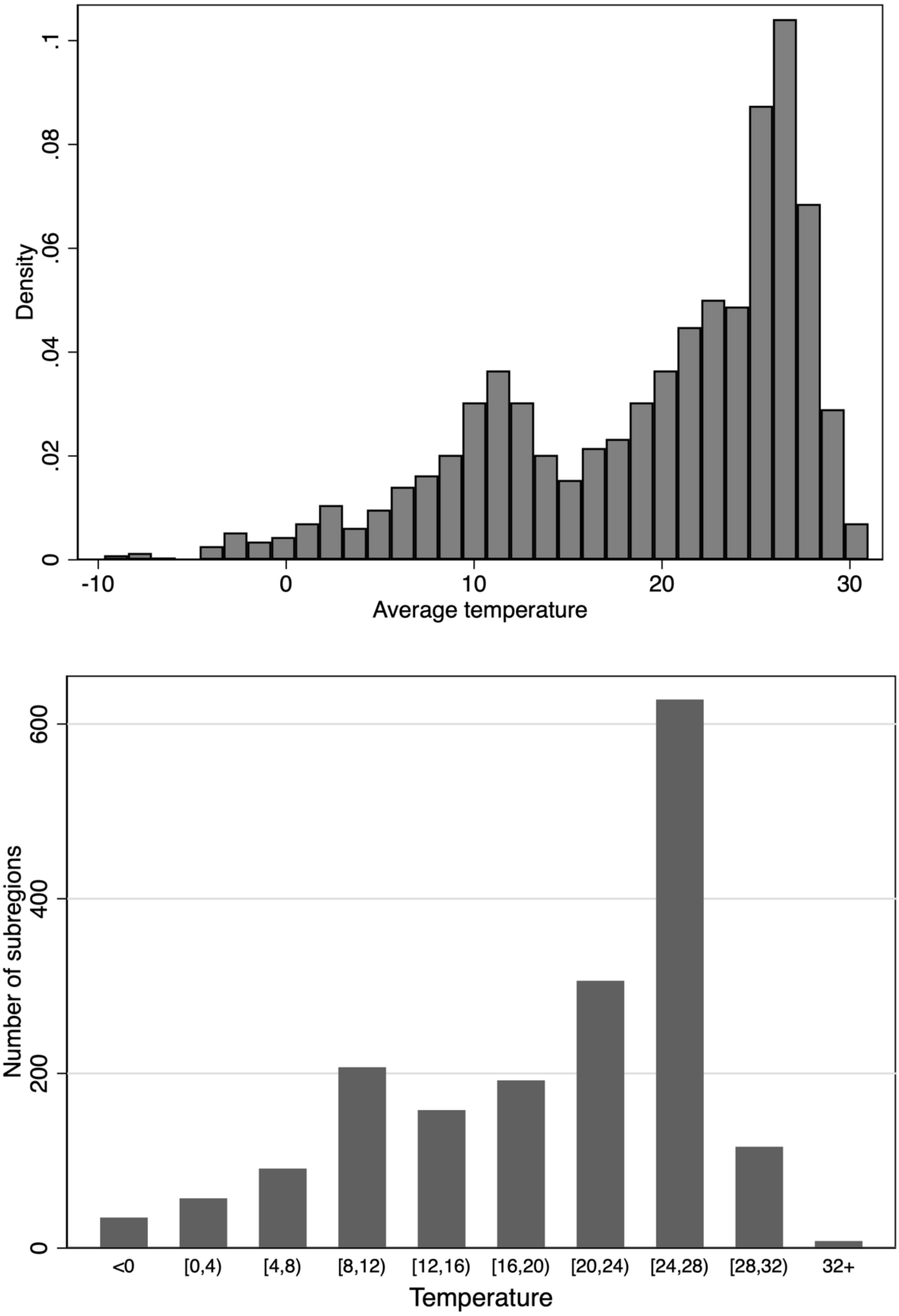
Table 3: Effects of temperature on agriculture

Crop yield	Rice	Maize	Soybean	Wheat
	(1)	(2)	(3)	(4)
Temperature	-0.064***	-0.033***	-0.020***	0.003
	(0.009)	(0.007)	(0.003)	(0.007)
Controlling for rainfall	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Number of countries	53	82	19	70
Number of regions	660	955	189	670
Observations	10,257	14,870	2,953	10,178
Adjusted R-squared	0.703	0.669	0.677	0.725

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

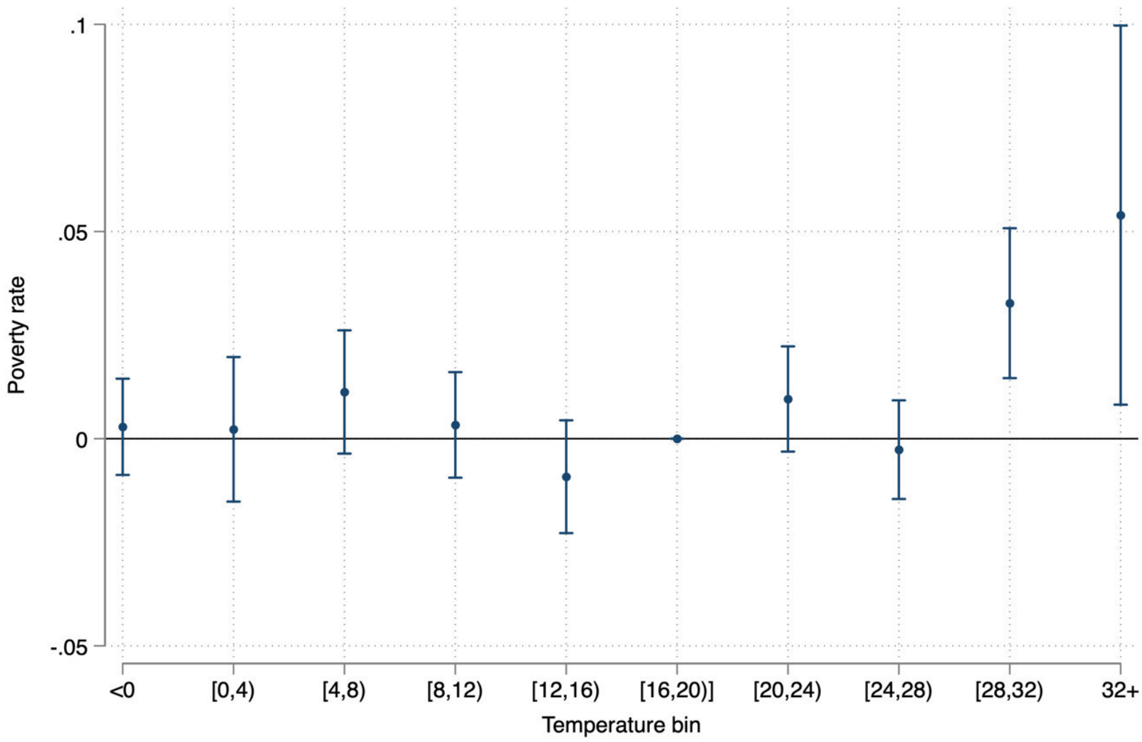
Appendix A: Additional Tables and Figures

