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**Does Global Warming Worsen Poverty and Inequality?
An Updated Review**

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Abstract
We offer an updated and comprehensive review of recent studies on the impact of climate change, particularly global warming, on poverty and inequality, paying special attention to data sources as well as empirical methods. While studies consistently find negative impacts of higher temperature on poverty across different geographical regions, with higher vulnerability especially in poorer Sub-Saharan Africa, there is inclusive evidence on climate change impacts on inequality. Further analyzing a recently constructed global database at the subnational unit level derived from official national household income and consumption surveys, we find that temperature change has larger impacts in the short term and more impacts on chronic poverty than transient poverty. The results are robust to different model specifications and measures of chronic poverty and are more pronounced for poorer countries. Our findings offer relevant inputs into current efforts to fight climate change.

JEL Classification: Q54; I32; O1
Key words: Climate change; temperature; poverty; inequality; subnational data

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1. Introduction

Climate change is a topic of global concern, where a fast-growing literature exists in economics that inform policies and policymakers (Hsiang, 2010; Jones and Olken, 2010; Dell *et al.*, 2012; Kotz *et al.*, 2021). However, despite considerable research on how climate change affects economic factors like GDP or economic growth, there has been less exploration of its distributional impacts, particularly on poverty and inequality (IPCC, 2022). Indeed, concerns have been raised that poorer countries, or vulnerable population groups in the same countries, might be more negatively affected by climate change (Hallegatte *et al.*, 2017; Barbier and Hochard, 2019; Hsiang *et al.*, 2019; Chancel *et al.*, 2023).

We make several new contributions in this paper. First, we offer an updated and comprehensive review of the empirical assessments of (past or future) consequences of hotter temperature on poverty and inequality. The literature that we review focuses on the longer-term impacts of gradual changes in temperature, but also includes some of the recent papers estimating the impacts of other climate change phenomena such as changing precipitation (rainfall) patterns, sea level rises, and natural disasters on poverty or inequality. We pay special attention to studies' data sources as well as empirical methods, which have received relatively less attention in the literature. While studies are difficult to compare and aggregate due to different poverty metrics, assumptions, and country contexts, they consistently indicate a negative impact of temperature changes (and most of the other climate change phenomena) on poverty across different geographical regions, with higher vulnerability in poorer countries and especially in Sub-Saharan Africa. In contrast with these consistent results for poverty, there appears no agreement on climate change impact on inequality, with different studies reaching different conclusion on directions of the effects.

The challenge with comparing results from various studies covering different countries or regions calls for the use of standardized datasets that are comparable across countries. Our second contribution is to offer new, global estimates for the impacts of hotter temperature on poverty dynamics (including chronic and transient poverty) at the subnational level. We analyze the Subnational Poverty and Inequality Database (SPID), a recently constructed global database derived from official national household income and consumption surveys, incorporating over 1,594 subnational units from 134 countries, and spanning the period from 2003 to 2019 (Nguyen *et al.*, 2023).

Using this database, we obtain new global headcount poverty rates at the subnational unit level, using different poverty lines (from the extreme poverty line at $2.15/day to the higher poverty line at $6.85/day).[2] We further analyze richer poverty outcomes by classifying each subnational unit as being in chronic poverty (i.e., poverty extending over multiple consecutive periods), or transient poverty (i.e., temporary poverty lasting over non-consecutive periods). To our knowledge, these estimates on chronic and transient poverty at a global scale are not available before. The policies to address transient poverty are distinctly different from those for chronic poverty. Specifically, strong social protection programs would most effectively address transient poverty (e.g., as they help prevent the non-poor but vulnerable households from falling into poverty), but longer-term investments in human capital and infrastructure would better tackle chronic poverty.[3]

Our analysis suggests that change in temperature has a large impact on poverty at the subnational unit level, with larger impacts over the short-term than over the long-term, suggesting different impact channels at different timescales and a potential a role of longer-term adaptation. We also find that climate change has a more pronounced impact on chronic

[2] Unless otherwise noted, all our estimates in this paper are at the subnational unit level. Our poverty measures are adjusted to real values using 2017 PPP dollars.
[3] See, e.g., Barret (2005) and Ravallion (2016) for further discussion on different policy interventions regarding chronic poverty versus transitory poverty. Furthermore, distinguishing between chronic and transient poverty has much policy relevance, given the debate over whether and how much shocks that trigger transient poverty can generate chronic poverty, especially in places with low income and limited access to financial tools, through poverty traps (Barrett and Carter, 2013).

(subnational unit) poverty compared to transient poverty. Specifically, a 1°C increase in temperature can result in around 6% increases for different measures of chronic poverty. This disparity suggests that climate change affects long-term trends and structural poverty, with harmful consequences extending beyond short-term losses that typically follow unexpected shocks.

