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JEL Cassification: Q54, I32, O1

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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 (Barbier and Hochard, 2018a; Hallegatte et al., 2020). 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). While poor households are observed to be more vulnerable to climate change,[1] no study currently exists on the direct linkage 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, 2021a), 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.[2]

[1] For example, Barbier and Hochard (2018a) estimate the number of poor people who are vulnerable to climate change to be approximately 590 million in less favored agricultural areas and around 270 million in rural low-elevation coastal zones.

[2] Recent 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

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.[3] 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 0.5 percent) to extremely high in the Central and Eastern regions (highest rate of 52.8 percent) (Panel A).[4] Average 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 22˚C (16 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 introduce and analyze a new subnational panel database that we constructed based on the Global Subnational Atlas of Poverty (GSAP) (World Bank,

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.

[3] 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.

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

2021b), which provides headcount poverty estimates for 1,650 subnational areas in 139 economies from 2003 to 2019. This database is generated using household income and consumption surveys from the World Bank's Global Monitoring Database (GMD), which underlie country official poverty statistics, and offers the most detailed subnational poverty data on a global scale to date. We further combine it with historical climatic data (i.e., temperature and precipitation) during 1979 – 2019 from the European Centre for Medium-Range Weather Forecasts Reanalysis 5 (ERA-5) and various other data sources.

We employ different identification strategies to estimate the effects of warmer temperature on subnational poverty. As the main specification, we use a fixed effects panel regression model which is less prone to omitted variable bias and controls for unobserved time-invariant heterogeneity at the regional level (Dell et al., 2012; Kalkuhl and Wenz, 2020). The fixed effects model, however, exploits only annual temperature variability (within region) and thus does not provide an estimate of the long-term effects of temperature. To supplement our panel estimates, we use a long differences model that accounts for potential adaptation to permanent changes in weather that may have taken place over time. We also consider several variants of each model to check the robustness of our estimates.

We find strong and statistically significant effects of higher temperature on subnational poverty. This result is robust to various robustness checks including different sources of poverty data, alternative measures of temperature, controlling for additional covariates, and analyzing various data subsamples. Our preferred fixed effects model shows that a one-degree Celsius (i.e., 1˚C) 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 effects using long differences model are less pronounced at 0.5, 1.7, and 2.0 percentage points increases in poverty (which correspond to 5.2 percent, 8.4 percent, and 5.9 percent increases), suggesting household adaptation to gradual warmer temperature over time. We also find some evidence for even stronger negative effects for hotter-than-average regions.

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, soybean, and wheat. 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 in poorer regions and under scenarios of higher greenhouse gas emissions without mitigation policies.

To our knowledge, we offer the first global assessment of warmer temperature on poverty using novel subnational panel data from 139 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 health shocks.[5] However, the global, slow-onset effects of rising temperature, which slowly but steadily increase poverty via different mechanisms, have received barely any attention. The only exception is Azzarri and Signorelli (2020), who analyze cross-sectional 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.[6]

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

[5] 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.

[6] In addition to the key difference between panel data and cross-sectional data analysis, our study is different from Azzarri and Signorelli (2020) in several aspects. Besides the regional focus, Azzarri and Signorelli (2020) employ older surveys that are implemented up to 2014 and 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). We also provide early empirical evidence for agriculture as a key linkage between global warming and poverty.

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; Kahn et al., 2021; 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 has negative effects on economic growth (Kotz et al., 2021).[7] 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 strongly observed using analysis at the subnational level, such effects are not easily discernible based on similar analysis 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.

2. Data

We construct the data from multiple sources. For the main outcomes, we build on the World Bank's cross-sectional Global Subnational Atlas of Poverty (GSAP) (World Bank, 2021b) and assemble a new panel dataset that provides (headcount) poverty rates using the daily poverty lines of US $1.90, $3.20, and $5.50 (based on the revised 2011 Purchasing Power Parity (PPP) dollars).[8] Using harmonized household survey data from the GMD, our new dataset offers

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[7] Other studies have analyzed subnational data and found negative effects of rainfall shocks on economic growth (e.g., Damania et al., 2020; Kotz et al., 2022).
[8] The data are accessible on the Harvard Dataverse depository at https://doi.org/10.7910/DVN/MLHFAF.

global poverty estimates from 2003 to 2019, which are statistically representative of more than 1,650 subnational units across 139 countries, with more than 90 percent of the data ranging from 2010 to 2019. 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).

While the GSAP offers high-quality subnational poverty data and is our preferred data for analysis, we also note that the data mostly focus on countries in the developing world. Therefore, we examine for robustness checks using 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.[9] 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.[10]

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) cross-sectional model; (ii) panel model; and (iii) long differences model.[11] We start first with estimating the following cross-sectional model

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

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 annual temperature in degrees Celsius. Following previous studies' suggestion that

[9] 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.

[10] Estimated growth rates of consumption based on national accounts are long found to be different from and tend to be larger than those based on household surveys, both across countries and over time (Dang and Serajuddin, 2020; Deaton, 2005; Ravallion, 2003).

[11] We provide a summary of econometric models used in recent studies on global warming in Table B4 (Appendix B). See also Hsiang (2016) and Massetti and Mendelsohn (2018) for recent reviews on the econometric methods commonly employed in climate change studies.

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. ϵ_{it} is an idiosyncratic error term.

The cross-sectional poverty data can, however, result in biased estimates for β_{CS} in Equation (1). 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. To address this issue, we estimate the following panel model with location and year fixed effects (FE)

$$Y_{i,t} = \beta_{FE}T_{i,t} + \gamma_{FE}P_{i,t} + \alpha_i + \pi_t + \epsilon_{i,t} \tag{2}$$

Our variable of interest $T_{i,t}$ is the same as specified in Equation (1), and β_{FE} is expected to be positive (i.e., global warming likely increases poverty). 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 each year. We cluster our errors at the subnational level (or the country level for the country-level analysis) to allow for potential serial correlation over time within a region (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 regressions are weighted by (country) region population.

Our model specification in Equation (2) 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 (2) including (i) capturing the non-linear effects of temperature by adding a quadratic term ($T_{i,t}^2$) and cubic term ($T_{i,t}^3$); (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 ($T_{i,t} \times \Delta T_{i,t}$). To further investigate whether misspecification of the functional form of temperature remains an issue, 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)

$$Y_{i,t} = \sum_{j=1}^{10} \beta_{TB} T_{i,j}, t + \gamma_{TB} P_{i,t} + \theta_i + \sigma_t + \vartheta_{i,t} \quad (3)$$

Specifically, we divide temperature into ten five-degrees Celsius bins, where extreme low temperature is captured as temperature less than 0^{o}C and extreme high temperature is captured as temperature greater than 32^{o}C. The temperature shock variable reflects the number of days when the daily average temperature in a region is within a specific bin in a particular year. Since the number of days falling into these 10 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 16^{o}C–20^{o}C, as the baseline group. The coefficient on temperature variable is thus interpreted as the effects of exchanging a day in the 16^{o}C–20^{o}C range with a day in the other bins.

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 (2) can identify the effects of temperature changes on poverty in the short run. Yet, Equation (2) 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; Hsiang, 2016). To complement Equation (2), we estimate the following long differences regression for the long-run temperature effects on poverty

$$\Delta Y_i = \beta_{LD} \Delta T_i + \gamma_{LD} \Delta P_i + \omega_i \quad (4)$$

In Equation (4), 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 3-year difference averages. That is, for all the variables in Equation (4) 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. 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 (2), 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 4-year, 5-year, and 10-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 (2).

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 133 countries over the period 1979 – 2019 and analyze three poverty indicators at the daily poverty lines of \$1.90, \$3.20, and \$5.50.[12] For each outcome, we start with the cross-sectional model (Equation 1), country and year FE panel approach (Equation 2), followed by the long differences model (Equation 3). In all the regressions, we control for precipitation given that changes in rainfall

[12] We select from WDI dataset countries that are also available in our GSAP panel for comparison purpose. The results using all countries are presented in Table A1 (Appendix A), which are qualitatively similar to those presented in Table 1.

can be an important aspect of long-run climate trends affecting poverty rate. We find little evidence of the effects of higher temperature on poverty at the country level, except for the results using the 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.

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 cross-sectional model (Equation (1)). The results are strongly statistically significant at the 1 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 0.6 percentage points (or 5.6 percent) increase in poverty, using the daily poverty line $1.90. However, as discussed earlier, the results with the cross-sectional model can be biased due to omitted variables.