Figure A1: The effects of temperature on poverty by region



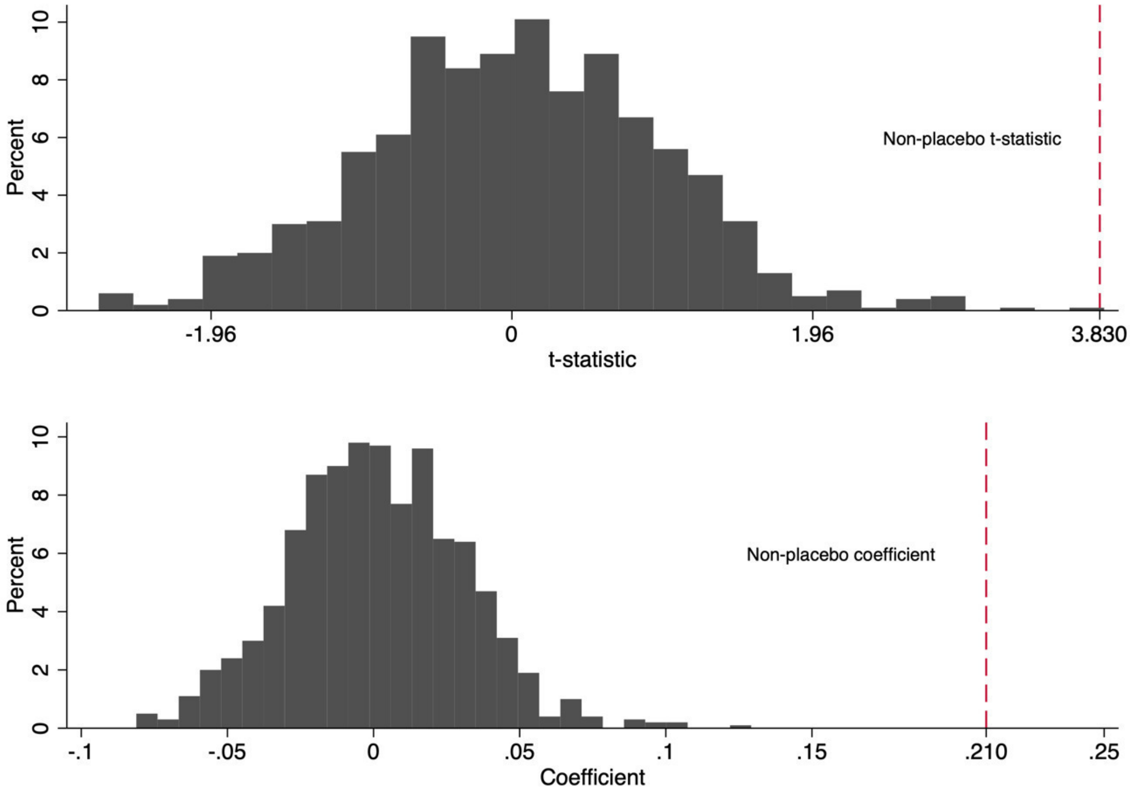
Notes: Temperature data is taken from the European Centre for Medium-Range Weather Forecasts Reanalysis 5 (ERA-5).

Figure A2: Non-linear effects of temperature on poverty – Bin approach



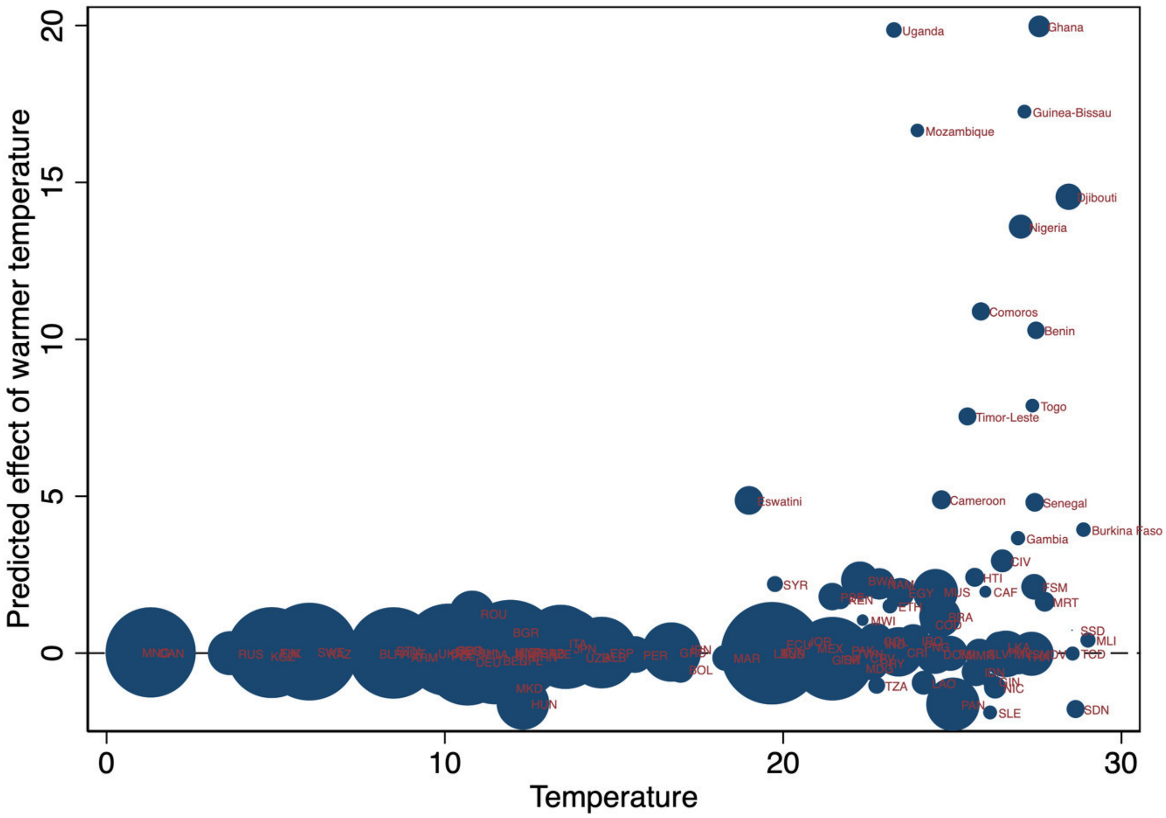
Notes: Global Subnational Poverty Headcount Ratio at $1.90 a day in 2018. The reference temperature bin is [16,20).