The paper has five sections. We present in the next section a simple analytical framework linking climate change and disasters to poverty and inequality (Section 2.1) before summarizing the methodologies and data commonly employed in the literature (Section 2.2). In Section 3, we subsequently review existing studies on the impacts of temperature change on poverty (Section 3.1), inequality (Section 3.2), and other related outcomes (Section 3.3). In Section 4, we discuss the data and our empirical framework (Section 4.1) before presenting our new estimates on general poverty (Section 4.2), poverty dynamics including chronic poverty and transient poverty (Section 4.3), as well as robustness checks (Section 4.4). We finally conclude in Section 5.

2. Analytical Framework

2.1. Theoretical Motivations

In order to provide a comprehensive overview of the effects of temperature change on poverty and inequality, this section outlines a simple conceptual model of the pathways through which higher temperature might influence these outcomes. Recognizing the intricate nature of this relationship, Figure 1 unfolds several interconnected mechanisms including economic growth, agriculture, labor productivity and human capital, migration, and other channels (such as rising sea levels). While the channels could carry a mix of both positive and negative impacts from temperature change, the impacts might vary from location to location and are highly context specific. Furthermore, these impacts can also differ in magnitude. As a result, Figure 1 represents our attempt to broadly sign these effects using evidence from either the majority of existing studies or most recent studies. Clearly, understanding the context-specific complexities is essential for developing effective mitigation and adaptation strategies.

Economic growth stands as the key channel through which temperature change affect poverty and inequality. Rising temperatures can dampen economic growth rates, negatively affecting income levels and job opportunities, which can lead to increased poverty and inequality (Hsiang, 2010; Jones and Olken, 2010; Dell *et al.*, 2012; Kotz *et al.*, 2021).[4] However, the impacts of these changes are unevenly distributed, with research showing differing effects between richer and poorer countries (Moore and Diaz, 2015; Newell *et al.*, 2021). Furthermore, the relationship between temperature and economic growth can be non-linear, yielding both positive and negative impacts depending on the temperature ranges and geographical locations. For example, warmer temperatures can foster economic production in colder countries up to a certain threshold, but beyond which they have negative impacts (Burke *et al.*, 2015). Given the complex interplay between climate change and economic growth, the influence of temperature change on poverty and inequality can also vary dynamically. This underscores the necessity for nuanced and context-specific strategies in responding to these multifaceted challenges.

Specifically, global warming can impact the agriculture sector, which plays a critical role in poverty and inequality in developing economies that heavily depend on this sector for livelihoods and GDP (Mendelsohn, 2009; Schlenker and Lobell, 2010; Aragón *et al.*, 2021). For instance, higher temperatures and changing rainfall patterns can alter the conditions necessary for plant growth, resulting in decreased crop yields and increased crop failure. This is particularly devastating for farmers with small land holdings or those engaged in subsistence

[4] There is not a straightforward relationship between economic growth and poverty and inequality. Economic growth is generally beneficial for poverty reduction, but this relationship can change depending on inequality levels (Cerra *et al.*, 2022; Ferreira *et al.*, 2022).

farming, often leading to a cycle of diminished income, and ultimately, poverty (Morton, 2007). Similar to its impacts on economic growth, temperature can also exhibit non-linear effects on crop yields. A certain amount of warming might improve crop yields initially, but beyond an optimal point, any additional temperature increase can drastically reduce productivity (Schlenker and Roberts, 2009; Lobell *et al.*, 2011). Furthermore, the negative impacts on agriculture do not solely affect those directly involved in farming but can also reverberate through the broader economy. For example, reduced agricultural output can lead to increased food prices and food insecurity (Wheeler and Von Braun, 2013), which in turn, can have negative consequences on the whole economy and exacerbate poverty and inequality.

Another key channel that global warming can affect poverty and inequality is through labor productivity and human capital. While outdoor sectors such as agriculture, construction, and tourism are most vulnerable under hotter temperatures, indoor work activities without adequate cooling can suffer. Previous studies show that heat stress can negatively affect physical labor capacity and cognitive function (Graff Zivin and Neidell, 2014; Zhang *et al.*, 2018; Somanathan *et al.*, 2021; LoPalo, 2023). As temperatures rise, workers may be unable to work effectively, leading to declined labor productivity. This would negatively impact earnings and employment, pushing more people into poverty and widening income gaps (Deryugina and Hsiang, 2014).

The global warming-induced negative impacts on human capital can be further demonstrated with health and education outcomes. Indeed, negative health effects of temperature change can be observed even before birth. Previous studies have found that high temperatures are negatively associated with birth indicators, leading to premature birth and low birth weight (Deschênes *et al.*, 2009; Deschênes and Greenstone, 2011; Molina and Saldarriaga, 2017). These early health issues could result in harmful, lifelong consequences for health and other outcomes (Graff Zivin *et al.*, 2018). Similarly, exposure to extreme temperatures over the life course can also contribute to worsening physical and mental health outcomes (Barreca, 2012; Barreca *et al.*, 2016; Mullins and White, 2019), which limit an individual's capacity to work and their long-term income-earning potential (Fishman *et al.*, 2019).