We next present the results using our preferred specification, the panel model that controls for region and year fixed effects (using Equation (2)). Overall, we document positive, statistically significant effects of hotter temperature on poverty. Column (2) shows that a 1°C increase in temperature causes a 0.9 percentage points 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. Furthermore, the impact magnitudes are higher for higher poverty lines (1.8 percentage points and 2.3 percentage points increases for the daily poverty lines of $3.20 and $5.50, respectively). These results also suggest that estimates derived from the cross-sectional model are likely to underestimate the effects of warmer temperature on poverty.

Using the same data, we show the estimated long-term effects of temperature on poverty in Table 2, Columns (3), (6), and (9) (using Equation (4)). The results of the long differences model are qualitatively similar, indicating positive and strongly statistically significant effects of higher temperature on poverty.[13] In addition, the long differences coefficient estimates are smaller in absolute value than the corresponding panel coefficient estimates. For instance, a 1°C increase in temperature is now estimated to result in a poverty increase of 0.5 percentage points (5.2 percent) (also using the daily poverty line $1.90) under the long differences specification (Column 3). The difference between the panel estimates and the long differences estimates implies that longer-run adaptations appear to have offset the large negative short-run impacts of temperature on poverty by 3.9 percent. These findings are consistent with previous studies that confirm the role of 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 2 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 3), but the opposite is found in the panel model (e.g., Column 2). This ambiguity is, however, 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. Robustness tests and heterogeneity analysis

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 models that were employed in recent studies (e.g., Kalkuhl and Wenz, 2020; Kotz et al., 2021). They include adding country

[13] The long differences estimation is based on cross-sectional data with a much smaller sample size (compared with panel data). We also use the sample size in the long-differences model and re-estimate the effects of temperature using cross-sectional and panel models. The results presented in Table A12 (Appendix A) are similar to our estimates in Table 2.

linear time trend, 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 length. We also exploit alternative sources of temperature and subnational GDP data as well as controlling for additional covariates. The results, shown in Tables A2-A4 (Appendix A), indicate that our findings remain robust, and the results are consistent across different specifications.

We further provide a battery of robustness tests on our preferred fixed effects panel specification. They include (i) using alternative measures of temperature;[14] (ii) accounting for the non-linear effects of temperature on poverty using the flexible temperature-bin approach in Equation (3); (iii) using different subsamples; and (iv) testing for potential reverse causality of temperature on poverty. Again, the results of these tests deliver qualitatively similar findings and do not support the reverse causality hypothesis (Appendix A, Tables A5-A6). Figure A2 (Appendix A) shows even stronger (contemporaneous and cumulative) negative effects of temperature on poverty at high temperature bins (i.e., temperature being above 28°C).[15] 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).

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

[14] These include using (i) log of temperatures; (ii) the temperature data from CRU; (iii) the number of days that temperature is above 28ºC; (iv) dropping regions with temperature being above that level; and (v) temperature shock, defined as the difference between actual temperature and long-term temperature being greater (less) than 2 (-2) standard deviations (Appendix A, Table A5).

[15] We examine the cumulative effect of temperature on poverty by imposing a lag structure on the temperature bins (Chen and Yang, 2019; Somanathan et al., 2021). In particular, we include the contemporaneous effect of temperature and its lag effects of up to three years (i.e., *t-3*, *t-2*, and *t-1*).

in other richer regions. We also plot the estimated effects for each country, adjusted by their real GDP per capital, and find that countries bearing the largest effects of global warming tend to be poorer (Appendix A, Figure A4). Futhermore, we examine whether the impacts of temperature differ by country characteristics. Estimation results, shown in Table A8 (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 (Appendix A, Table A9).

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 the panel fixed effects model and long differences model as in Equations (2) and (4), we find consistent and negative effects of higher temperature on different crop yields including rice, maze, and soybean, as shown in Table 3. 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 A10).

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 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 A6 (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.[16]

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 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

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

energy.[17] 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 by multiplying with the baseline estimates in columns (3), (6), and (9) 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 A11 (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). The largest poverty increase would occur in the scenario without any countervailing strategies based on renewable energy to address climate change between 2021 and 2099.

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 the projected temperature effects across regions in our sample under the RCP8.5 emission pathways.[18] It

[17] 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, 2021b).
[18] We present the projected effects under RCP4.5 emission pathways in Figure A7 (Appendix A).

reaffirms our previous findings that poor countries in Africa continue to be most vulnerable to hotter temperature.

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 introduce and analyze a new global poverty panel dataset representative of subnational areas in 139 countries (based on the GSAP data) 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 other datasets. Some evidence exists for even stronger negative effects for hotter-than-average regions.

Our preferred specification shows that a 1°C increase in temperature leads to a 0.9 percentage points (9.1 percent) increase in the headcount poverty ratio using the daily poverty line of $1.90. Yet, the long-run effects of temperature are less pronounced at a 0.5 percentage points (5.2 percent) increase in poverty, perhaps due to potential household adaptation. At the same time, we generally do not find strong evidence of such effects when using the country-level analysis, which are likely masked by large variations of temperature and poverty within a country. We find that Sub-Saharan Africa and South Asia are the regions that are most susceptible to higher temperature. We also offer suggestive evidence of agriculture as a key channel through which higher temperature can increase poverty.