Figure A3: Placebo test



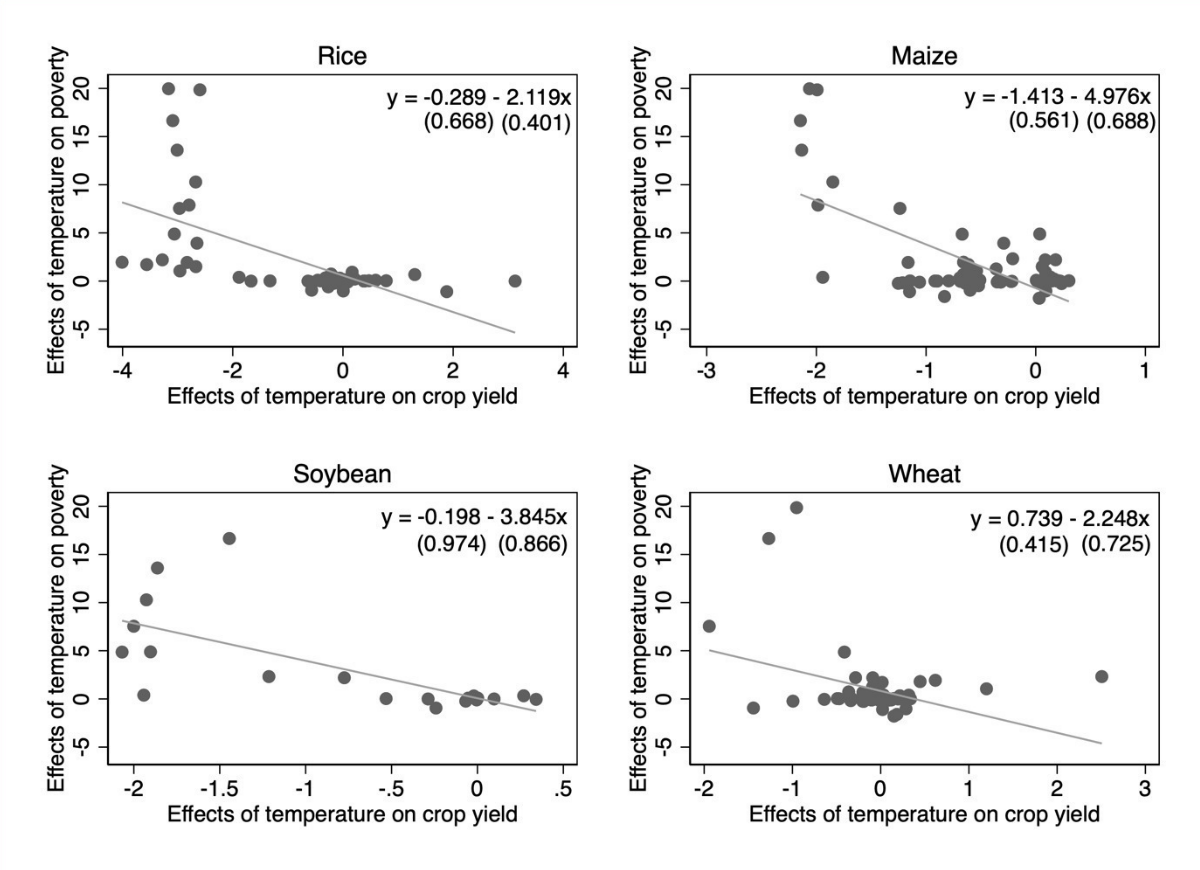
Notes: Results of placebo exercise using 1,000 randomizations of regions. The outcome is poverty headcount ratio at $1.90. All regressions include precipitation and country fixed effects.

Figure A4: The effects of temperature on poverty across countries



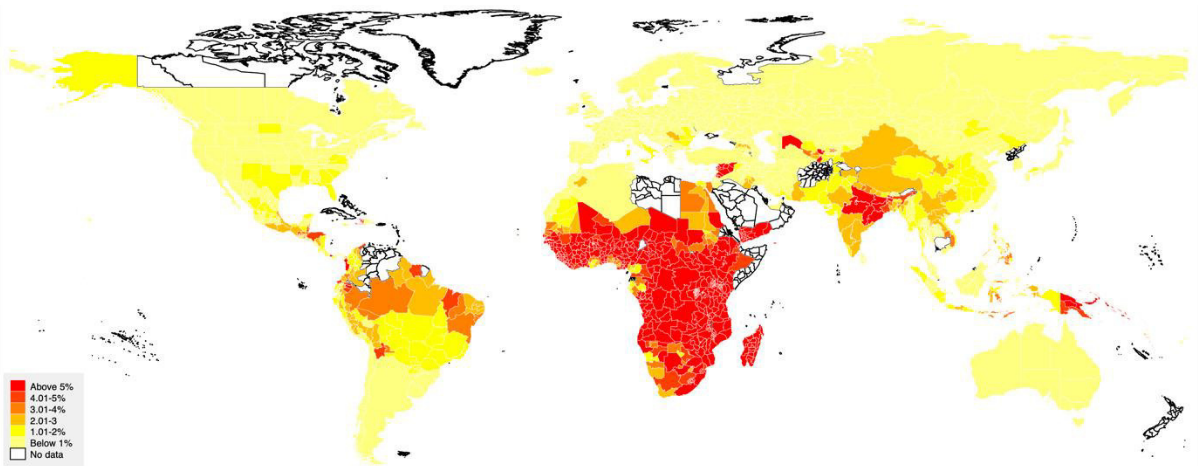
Notes: Poverty is measured by the headcount ratio at $1.90 a day. The figure shows the point estimates of temperature and the country dummies using regression with control variable and country fixed effects. Countries are depicted with their real GDP per capital in 2018 from the WDI database.