Finally, our projection shows alarming effects on increased poverty of up to 31.3 percent as a result of global warming. This finding is especially relevant from a policy perspective, considering that more than 10 percent of the developing world are living in extreme poverty (as measured against the daily poverty line of US$ 1.90) and nearly 40 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. While our study provides robust empirical evidence that agriculture is an important factor influencing climate-induced poverty, alternative channels, such as civil conflicts, labor productivity, and migration, could offer another direction. For example, higher temperature may result in lower probability of migration and thus lead to higher poverty, but it may also reduce poverty by higher remittances among households with migrants. 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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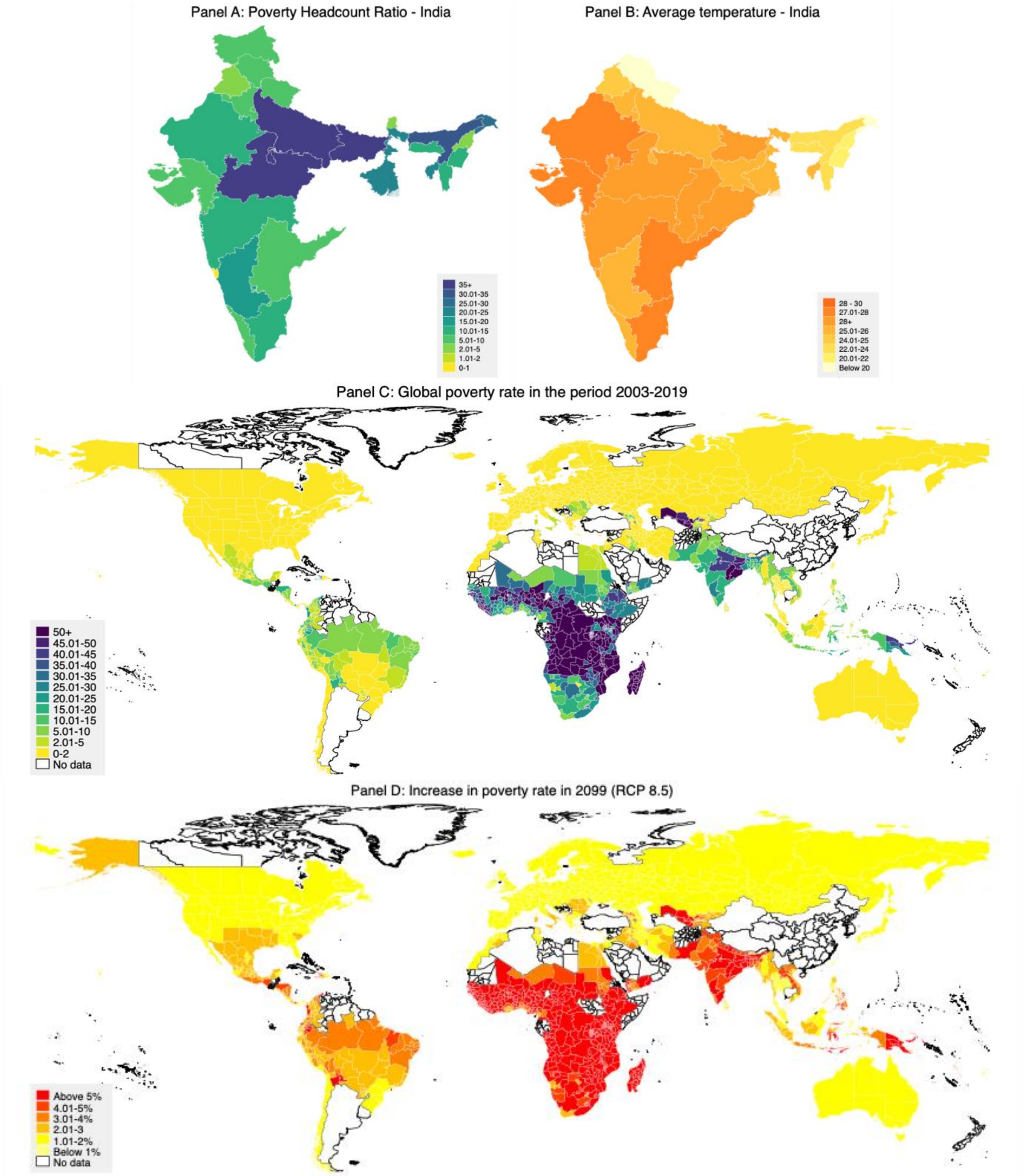
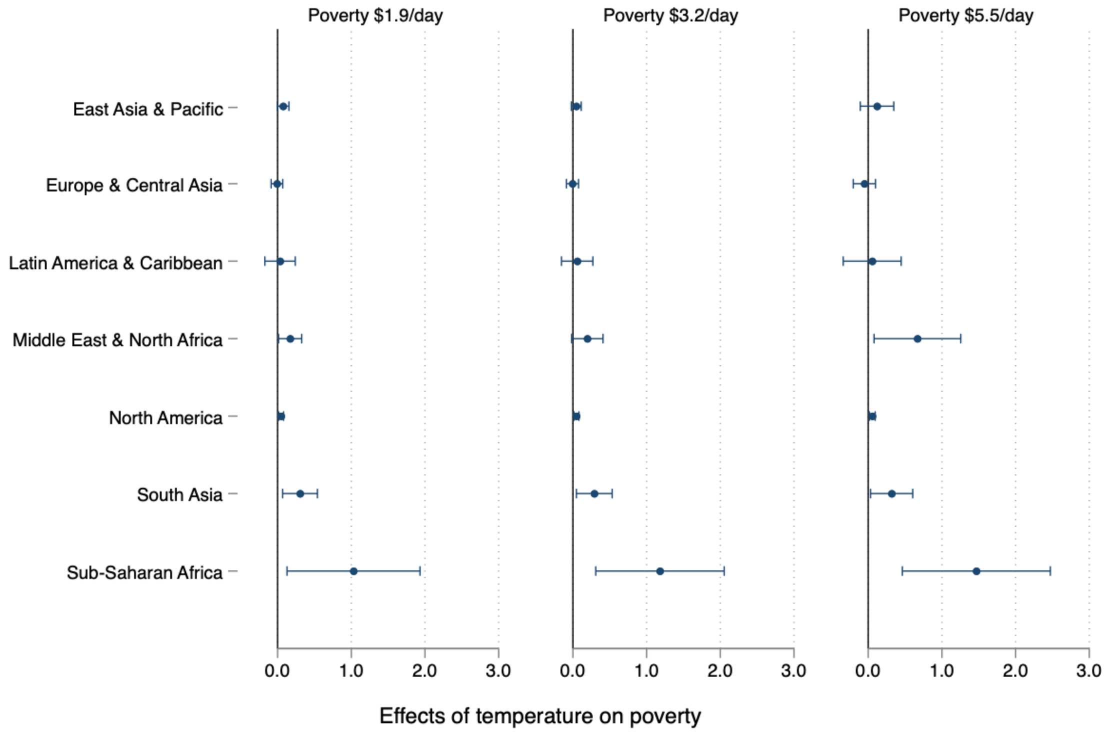
Figures and Tables

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



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). In panels A and B, poverty rate and temperature data are measured in the period 2003 – 2019. The projection in Panel D is estimated using the coefficient on the effects of temperature on poverty reported in Column (3) of Table 2 and the average temperature of during the period 1979 – 2019.

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 subnational fixed effects. Robust standard errors are clustered at the subnational level. Regressions are weighted by region population.

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

	Poverty rate $1.90			Poverty rate $3.20			Poverty rate $5.50		
	Cross-sectional	Panel FE	Long differences	Cross-sectional	Panel FE	Long differences	Cross-sectional	Panel FE	Long differences
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Temperature	0.953***	0.452	0.263	1.520***	0.426	-1.688	1.956***	-0.188	-0.767
	(0.150)	(0.359)	(7.395)	(0.231)	(0.505)	(11.400)	(0.326)	(0.685)	(14.194)
Precipitation	-0.023	-0.002	0.293	-0.021	-0.016	0.292	-0.011	-0.027	0.340
	(0.018)	(0.011)	(0.273)	(0.031)	(0.016)	(0.408)	(0.039)	(0.018)	(0.475)
Country FE	No	Yes	No	No	Yes	No	No	Yes	No
Year FE	No	Yes	No	No	Yes	No	No	Yes	No
Number of countries	133	133	130	133	133	130	133	133	130
Observations	1,544	1,544	130	1,544	1,544	130	1,543	1,543	130
Adjusted R-squared	0.291	0.291	0.007	0.353	0.385	0.012	0.370	0.417	0.012
Mean headcount poverty rate (percent)	10.107	10.107	10.107	19.196	19.196	19.196	31.520	31.520	31.520

Notes: Robust standard errors in parentheses. Standard errors are clustered at the country level. Regressions are weighted by country population. 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 3-year period (1979–1981) and averages of the latest 3-year period (2017–2019). 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 2: The effects of temperature on poverty – Subnational level analysis

	Poverty rate $1.90			Poverty rate $3.20			Poverty rate $5.50		
	Cross-sectional	Panel FE	Long differences	Cross-sectional	Panel FE	Long differences	Cross-sectional	Panel FE	Long differences
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Temperature	0.565***	0.921***	0.525***	1.229***	1.835***	1.714***	2.048***	2.296***	1.987***
	(0.055)	(0.160)	(0.038)	(0.124)	(0.213)	(0.143)	(0.204)	(0.308)	(0.107)
Precipitation	-0.390**	0.236***	-0.360***	0.710**	0.368**	-1.599***	2.337***	-0.073	-0.170
	(0.159)	(0.069)	(0.091)	(0.316)	(0.166)	(0.425)	(0.424)	(0.160)	(0.248)
Subnational FE	No	Yes	No	No	Yes	No	No	Yes	No
Year FE	No	Yes	No	No	Yes	No	No	Yes	No
Number of countries	139	139	95	139	139	95	139	139	95
Number of regions	1,650	1,650	1,116	1,650	1,650	1,116	1,650	1,650	1,116
Observations	5,090	5,090	1,116	5,090	5,090	1,116	5,090	5,090	1,116
Adjusted R-squared	0.256	0.393	0.113	0.494	0.583	0.287	0.616	0.622	0.343
Mean headcount poverty rate (percent)	10.134	10.134	10.134	20.344	20.344	20.344	33.917	33.917	33.917

Notes: Robust standard errors in parentheses. Standard errors are clustered at the subnational level. Regressions are weighted by region population. Poverty rate is taken from the GSAP panel dataset. Poverty rates and weather variables in the long-differences model are measured by the difference between averages of the earliest 3-year period (2003–2005) and averages of the latest 3-year period (2017–2019). 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

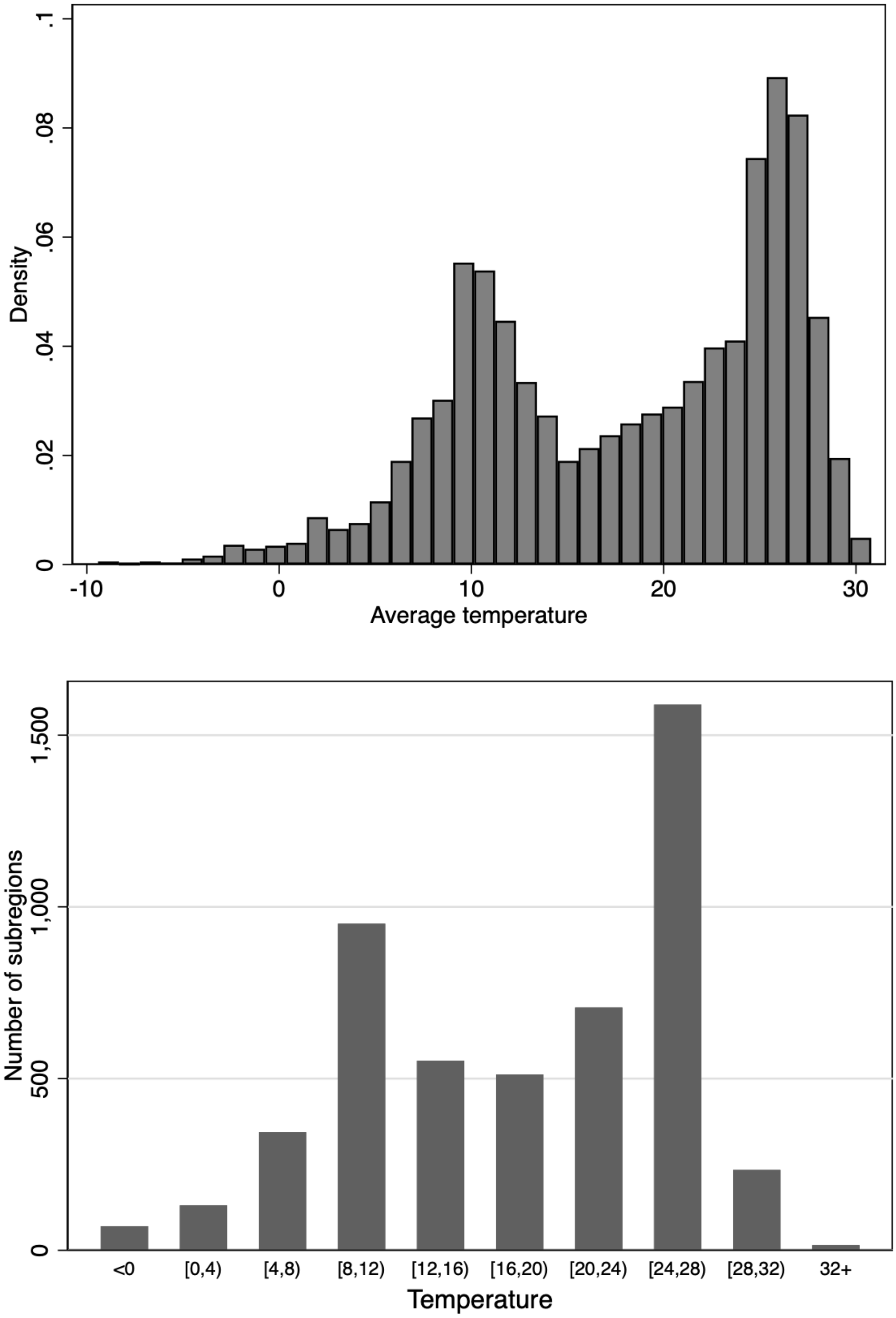
Table 3: Effects of temperature on agriculture

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***	-0.166***	-0.183***	-0.172***	-0.042***	-0.041***	0.010	-0.000
	(0.021)	(0.020)	(0.013)	(0.012)	(0.011)	(0.011)	(0.014)	(0.015)
Controlling for rainfall	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Subnational FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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
R-squared	0.230	0.161	0.284	0.313	0.066	0.055	0.081	0.002
Mean crop yield (tonnes/hectare)	3.215	3.215	2.412	2.412	1.719	1.719	3.350	3.350

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). 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

Appendix A: Additional Tables and Figures

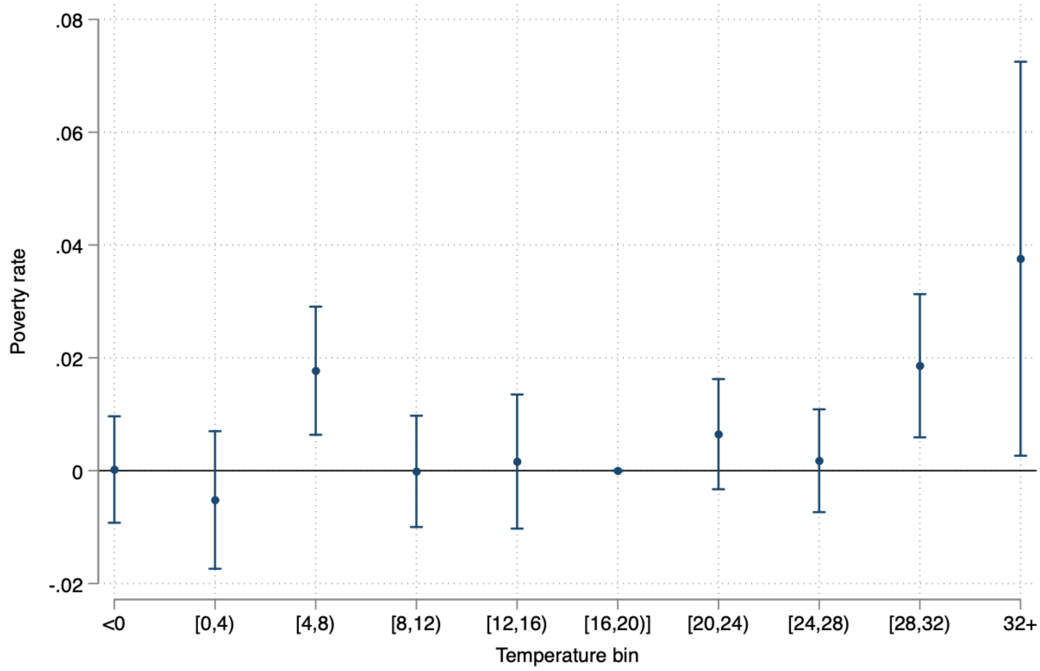
Figure A1: The effects of temperature on poverty by region



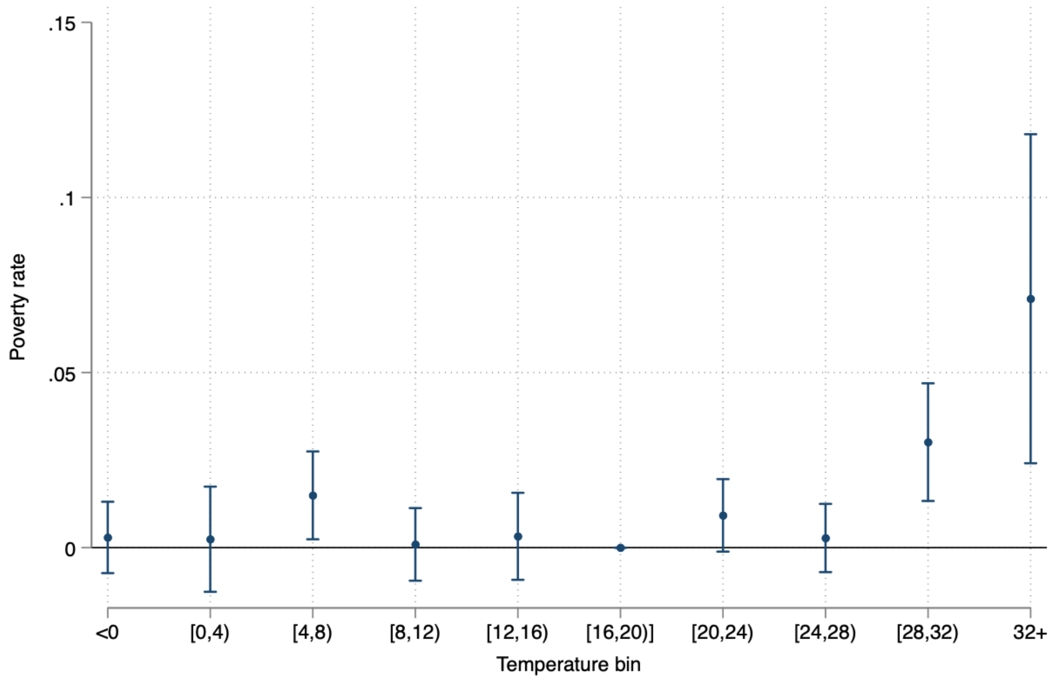
Notes: Temperature data is taken from the European Centre for Medium-Range Weather Forecasts Reanalysis 5 (ERA-5).