Figure A5: The effects of temperature on poverty and agriculture



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

Figure A6: Temperature effects on poverty rate in 2099 using the Representative Concentration Pathway (RCP) 4.5



Notes: Data on simulated weather conditions at the subnational level are from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP). Poverty rate is measured using the Global Subnational Poverty Headcount Ratio at $1.90 a day in 2018. The projection is estimated using the coefficient on the effects of temperature on poverty reported in Columns (3) of Table 2 and the average temperature of during the period 1979 – 2018.

Table A1: The effects of temperature on poverty – Alternative specifications of panel model and long-difference model

Dependent variable:	Panel model					Long differences model				
Poverty rate at $1.90	Temperature provided by CRU	Adding country linear time trend	Adding temperature change	Adding temperature squared term	Adding temperature interaction term	Temperature provided by CRU	5-year average	15-year average	Adding time-invariant covariates	Adding temperature interaction term
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Temperature	1.226***	0.198***	0.317**	-2.503***	-2.425***					-0.682***
	(0.280)	(0.069)	(0.156)	(0.403)	(0.502)					(0.223)
ΔTempearture			-0.124	0.695***	0.601**	1.420*	1.413*	4.475*	5.401*	3.080
			(0.087)	(0.154)	(0.250)	(0.838)	(0.727)	(2.625)	(2.993)	(3.216)
Temperature squared				0.079***	0.076***					0.027***
				(0.016)	(0.024)					(0.007)
Temperature*ΔTempearture					0.005					0.270
					(0.027)					(0.219)
Controlling for rainfall	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Subnational FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
Number of countries	77	74	74	74	74	59	65	59	61	61
Number of regions	1,545	3,394	3,394	3,394	3,394	1,179	1,265	1,275	1,304	1,304
Observations	47,243	138,060	138,060	138,060	138,060	1,179	1,265	1,275	1,304	1,304
Adjusted R-squared	0.512	0.331	0.378	0.637	0.637	0.319	0.403	0.559	0.509	0.514

Notes: Robust standard errors in parentheses. Standard errors are clustered at the subnational level. Poverty incidence is calculated using subnational GDP from Kalkuhl and Wenz (2020) and the poverty line from WDI. Control variables in Column (3) are taken from Kalkuhl and Wenz (2020) which include cumulative oil gas, distance to coast, distance to river, and altitude. *** p<0.01, ** p<0.05, * p<0.1

Table A2: 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***		-0.058***
	(0.022)	(0.060)		(0.006)
ΔTempearture		0.870***	0.862***	0.490***
		(0.033)	(0.113)	(0.131)
Temperature squared		0.092***		0.001***
		(0.002)		(0.000)
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 subnational level. Poverty incidence is calculated using subnational GDP from Kummu et al. (2018) and the poverty line from WDI. *** p<0.01, ** p<0.05, * p<0.1

Table A3: Robustness test – Alternative measures of temperature

	Dependent variable: Poverty rate at $1.90						
	5-year average temperature	15-year average temperature	20-year average temperature	Temperature provided by CRU	Number of days temperature above 28	Dropping subregions with temperature above 28	Temperature shock
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Temperature	0.208**	0.205**	0.207**	0.140**	0.035**	0.151**	1.234*
	(0.091)	(0.090)	(0.091)	(0.069)	(0.017)	(0.075)	(0.644)
Controlling for rainfall	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of countries	164	164	164	163	161	152	164
Number of regions	1,780	1,780	1,780	1,737	1,698	1,666	1,780
Observations	1,780	1,780	1,780	1,737	1,698	1,666	1,780
R-squared	0.858	0.858	0.858	0.856	0.866	0.870	0.857

Notes: Robust standard errors in parentheses. Standard errors are clustered at the country level. In Column (7), 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 A4: Non-linear effects of temperature on poverty

Poverty rate at:	$1.90	$3.20	$5.50
	(1)	(2)	(3)
Panel A: Quadratic term			
Temperature	-0.211	-0.168	-0.158
	(0.129)	(0.169)	(0.264)
Temperature squared	0.016**	0.018**	0.017*
	(0.006)	(0.008)	(0.010)
Observations	1,780	1,749	1,749
R-squared	0.859	0.905	0.932
Panel B: Cubic term			
Temperature	0.022	0.054	-0.064
	(0.074)	(0.099)	(0.179)
Temperature squared	-0.022	-0.021	-0.002
	(0.015)	(0.022)	(0.025)
Temperature 3rd degree	0.001**	0.001	0.001
	(0.000)	(0.001)	(0.001)
Observations	1,780	1,749	1,749
R-squared	0.859	0.905	0.932
Number of countries	164	163	163
Number of regions	1,780	1,749	1,749
Controlling for rainfall	Yes	Yes	Yes
Country FE	Yes	Yes	Yes

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

Table A5: Adding additional controls

	Dependent variable: Poverty rate at $1.90				
	(1)	(2)	(3)	(4)	(5)
Temperature	0.228***	0.567**	0.402***	0.216**	0.616**
	(0.087)	(0.248)	(0.138)	(0.093)	(0.238)
Population density	-0.001***				-0.002***
	(0.000)				(0.001)
Elevation		0.003**			0.002**
		(0.001)			(0.001)
Distance to nearest coastal			-0.009**		-0.008**
			(0.004)		(0.003)
$PM_{2.5}$				-0.007	0.027
				(0.049)	(0.059)
Controlling for rainfall	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Number of countries	164	164	164	164	164
Number of regions	1,777	1,780	1,778	1,763	1,763
Observations	1,777	1,780	1,778	1,763	1,763
R-squared	0.863	0.860	0.863	0.858	0.870

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

Table A6: Weighted regression

Poverty rate at:	\$1.90	\$3.20	\$5.50
	(1)	(2)	(3)
Temperature	0.502**	0.302**	0.160
	(0.226)	(0.150)	(0.114)
Controlling for rainfall	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Number of countries	157	160	162
Number of regions	1,420	1,574	1,695
Observations	1,420	1,574	1,695
R-squared	0.772	0.648	0.793

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

Table A7: Robustness test – Alternative samples

	Dependent variable: Poverty rate at $1.90							
	Dropping countries with few subregions	Excluding China	Excluding United States	Excluding India	Excluding 10 percent cold countries	Excluding 10 percent hot countries	Spatially-corrected Conley S.E.	Temperature in 2020-2030 (residuals)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Temperature	0.203**	0.238**	0.222**	0.199*	0.273**	0.174**	0.210***	-0.319
	(0.097)	(0.097)	(0.099)	(0.101)	(0.117)	(0.085)	(0.052)	(0.260)
Controlling for rainfall	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of countries	86	163	163	163	147	149	164	164
Number of regions	1,392	1,749	1,729	1,745	1,594	1,625	1,780	1,780
Observations	1,392	1,749	1,729	1,745	1,594	1,625	1,780	1,780
R-squared	0.852	0.857	0.856	0.861	0.851	0.869	0.857	0.857