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

Panel A: Contemporaneous effect

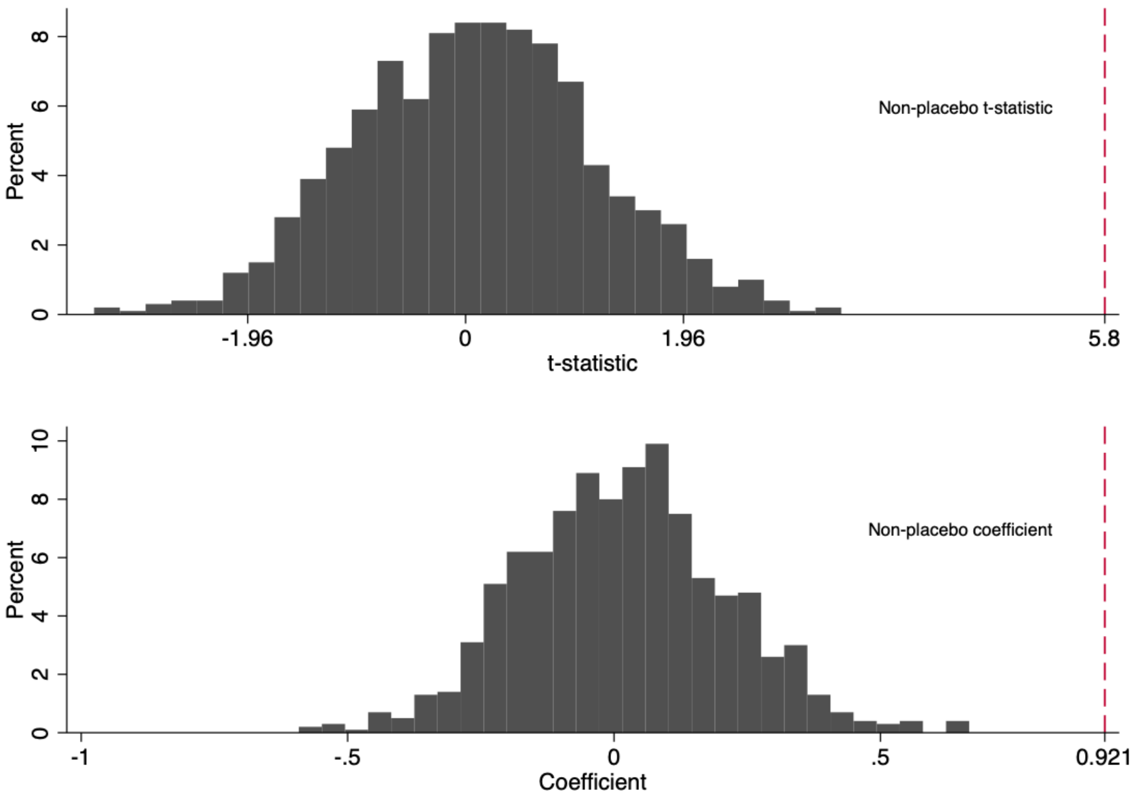


Panel B: Cumulative effect



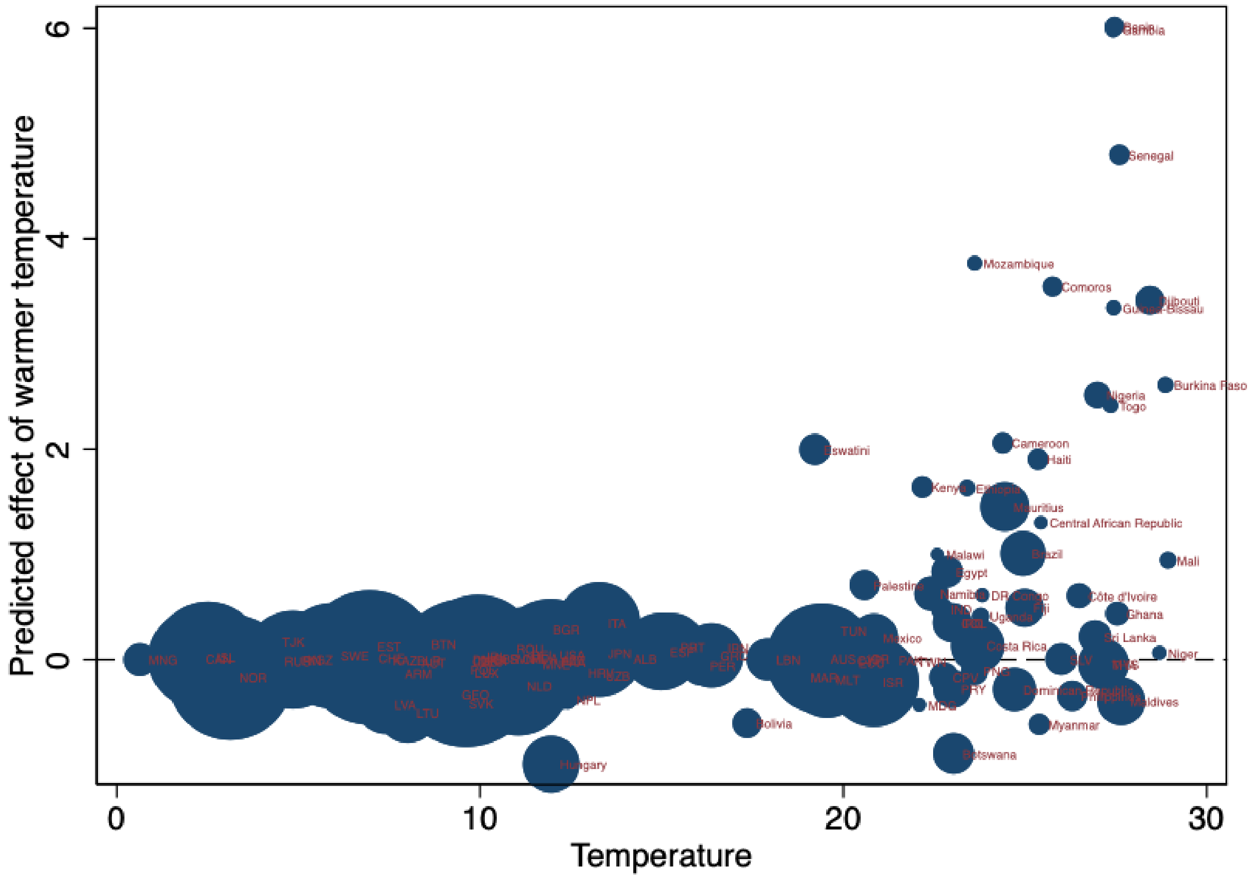
Notes: Poverty rate is measured by the Subnational Poverty Headcount Ratio at $1.90 a day. The reference temperature bin is [16,20).

Figure A3: Placebo test



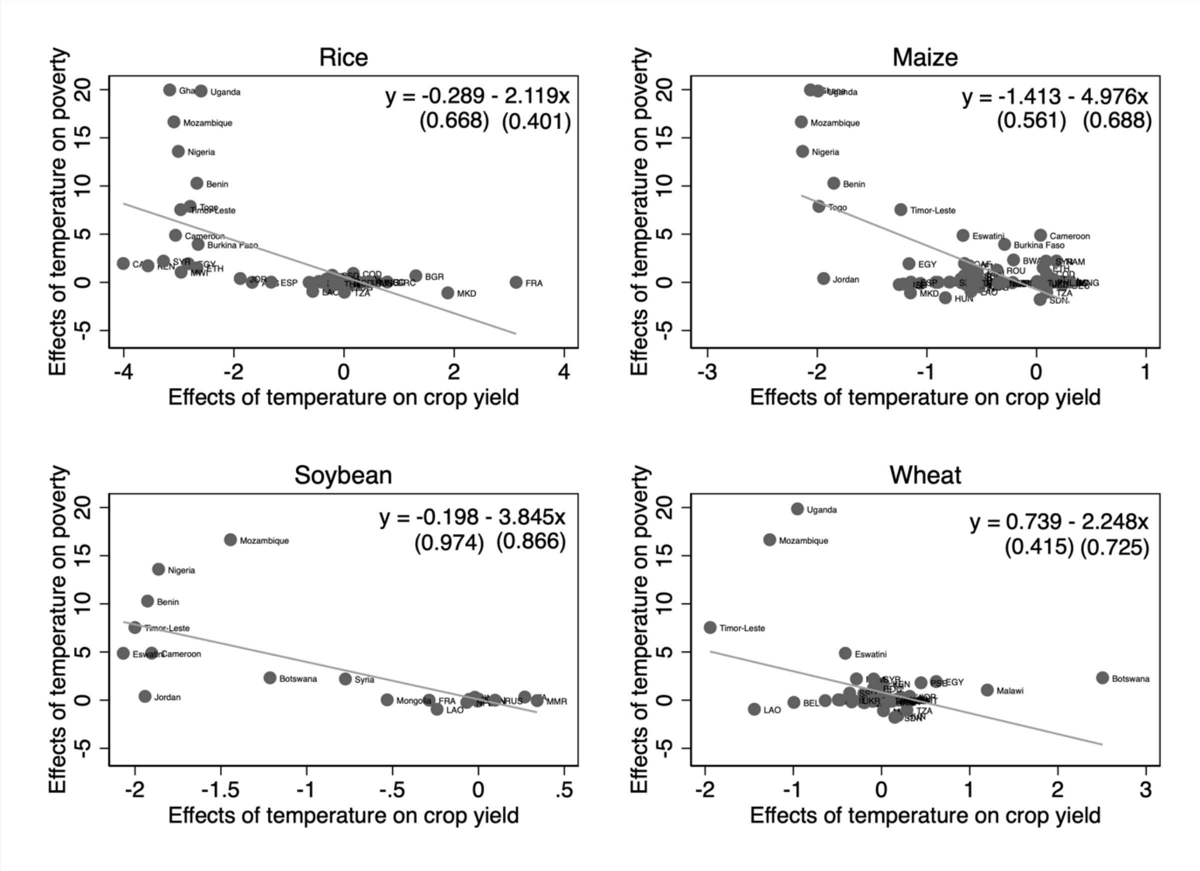
Notes: Results of placebo exercise using 1,000 randomizations of regions. The outcome is poverty headcount ratio at $1.90. All regressions include precipitation and subnational fixed effects. Regressions are weighted by region population.

Figure A4: The effects of temperature on poverty across countries



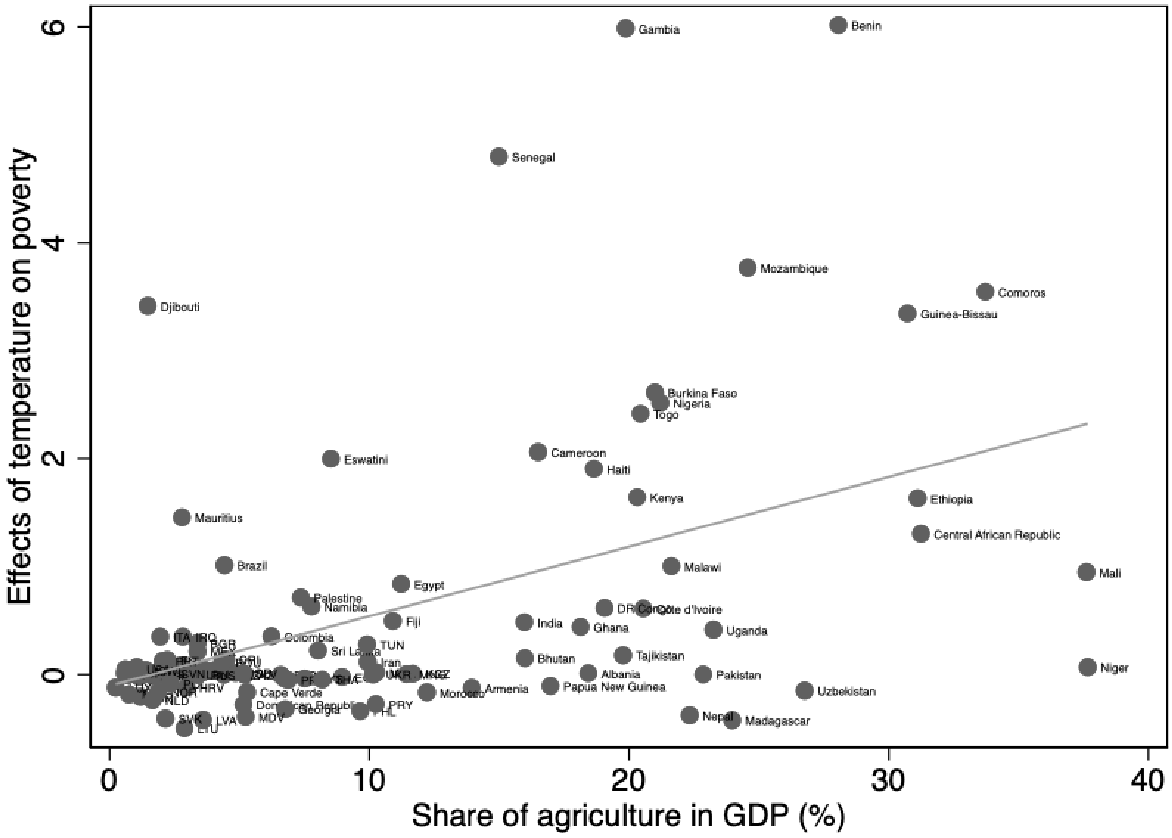
Notes: Poverty rate is measured by the Subnational Poverty Headcount Ratio at $1.90 a day. The figure shows the point estimates of temperature and the country dummies using regression with control variable and subnational fixed effects. Countries are depicted with their real GDP per capital from the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

Figure A5: The effects of temperature on poverty and agriculture



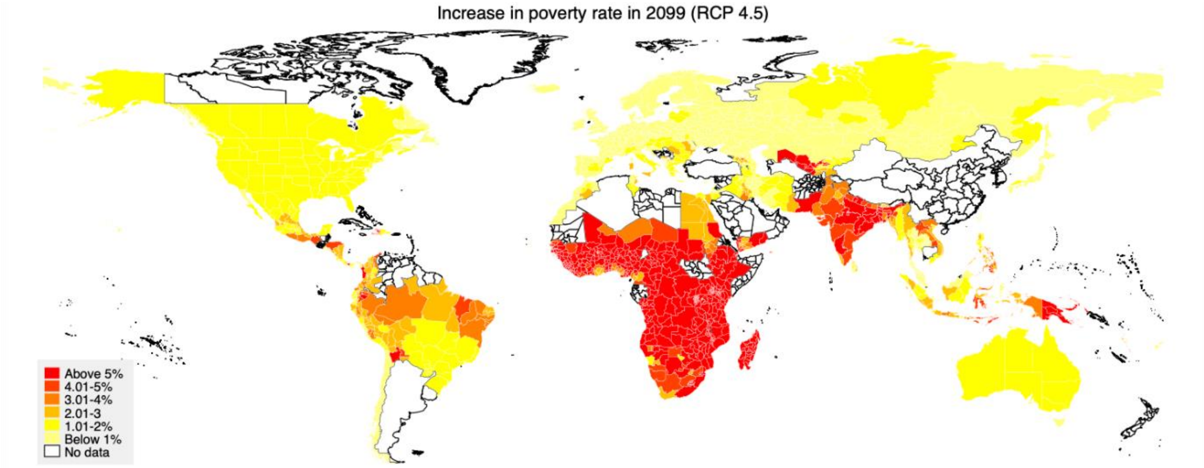
Notes: The figure shows the point estimates of temperature effects on poverty (y-axis) and crop yield (x-axis) using regressions with control variable and subnational fixed effects. We then use an OLS regression of the poverty effects on crop yield effects. Standard errors are in parentheses. Poverty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

Figure A6: The effects of temperature on poverty by share of agriculture



Notes: The figure shows the point estimates of temperature effects on poverty (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. Share of agriculture in GDP is taken from WDI database.

Figure A7: 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 by the Subnational Poverty Headcount Ratio at $1.90 a day. 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 – 2019.