Notes: Robust standard errors in parentheses. Standard errors are clustered at the country level. In Column (8), the residuals are taken from a regression of future temperature (2020-2030) on current temperature (2018) and other control variables. The future temperature data is provided by the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP). *** p<0.01, ** p<0.05, * p<0.1

Table A8: The effects of temperature on poverty by region

Poverty rate at:	$1.90	$3.20	$5.50
	(1)	(2)	(3)
Reference group: Sub-Saharan Africa			
Temperature*East Asia and Pacific	-1.422***	-2.105***	-2.186***
	(0.434)	(0.534)	(0.630)
Temperature*Europe and Central Asia	-1.369***	-1.683***	-1.271***
	(0.433)	(0.489)	(0.463)
Temperature*Latin America and Caribbean	-1.299***	-1.621***	-1.050
	(0.447)	(0.554)	(0.663)
Temperature*Middle East and North Africa	-0.959**	-0.731	0.319
	(0.481)	(0.554)	(0.742)
Temperature*North America	-1.296***	-1.661***	-1.197***
	(0.434)	(0.495)	(0.459)
Temperature*South Asia	-1.124**	-1.316***	-0.945
	(0.436)	(0.502)	(0.657)
Controlling for rainfall and regions	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Number of countries	164	163	163
Number of regions	1,780	1,749	1,749
Observations	1,780	1,749	1,749
R-squared	0.860	0.907	0.934

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

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

Poverty rate at:	$1.90	$3.20	$5.50
	(1)	(2)	(3)
Panel A: Regime type (Reference group: Democracy)			
Temperature*Hybrid regime	0.224*	0.353*	0.521**
	(0.133)	(0.201)	(0.215)
Temperature*Authoritarian regime	-0.069	0.140	0.394**
	(0.113)	(0.199)	(0.195)
Observations	1,719	1,688	1,688
R-squared	0.852	0.903	0.931
Panel B: Location (Reference group: Countries near equator)			
Temperature* Countries near equator	0.716**	0.746**	0.947***
	(0.297)	(0.336)	(0.332)
Observations	1,780	1,749	1,749
R-squared	0.859	0.905	0.932
Panel C: Share of agriculture in GDP (Reference group: Low share)			
Temperature*High agriculture share	0.030***	0.033***	0.008
	(0.011)	(0.013)	(0.013)
Observations	1,758	1,727	1,727
R-squared	0.858	0.904	0.930
Panel D: Share of manufacturing in GDP (Reference group: Low share)			
Temperature*High manufacturing share	-0.022***	-0.078***	-0.149***
	(0.007)	(0.025)	(0.032)
Observations	1,659	1,628	1,628
R-squared	0.845	0.896	0.926
Panel E: Share of trade in GDP (Reference group: Low share)			
Temperature*High trade share	-0.004	-0.003	-0.004
	(0.002)	(0.003)	(0.005)
Observations	1,690	1,659	1,659
R-squared	1,690	1,659	1,659
Controlling for rainfall	Yes	Yes	Yes
Country FE	Yes	Yes	Yes

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

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

Poverty rate at:	$1.90	$3.20	$5.50
	(1)	(2)	(3)
Panel A: ICT Development index			
Temperature* ICT Index	-0.117***	-0.131***	-0.048
	(0.036)	(0.043)	(0.041)
Number of countries	146	145	145
Number of regions	1,616	1,585	1,585
Observations	1,616	1,585	1,585
R-squared	0.856	0.900	0.929
Panel B: Internet 2G			
Temperature*Internet coverage	-0.921***	-1.080***	-1.066***
	(0.255)	(0.278)	(0.236)
Number of countries	157	156	156
Number of regions	1,706	1,675	1,675
Observations	1,706	1,675	1,675
R-squared	0.863	0.910	0.934
Panel C: Internet 3G			
Temperature*Internet coverage	-0.597***	-0.626**	-0.680**
	(0.212)	(0.288)	(0.324)
Number of countries	149	148	148
Number of regions	1,405	1,397	1,397
Observations	1,405	1,397	1,397
R-squared	0.851	0.905	0.937
Panel D: Internet 4G			
Temperature*Internet coverage	-0.226*	-0.402**	-0.713***
	(0.117)	(0.195)	(0.259)
Number of countries	108	107	107
Number of regions	796	793	793
Observations	796	793	793
R-squared	0.899	0.918	0.937
Controlling for rainfall	Yes	Yes	Yes
Country FE	Yes	Yes	Yes

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

Table A11: 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***	-0.003	-0.008	-0.035***
	(0.015)	(0.016)	(0.006)	(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 A12: 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	0.292	0.417	0.552	0.259	0.444	1.260
Increase in poverty rate $3.20	0.451	0.645	0.855	0.401	0.687	1.950
Increase in poverty rate $5.50	0.412	0.589	0.781	0.367	0.628	1.782

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 (3), (6), and (9) of Table 2.

Table A13: The effects of temperature on poverty – Results of cross-sectional model using longitudinal data

Poverty rate at:	\$1.90	\$3.20	\$5.50
	(1)	(2)	(3)
Temperature	0.124***	0.234***	0.545***
	(0.043)	(0.060)	(0.086)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Number of countries	61	61	61
Number of regions	1,306	1,306	1,306
Observations	1,306	1,306	1,306
Adjusted R-squared	0.049	0.061	0.047

Notes: Robust standard errors in parentheses. Standard errors are clustered at the country 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. The analysis is based on data in 2016 – the latest year available in Kalkuhl and Wenz (2020). *** p<0.01, ** p<0.05, * p<0.1

Appendix B: Data

In this paper, we employ poverty data from different sources available at 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.

We leverage the second source of poverty data from the World Bank's Global Subnational Atlas of Poverty (GSAP), which harmonizes household survey data and offers poverty estimates with global coverage and statistical representativeness at the subnational level (World Bank, 2021b). National boundaries are disaggregated into subnational units, typically provinces or states (First level administrative boundaries – ADM1) but can also include custom groupings of subnational regions determined by the sampling strategy of household surveys.[15] Overall, this dataset covers 166 countries, disaggregated into 1,780 subnational units. Similar to the WDI dataset, the GSAP data offers several poverty estimates that measure the number of poor people by the daily expenditure thresholds of $1.90, $3.20, and $5.50. Because the household surveys necessary to measure poverty vary across countries in terms of time and frequency, all the estimates are converted to a common reference, or 'line-up' year.[16] Figure 1 (Panel C) shows a large variation of poverty rate within a country, which is further confirmed by the decomposition of variance presented in Table B2.

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 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.[17] While this is not our preferred poverty measure (dummy indicator), the longitudinal nature of the GRP dataset allows us to employ a fixed effect model which controls for unobservable characteristics at the regional level. 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 country in our datasets in Table B3.

We then match our poverty 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 A1 (Appendix A) 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

[15] The data is reported at the national level for 33 countries. As a robustness check, we exclude these countries and find a consistent effects of higher temperature on poverty.

[16] An exception is India which is based on its 2015 line-up. We find that our results are not sensitive to the exclusion of India.

[17] 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.

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 station. 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, 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.

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 description and summary statistics of all variables in Table B1.

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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	204	1,717	9.888	17.307	0.000	91.800
Poverty rate $3.20	Poverty Headcount Ratio at US$ 3.20 a day	204	1,717	18.997	25.481	0.000	98.500
Poverty rate $5.50	Poverty Headcount Ratio at US$ 5.50 a day	204	1,716	31.666	32.060	0.000	100.000
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	165	1,788	16.847	25.234	0.000	97.546
Poverty rate $3.20	Poverty Headcount Ratio at US$ 3.20 a day	164	1,757	30.152	33.972	0.000	99.668
Poverty rate $5.50	Poverty Headcount Ratio at US$ 5.50 a day	164	1,757	45.559	37.684	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

Satellite weather data (1979–2019)							
Source: European Union's Copernicus programme (https://sentinels.copernicus.eu/web/sentinel/missions/sentinel-5p)							
Temperature	Average temperature (C)	166	1,790	19.476	8.080	-9.691	30.991
Rainfall	Average rainfall (mm)	166	1,790	3.669	2.773	0.021	28.032
Source: Climatic Research Unit (https://crudata.uea.ac.uk/cru/data/hrg/)							
Temperature	Average temperature (C)	165	1,778	19.585	8.025	-11.418	30.132
Crop yield data							
Source: Iizumi 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 (Table A8)							
Regime type in 2018 (*Source: The Economist* - https://www.eiu.com/n/)							
Democracy	=1 if democracy score more than 7	152	1,729	0.193	0.394	0.000	1.000
Hybrid	=1 if democracy score between 4 and 7	152	1,729	0.515	0.500	0.000	1.000
Authoritarian	=1 if democracy score less than 4	152	1,729	0.292	0.455	0.000	1.000
Share of agriculture in GDP in 2018 (*Source: The World Bank - https://datacatalog.worldbank.org/home*)							
Low share	=1 if share of agriculture in GDP less than 10 percent	162	1,767	0.561	0.496	0.000	1.000
High share	=1 if share of agriculture in GDP equal to or greater than 10 percent	162	1,767	0.439	0.496	0.000	1.000
Broadband internet (*Source*: https://www.collinsbartholomew.com/)							
2G	Internet coverage at subnational level in 2018	153	1,724	0.913	0.161	0.000	1.000
3G	Internet coverage at subnational level in 2018	129	1,423	0.809	0.264	0.000	1.000
4G	Internet coverage at subnational level in 2018	81	813	0.781	0.331	0.000	1.000
Other variables (Table A5)							
Source: NASA Socioeconomic Data and Applications Center (SEDAC) (https://sedac.ciesin.columbia.edu/)							

Population density	Population density in 2015	166	1,792	442.334	2,080.991	0.000	56,774.180
Elevation	Altimeter Corrected Elevations (1994–2005)	166	1,793	666.992	710.972	-8.386	4,877.710
Distance to nearest coastal	Distance to Nearest Coastline in 2012	166	1,796	-374.114	439.550	-2,285.311	26.000
$PM_{2.5}$	Particulate matter of 2.5 micrometers or smaller (1998–2019)	166	1,773	22.169	18.384	1.000	147.714

Notes: The poverty rate presented in the Table is unweighted.

Table B2: Decomposition of variance

Variable		Mean	Std. dev.	Min	Max	Observations
Poverty rate $1.90	Overall	9.888	17.307	0.000	91.800	N = 1,717
	Between		21.831	0.000	79.500	n = 161
	Within		6.677	-18.745	54.746	bar = 10.665
Poverty rate $3.20	Overall	18.997	25.481	0.000	98.500	N = 1,717
	Between		29.896	0.000	93.300	n = 161
	Within		9.078	-17.910	69.240	bar = 10.665
Poverty rate $5.50	Overall	31.666	32.060	0.000	100.000	N = 1,716
	Between		34.300	0.050	98.050	n = 161
	Within		10.402	-8.334	88.898	bar = 10.658

Table B3: List of country

No.	Region	GSAP	Kalkuhl and Wenz (2020)	Kummu et al. (2018)
1	East Asia & Pacific	Australia	Australia	Australia
2	East Asia & Pacific	China	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	Kiribati		
7	East Asia & Pacific	Korea, Rep.		Korea, Rep.
8	East Asia & Pacific	Lao PDR		Lao PDR
9	East Asia & Pacific	Malaysia	Malaysia	Malaysia
10	East Asia & Pacific	Micronesia, Fed. Sts.		
11	East Asia & Pacific	Mongolia	Mongolia	Mongolia
12	East Asia & Pacific	Myanmar		
13	East Asia & Pacific	Papua New Guinea		
14	East Asia & Pacific	Philippines	Philippines	Philippines
15	East Asia & Pacific	Samoa		
16	East Asia & Pacific	Solomon Islands		
17	East Asia & Pacific	Taiwan, China		
18	East Asia & Pacific	Thailand	Thailand	Thailand
19	East Asia & Pacific	Timor-Leste		
20	East Asia & Pacific	Tonga		
21	East Asia & Pacific	Tuvalu		
22	East Asia & Pacific	Vanuatu		
23	East Asia & Pacific	Vietnam	Vietnam	Vietnam
24	Europe & Central Asia	Albania	Albania	Albania
25	Europe & Central Asia	Armenia		
26	Europe & Central Asia	Austria	Austria	Austria
27	Europe & Central Asia	Azerbaijan	Azerbaijan	
28	Europe & Central Asia	Belarus	Belarus	
29	Europe & Central Asia	Belgium	Belgium	Belgium
30	Europe & Central Asia	Bosnia and Herzegovina	Bosnia and Herzegovina	Bosnia and Herzegovina
31	Europe & Central Asia	Bulgaria	Bulgaria	Bulgaria
32	Europe & Central Asia	Croatia	Croatia	Croatia
33	Europe & Central Asia	Cyprus		
34	Europe & Central Asia	Czech Republic	Czech Republic	Czech Republic
35	Europe & Central Asia	Denmark	Denmark	Denmark
36	Europe & Central Asia	Estonia	Estonia	Estonia
37	Europe & Central Asia	Finland	Finland	Finland
38	Europe & Central Asia	France	France	France
39	Europe & Central Asia	Georgia	Georgia	Georgia
40	Europe & Central Asia	Germany	Germany	Germany