Table A1: The effects of temperature on poverty – Country-level analysis using all countries in WDI

	Poverty rate \$1.90			Poverty rate \$3.20			Poverty rate \$5.50		
	Cross-sectional	Panel FE	Long differences	Cross-sectional	Panel FE	Long differences	Cross-sectional	Panel FE	Long differences
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Temperature	0.881***	0.544	-4.384	1.429***	0.510	-2.181	1.881***	-0.211	-4.417
	(0.137)	(0.337)	(3.760)	(0.215)	(0.483)	(4.702)	(0.308)	(0.652)	(5.413)
Precipitation	-0.019	-0.008	-0.050	-0.017	-0.023	-0.002	-0.010	-0.034**	0.119
	(0.016)	(0.011)	(0.155)	(0.029)	(0.015)	(0.141)	(0.036)	(0.016)	(0.126)
Country FE	No	Yes	No	No	Yes	No	No	Yes	No
Year FE	No	Yes	No	No	Yes	No	No	Yes	No
Number of countries	161	161	131	161	161	131	161	161	131
Observations	1,717	1,717	131	1,717	1,717	131	1,717	1,716	131
Adjusted R-squared	0.262	0.283	0.005	0.326	0.372	0.014	0.355	0.410	0.005
Mean headcount poverty rate (percent)	9.888	9.888	9.888	18.997	18.997	18.997	31.666	31.666	31.666

Notes: Robust standard errors in parentheses. Standard errors are clustered at the country level. Regressions are weighted by country population. 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 3-year period (1979–1981) and averages of the latest 3-year period (2017–2019). 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 A2: 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	Adding country 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	0.781***	0.293***	0.249***	0.240*	0.174***	0.175***				-0.045
	(0.116)	(0.070)	(0.092)	(0.123)	(0.043)	(0.043)				(0.127)
ΔTempearture		-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	139	139	139	139	139	139	95	95	95	95
Number of regions	1,650	1,650	1,650	1,650	1,650	1,650	1,116	1,116	1,116	1,116
Observations	5,090	5,090	5,090	5,090	5,090	5,090	1,246	1,369	1,114	708
Adjusted R-squared	0.366	0.259	0.318	0.318	0.183	0.183	0.093	0.101	0.168	0.152

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

Table A3: 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 A4: 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 A5: Robustness test – Alternative measures of temperature

	Dependent variable: Poverty rate at $1.90				
	Log temperature	Temperature provided by CRU	Number of days temperature above 28	Dropping subregions with temperature above 28	Temperature shock
	(1)	(2)	(3)	(4)	(5)
Temperature	2.218***	0.760***	0.070***	0.666***	0.337***
	(0.481)	(0.118)	(0.025)	(0.111)	(0.114)
Controlling for rainfall	Yes	Yes	Yes	Yes	Yes
Subnational FE	Yes	Yes	Yes	Yes	Yes
Number of countries	139	139	139	139	139
Number of regions	1,650	1,650	1,650	1,650	1,650
Observations	5,090	5,059	5,059	4,856	5,090
R-squared	0.361	0.364	0.434	0.384	0.317

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 A6: Robustness test – Alternative samples

	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	139	139	139	139	139	139
Number of regions	1,650	1,650	1,650	1,650	1,650	1,650
Observations	4,055	4,580	5,020	4,679	4,806	5,089
R-squared	0.404	0.366	0.345	0.371	0.415	0.005

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 A7: The effects of temperature on poverty by region

Poverty rate at:	$1.90	$3.20	$5.50
	(1)	(2)	(3)
Temperature	1.882***	2.026***	2.247***
	(0.518)	(0.479)	(0.722)
By region (Reference group: Sub-Saharan Africa)			
Temperature*East Asia and Pacific	-2.747***	-3.112***	-4.674***
	(0.760)	(0.884)	(1.470)
Temperature*Europe and Central Asia	-1.840***	-1.975***	-2.176***
	(0.518)	(0.479)	(0.723)
Temperature*Latin America and Caribbean	-1.533***	-1.632***	-1.513**
	(0.535)	(0.499)	(0.760)
Temperature*Middle East and North Africa	-1.656***	-1.772***	-1.220
	(0.523)	(0.493)	(0.801)
Temperature*North America	-1.843***	-1.985***	-2.187***
	(0.519)	(0.480)	(0.724)
Temperature*South Asia	-1.534***	-1.698***	-2.103***
	(0.545)	(0.511)	(0.765)
Controlling for rainfall and regions	Yes	Yes	Yes
Subnational FE	Yes	Yes	Yes
Number of countries	139	139	139
Number of regions	1,650	1,650	1,650
Observations	5,089	5,089	5,089
R-squared	0.780	0.753	0.829

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 A8: 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	0.735*	-0.479	-0.051
	(0.444)	(0.528)	(0.781)
Temperature*Authoritarian regime	1.395***	1.273**	1.925**
	(0.431)	(0.555)	(0.766)
Observations	5,024	5,024	5,024
R-squared	0.390	0.519	0.650
Panel B: Location (Reference group: Countries near equator)			
Temperature* Countries near equator	0.943***	0.861***	1.455***
	(0.293)	(0.316)	(0.507)
Observations	5,090	5,090	5,090
R-squared	0.395	0.480	0.657
Panel C: Share of agriculture in GDP (Reference group: Low share)			
Temperature*High agriculture share	0.155***	0.158***	0.208***
	(0.051)	(0.052)	(0.045)
Observations	5,031	5,031	5,031
R-squared	0.366	0.426	0.576
Panel D: Share of manufacturing in GDP (Reference group: Low share)			
Temperature*High manufacturing share	-0.076**	-0.127**	-0.315***
	(0.039)	(0.052)	(0.081)
Observations	4,915	4,915	4,915
R-squared	0.319	0.325	0.412
Panel E: Share of trade in GDP (Reference group: Low share)			
Temperature*High trade share	-0.005	-0.004	-0.014
	(0.003)	(0.003)	(0.009)
Observations	4,928	4,928	4,928
R-squared	0.319	0.323	0.401
Controlling for rainfall	Yes	Yes	Yes
Subnational FE	Yes	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 A9: 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	-0.178***	-0.160***	-0.234***
	(0.031)	(0.029)	(0.054)
Observations	4,818	4,818	4,818
R-squared	0.407	0.403	0.694
Panel B: Internet 2G			
Temperature*Internet coverage	-2.980***	-3.569***	-8.096***
	(0.997)	(1.029)	(1.732)
Observations	4,946	4,946	4,946
R-squared	0.324	0.327	0.398
Panel C: Internet 3G			
Temperature*Internet coverage	-1.594***	-1.687***	-2.679***
	(0.428)	(0.462)	(0.665)
Observations	4,347	4,347	4,347
R-squared	0.399	0.467	0.610
Panel D: Internet 4G			
Temperature*Internet coverage	-0.762**	-0.768**	-0.559
	(0.297)	(0.310)	(0.621)
Observations	2,754	2,754	2,754
R-squared	0.508	0.489	0.479
Controlling for rainfall	Yes	Yes	Yes
Subnational FE	Yes	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: 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 A11: 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	0.729	1.042	1.381	0.648	1.110	3.149
Increase in poverty rate $3.20	2.379	3.401	4.510	2.117	3.623	10.282
Increase in poverty rate $5.50	2.758	3.942	5.228	2.454	4.201	11.920

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 A12: The effects of temperature on poverty – Subnational level analysis using sample in long-differences model

	Poverty rate $1.90		Poverty rate $3.20		Poverty rate $5.50	
	Cross-sectional	Panel FE	Cross-sectional	Panel FE	Cross-sectional	Panel FE
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature	0.459***	0.845***	1.147***	1.807***	2.033***	2.293***
	(0.047)	(0.144)	(0.107)	(0.232)	(0.162)	(0.308)
Precipitation	-0.245*	0.213***	0.897***	0.200	2.566***	-0.142
	(0.132)	(0.066)	(0.276)	(0.150)	(0.423)	(0.159)
Subnational FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of countries	95	95	95	95	95	95
Number of regions	1,116	1,116	1,116	1,116	1,116	1,116
Observations	4,246	4,246	4,246	4,246	4,246	4,246
R-squared	0.178	0.449	0.388	0.637	0.563	0.656

Notes: Robust standard errors in parentheses. Standard errors are clustered at the subnational level. Regressions are weighted by region population. Poverty rate is taken from the GSAP panel dataset. *** p<0.01, ** p<0.05, * p<0.1

Appendix B: Data

B1. Global Subnational Atlas of Poverty (GSAP) - Panel database

The Global Subnational Atlas of Poverty (GSAP) is 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 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 mores 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)[20] 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 overtime, constructing a panel data of poverty at area-level is not a simple task. When there is a change in the boundary overtime or survey representativeness is different, efforts are needed to maintain for a long

[20] 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.

panel of data to have comparable statistics spatially and overtime. 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 overtime. In this version of the panel data, on average a country has data for 14 geographical areas over the period of 3 years.