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

84	Latin America & Caribbean	Guyana		
85	Latin America & Caribbean	Haiti		
86	Latin America & Caribbean	Honduras	Honduras	Honduras
87	Latin America & Caribbean	Jamaica		
88	Latin America & Caribbean	Mexico	Mexico	Mexico
89	Latin America & Caribbean	Nicaragua		
90	Latin America & Caribbean	Panama	Panama	Panama
91	Latin America & Caribbean	Paraguay	Paraguay	Paraguay
92	Latin America & Caribbean	Peru	Peru	Peru
93	Latin America & Caribbean	St. Lucia		
94	Latin America & Caribbean	Suriname		
95	Latin America & Caribbean	Trinidad and Tobago		
96	Latin America & Caribbean	Uruguay	Uruguay	Uruguay
97	Latin America & Caribbean	Venezuela, RB		
98	Middle East & North Africa	Algeria		
99	Middle East & North Africa	Djibouti		
100	Middle East & North Africa	Egypt, Arab Rep.		
101	Middle East & North Africa	Iran, Islamic Rep.		
102	Middle East & North Africa	Iraq		
103	Middle East & North Africa	Israel		Israel
104	Middle East & North Africa	Jordan		Jordan
105	Middle East & North Africa	Lebanon		Lebanon
106	Middle East & North Africa	Malta		
107	Middle East & North Africa	Morocco	Morocco	Morocco
108	Middle East & North Africa	Syrian Arab Republic		
109	Middle East & North Africa	Tunisia		
110	Middle East & North Africa	United Arab Emirates		United Arab Emirates
111	Middle East & North Africa	West Bank and Gaza		
112	Middle East & North Africa	Yemen, Rep.		
113	North America	Canada	Canada	Canada
114	North America	United States		United States
115	South Asia	Bangladesh		Bangladesh
116	South Asia	Bhutan		
117	South Asia	India	India	India
118	South Asia	Maldives		
119	South Asia	Nepal		
120	South Asia	Pakistan	Pakistan	Pakistan
121	South Asia	Sri Lanka		
122	Sub-Saharan Africa	Angola		
123	Sub-Saharan Africa	Benin		Benin
124	Sub-Saharan Africa	Botswana		
125	Sub-Saharan Africa	Burkina Faso		
126	Sub-Saharan Africa	Burundi		

127	Sub-Saharan Africa	Cabo Verde		
128	Sub-Saharan Africa	Cameroon		Cameroon
129	Sub-Saharan Africa	Central African Republic		
130	Sub-Saharan Africa	Chad		
131	Sub-Saharan Africa	Comoros		
132	Sub-Saharan Africa	Congo, Dem. Rep.		
133	Sub-Saharan Africa	Congo, Rep.		
134	Sub-Saharan Africa	Côte d'Ivoire		
135	Sub-Saharan Africa	Eswatini		
136	Sub-Saharan Africa	Ethiopia	Ethiopia	
137	Sub-Saharan Africa	Gabon		Gabon
138	Sub-Saharan Africa	Gambia, The		
139	Sub-Saharan Africa	Ghana		Ghana
140	Sub-Saharan Africa	Guinea		
141	Sub-Saharan Africa	Guinea-Bissau		
142	Sub-Saharan Africa	Kenya	Kenya	Kenya
143	Sub-Saharan Africa	Lesotho		
144	Sub-Saharan Africa	Liberia		
145	Sub-Saharan Africa	Madagascar		
146	Sub-Saharan Africa	Malawi		Malawi
147	Sub-Saharan Africa	Mali		
148	Sub-Saharan Africa	Mauritania		
149	Sub-Saharan Africa	Mauritius		
150	Sub-Saharan Africa	Mozambique	Mozambique	Mozambique
151	Sub-Saharan Africa	Namibia		Namibia
152	Sub-Saharan Africa	Niger		
153	Sub-Saharan Africa	Nigeria		
154	Sub-Saharan Africa	Rwanda		
155	Sub-Saharan Africa	São Tomé and Principe		
156	Sub-Saharan Africa	Senegal		Senegal
157	Sub-Saharan Africa	Seychelles		
158	Sub-Saharan Africa	Sierra Leone		
159	Sub-Saharan Africa	South Africa	South Africa	South Africa
160	Sub-Saharan Africa	South Sudan		
161	Sub-Saharan Africa	Sudan		
162	Sub-Saharan Africa	Tanzania	Tanzania	Tanzania
163	Sub-Saharan Africa	Togo		
164	Sub-Saharan Africa	Uganda		Uganda
165	Sub-Saharan Africa	Zambia		Zambia
166	Sub-Saharan Africa	Zimbabwe		

Table B4: Summary of econometric models employed in recent studies

	Outcome	Weather variable	Data sample	Model
Burke et al. (2015b)	GDP per capita, (non)agricultural GDP	Temperature	Cross-country analysis	Panel model with country/ year fixed effects
Burke and Emerick (2016)	Corn/soy productivity	Temperature/precipitation	United States	Panel model/ Long differences model with county/state and year fixed effects
Cattaneo and Peri (2016)	Migration, urbanization	Temperature	Cross-country analysis	Panel model/ Long differences model with country/ year fixed effects
Damania et al. (2020)	GDP per capita	Precipitation	Cross-country, subnational analysis	Panel model with location/ year fixed effects
Dell et al. (2012)	GDP per capita, agriculture/industrial value added, investment	Temperature	Cross-country analysis	Panel model with country and region/year fixed effects
Diffenbaugh and Burke (2019)	GDP per capita	Temperature	Cross-country analysis	Panel model with country/ year fixed effects
Graff Zivin and Neidell (2014)	Labor productivity (time allocation in labor and indoor/outdoor leisure)	Temperature	United States	Cross-sectional model with county and year/month fixed effects
Kalkuhl and Wenz (2020)	Regional GDP per capita	Temperature/precipitation	Cross-country, subnational analysis	Panel model/ Long differences model/ Cross-sectional model with location/ year fixed effects
Kotz et al. (2021)	Regional GDP per capita	Temperature	Cross-country, subnational analysis	Panel model with location/ year fixed effects
Kotz et al. (2022)	Regional GDP per capita	Precipitation	Cross-country, subnational analysis	Panel model with location/ year fixed effects
Missirian and Schlenker (2017)	Asylum applications	Temperature	Cross-country analysis	Panel model with country/ year fixed effects

Appendix C: Further robustness checks and heterogeneity analysis

C1. Further 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 presented in Table 2 and show that our results are broadly consistent when using alternative source of weather data and model specifications. First, we use gridded climate data at 0.5° resolution from the Climate Research Unit of the University of East Anglia (CRU). The results present in Column (1) of Table A1 (Appendix A) are consistent with our main findings, although the number of regions covered in the CRU dataset is smaller than our main sample. Second, we follow previous studies and employ several variants of Equation (1) (Kalkuhl and Wenz, 2020; Kotz et al., 2021). In column (2), we add country linear time trend to account for potential bias stemming from time-varying variables measured at the country level. From Columns (3) to (5), we employ different functional forms of temperature including controlling for temperature change, quadratic term of temperature, and an interaction term between temperature and temperature change. We also conduct a similar exercise for the long differences model, as shown in Columns (6) and (10). Results of these exercises strengthen our main findings.

In our long differences model, we choose the 10-year difference as our baseline. Our results remain consistent when using difference choice of window length (i.e., 5-year and 15-year period), as shown in Columns (7) and (8) of Table A1. We also add a number of time-invariant covariates at the regional level including cumulative oil gas, distance to coast, distance to river, and altitude. Again, the results are qualitatively similar to our main finding (Column 9, Table A1). Next, we exploit the annual GDP data between 1990 and 2014 at a 0.5-degree resolution coming from Kummu et al. (2018). An advantage of the dataset is that it is collected at the grid level which provides a large sample for an examination of the relationship between temperature and poverty. Using both panel and long differences models, Table A2 (Appendix A) show that our findings are not sensitive to the alternative dataset, and the results are consistent across different specifications.

We now turn to our preferred specification using the GSAP data and provide a battery of tests on the estimation results. To make sure that our results are robust to the choice of temperature measures, we present the results in Table A3 (Appendix A) using (i) the 5-year, 10-year, and 20-year average temperatures (Columns (1)-(3)); (ii) the temperature data from CRU (Column 4); (iii) the number of days that temperature is above 28°C (Column 5);[18] (iv) dropping regions with temperature being above that level (Column 6); and (v) temperature shock, defined as the difference between actual temperature and long-term temperature being greater (less) than 2 (-2) standard deviation (Column 7). The results show little change from the baseline specification (Table 2).

In our main specification, temperature enters linearly, whereas one might suspect that temperature has non-linear effects. Indeed, the non-linear relationship between temperature and a variety of outcomes, such as labor productivity and crop yield, has been documented in the literature (e.g., Graff Zivin and Neidell, 2014; Schlenker and Roberts, 2009). However, it is unclear how this non-linearity at the micro level is reflected in macro-level data. Therefore, we employ a quadratic term for temperature variable as used by previous studies (e.g., Burke et al., 2015b; Damania et al., 2020). The results presented in Panel A of Table A4 confirm the non-linear effect with poverty rate plummeting at an annual average temperature of about 5-7°C and increasing strongly at higher temperatures. However, evidence of such non-linear

[18] We choose the temperature at 28°C as this is the most common temperature in our sample (see Figure A2, Appendix A).

relationship is not found when using higher order exponent (Panel B, Table A4). We also inquire further into the non-linear effect of temperature by using the temperature bins approach which has been used widely in the economic literature (Deschênes and Greenstone, 2011; Graff Zivin and Neidell, 2014). Specifically, we divide the daily average temperature into one of ten 5-degree temperature bins with the temperature between 16-20°C being the reference category and employ a specification as shown in Equation (4). The results are presented in Figure A2 (Appendix A) which show the negative effects of temperature on poverty at high temperature bins (i.e., temperature being above 28°C).

Another feature in the main analysis is that we do not control for regional characteristics, which are potentially endogenous to temperature, to avoid over controlling (Dell et al., 2014). As a robustness check, we add a number of covariates including population density, elevation, distance to nearest coastal, and air pollution measured by $PM_{2.5}$. The results, which are presented in Table A5 (Appendix A), show that the effects of temperature on poverty are similar to those in our baseline results. Similarly, we also check whether our results remain consistent when weighting for population. The results of population-weighting poverty rates, presented in Table A6 (Appendix A), confirm our expectation.

Furthermore, we replicate our main analysis to different subsamples to investigate the sensitivity of our finding. First, there are countries in our samples that contain only a small number of regions. We show in Column (1) of Table A7 (Appendix A) 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 China, United States, and India (Columns 2-4). We also employ subsamples of countries without extremely cold weather (Column 5) and extremely hot weather (Column 6) using the 10 percent threshold. In Column (7), we use Conley standard errors that allows 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. We also check whether any effects on poverty is observed when using the future temperature. Specifically, we regress the average future temperature (2020 – 2030) on current temperature (2018) and use the residuals to estimate its effect on current poverty rate while controlling for other fixed effects. The results of this falsification test are presented in Column (8) which show no evidence of future temperature on poverty.

Finally, we conduct another 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 3 of 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. The figure shows that none of the placebo runs generate values anywhere close to those derived under true assignment, denoted by the dashed vertical lines. It thus provides further support to our main estimate of the effect of temperature on poverty.

C2. Heterogeneity analysis

Consistent with the idea that warmer temperature leads to higher poverty rate, we also expect the impacts to be heterogenous across regions. Specifically, we split our sample into seven regions and plot the coefficient estimates of temperature in Figure 2. The heterogeneity analysis reveals interesting patterns that are complementary to our main findings – rising temperatures are associated with higher poverty rate in poor regions such as Sub-Saharan Africa, Middle

East and North Africa, and South Asia, but the effect is attenuated in other richer regions. We also provide further support to the regional heterogeneity by allowing the coefficient of temperature variable to vary between regions by adding a set of interactions with region dummies. The results presented in Table A8 (Appendix A) reaffirm our previous findings that Sub-Saharan Africa, our reference group, is most vulnerable to temperature change in terms of poverty. Finally, we also plot the estimated effect of temperature on poverty by country, adjusted by their real GDP per capital in 2018, in Figure A4 (Appendix A). We find 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's 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 categorise 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. Finally, we find a stronger effect among countries with lower share of trade, but our estimates are not statistically significant.

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 temperature. 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 a 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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