B2. Alternative poverty data

We also 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.

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.[21] 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.

B3. Weather data

We 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 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

[21] 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.

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 description and summary statistics of all variables in Table B1.

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Figure B1: Number of economies across World Bank regions

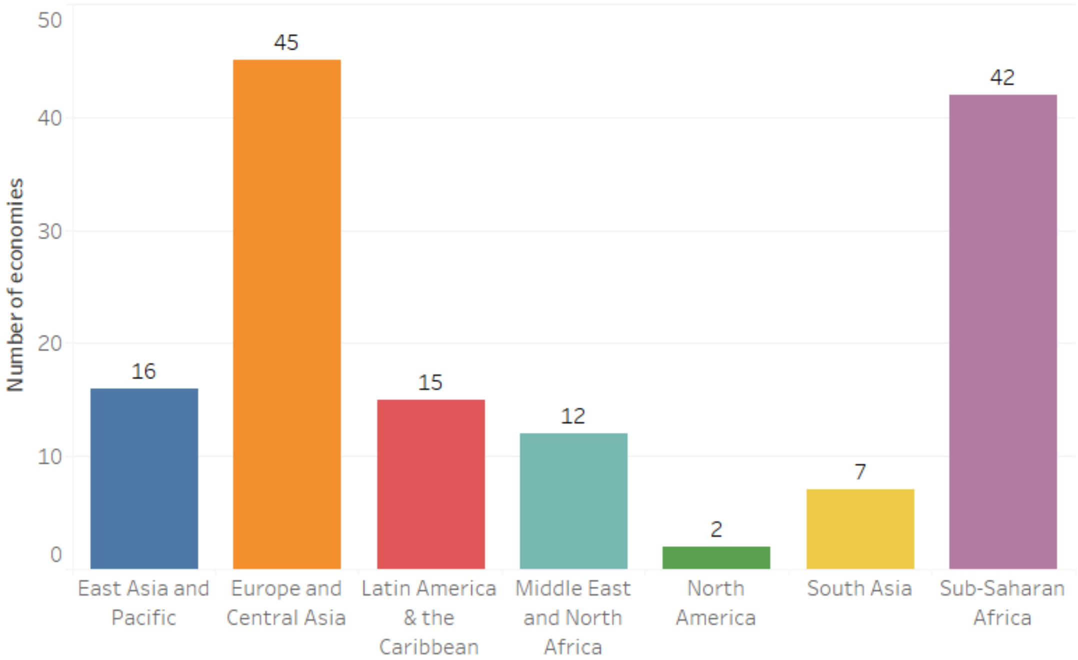

Figure B2: Number of areas over time

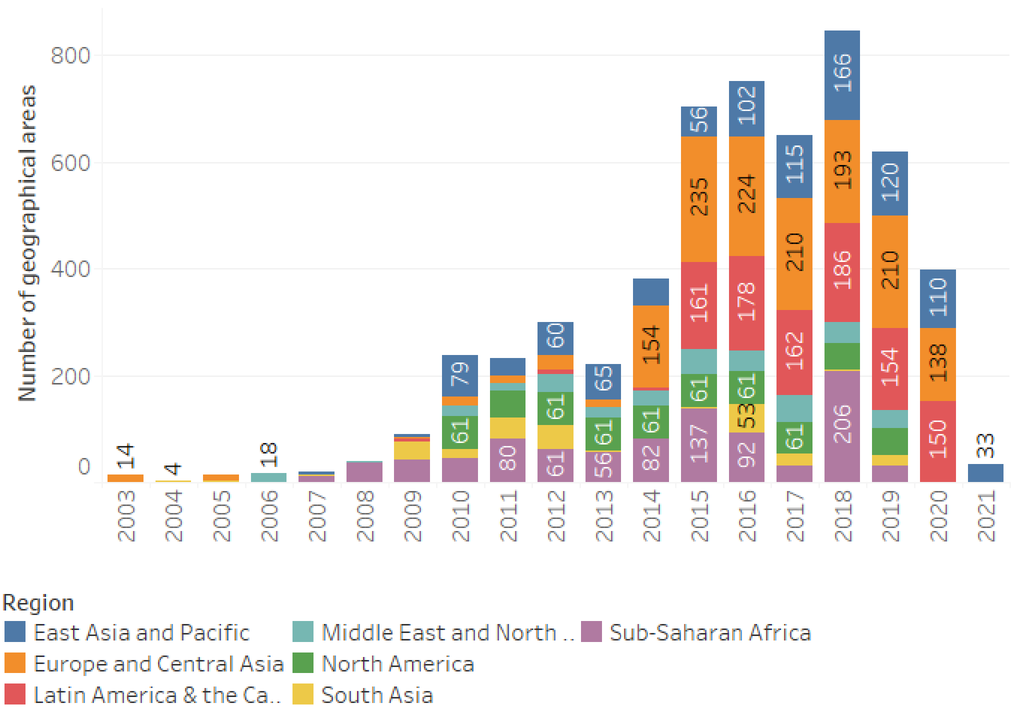

Table B1: Data sources and summary statistics

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	133	1,544	10.107	17.735	0.000	91.800
Poverty rate $3.20	Poverty Headcount Ratio at US$ 3.20 a day	133	1,544	19.196	26.032	0.000	98.500
Poverty rate $5.50	Poverty Headcount Ratio at US$ 5.50 a day	133	1,544	31.520	32.720	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	139	5,090	10.134	19.561	0.000	98.010
Poverty rate $3.20	Poverty Headcount Ratio at US$ 3.20 a day	139	5,090	20.344	28.611	0.000	99.724
Poverty rate $5.50	Poverty Headcount Ratio at US$ 5.50 a day	139	5,090	33.917	34.787	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)	139	5,090	18.185	7.996	-9.417	30.790
Rainfall	Average rainfall (mm)	139	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)	139	5,090	18.328	8.030	-11.082	30.426
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 A9 and A10)							
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

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

Notes: Poverty data are taken from WDA dataset (all countries).

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
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		
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	Czech Republic	Czech Republic	Czech Republic
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		Turkey	Turkey
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		

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 and long difference model presented in Table 2 and show that our results are broadly consistent when using alternative model specifications. First, we follow previous studies and employ several variants of Equation (2) (Kalkuhl and Wenz, 2020; Kotz et al., 2021). In column (1), we add country linear time trend to account for potential bias stemming from time-varying variables measured at the country level.

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, 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. We also conduct a similar exercise for the long differences model, as shown in Column (10). Results of these exercises strengthen our main findings.

In our long differences model, we choose the 3-year difference as our baseline. Our results remain consistent when using difference choice of window length (i.e., 4-year and 5-year period), as shown in Columns (7) and (8) of Table A2. 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 (subnational/grid level) GDP data coming from Kalkuhl and Wenz (2020) and Kummu et al. (2018). 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 A3 and A4 (Appendix A) show that our findings are not sensitive to the alternative datasets, 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 A5 (Appendix A) using (i) log of temperature (Column (1)); (ii) the temperature data at 0.5° resolution from the Climate Research Unit of the University of East Anglia (CRU) (Column 2); (iii) the number of days that temperature is above 28ºC (Column 3);[22] (iv) dropping regions with temperature being above that level (Column 4); and (v) temperature shock, defined as the difference between actual temperature and long-term temperature being greater (less) than 2 (-2) standard deviations (Column 5). The results show little change from the baseline specification (Table 2).

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 Panel A of Figure A2 (Appendix A) which show the negative effects of

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

temperature on poverty at high temperature bins (i.e., temperature being above 28°C). Furthermore, we also examine the cumulative effect of temperature on poverty by imposing a lag structure on the temperature bins (Chen and Yang, 2019; Somanathan et al., 2021). In particular, we include the contemporaneous effect of temperature and its lag effects of up to three years (i.e., *t-3*, *t-2*, and *t-1*). The cumulative effect is visualized in Panel B of Figure A2 (Appendix A) which suggest a large and statistically significant effect of temperature on poverty at higher bins.

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 A6 (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 United States and India (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 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.

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 A7 (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 A8 (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 A8 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 A9 (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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