Regarding education, prolonged exposure to heat has been found to impact learning ability, with studies showing that high temperatures cause lower school attendance and worse student performance on standardized tests (Randell and Gray, 2019; Park *et al.*, 2020; Park *et al.*, 2021; Park, 2022). Additionally, children may be required to stay at home to assist their parents or supplement family income to help cope with weather-related income shocks (Mottaleb *et al.*, 2015; Colmer, 2021), which can further reduce their learning opportunities. As a result, the negative effects of temperature increases on health and education erode human capital, leading to decreased future employment outcomes and subsequently more poverty and inequality.

Migration is another crucial pathway through which temperature increases can contribute to poverty and inequality. Changing climate conditions, particularly rising temperatures, can make certain areas less habitable or economically viable. Even worse, changing climate conditions can worsen conditions in poverty "hotspots" that are already vulnerable to climate change such as agricultural lands constrained by difficult terrain, poor soil quality, limited rainfall, or with limited access to markets or rural low-elevation coastal zones (Barbier and Hochard, 2018a and 2018b). For example, extreme heat can reduce agricultural productivity or increase prevalence of heat-related illnesses, making it difficult for individuals to sustain their livelihoods. Consequently, households facing these adverse conditions might be prompted to migrate, often from rural to urban areas within the same country, or even across national borders in search of better living conditions and economic opportunities (Marchiori *et al.*, 2012; Kubik and Maurel, 2016; Thiede *et al.*, 2016; Jessoe *et al.*, 2018). While this could lead to spatial inequality as people move from areas of lower to higher economic productivity, the results on poverty could be mixed. On one hand, migration could potentially decrease poverty if migrants send home remittances. On the other hand, these same climate-induced economic hardships can also reduce individuals' ability to migrate due to liquidity constraints (Cattaneo and Peri, 2016; Hirvonen, 2016; Letta *et al.*, 2023). It is possible that the worse the economic conditions caused by the climate shock, the less likely individuals have the financial means necessary to migrate. In such cases, households are forced to remain in "poverty traps", leading to increased poverty rates (Barrett and Carter, 2013; Kraay and McKenzie, 2014).

The simple theoretical framework discussed above focuses on temperature change as the most important factor of climate change affecting poverty and inequality. However, in the broader framework of climate change impacts, there are multiple temperature-related manifestations, which can profoundly influence the channels mentioned. For example, sea level rise, a significant aspect of climate change, can force many coastal populations to relocate, putting added pressure on urban resources and livelihoods through increased migration (Chen and Mueller, 2018; Hauer *et al.*, 2020). Additionally, sea level rise can also impact freshwater resources, leading to potential shortage, which can directly reduce agricultural productivity and consequently the earnings of those who rely on agricultural production (Dasgupta *et al.*, 2009; Chen *et al.*, 2012).

Parallel to this, another dimension of climate change – unusual shifts in rainfall patterns – has its own implications. For many economies, especially those reliant on agriculture, variations in rainfall can negatively affect productivity levels, harvest yields, and consequently, overall GDP (Sarsons, 2015; Barrios *et al.*, 2010; Damania *et al.*, 2020; Kotz *et al.*, 2022). Such reduced income caused by rainfall shocks can have adverse effects on human capital (Maccini and Yang, 2009). For example, families with limited resources may struggle to access proper healthcare, increasing their vulnerability to diseases and other health issues (Rosales-Rueda, 2018). Furthermore, children's education could be affected if parents find it challenging to afford school fees or other educational expenses. In some extreme cases, children might be pulled out of school to support the family financially (Colmer, 2021). In addition to these effects, studies have shown that rainfall variability induced by climate change is also associated with higher likelihoods of conflict and increased patterns of migration (Miguel *et al.*, 2004; Kleemans and Magruder, 2018). Given these various climate-induced factors, addressing climate change effects on poverty and inequality requires a comprehensive understanding of various manifestations and their intertwined impacts.[5]

Our proposed framework briefly describes household responses in the short term (i.e., coping) and in the longer term (i.e., adaptation). For example, households could adopt coping strategies to natural disasters by not sending children to school (Fuller *et al.*, 2018), or respond to climatic shifts by switching to more drought-resistant crops or altering their planting seasons (Roesch-McNally *et al.*, 2018; Ponce, 2020). While coping/ adaptation to climate change could lessen the impacts of global warming (say, through technological advancements (Hsiang *et al.*, 2017)), the intertwined linkages between short-term coping and longer-term adaption are complicated and could either reduce or exacerbate poverty and inequality depending on the time period under consideration. For example, a household's decision to withdraw their children from school might help cut expenses in the short term, but it could negatively affect their human capital achievement and could lead to worse poverty outcomes in the future. Or if the government subsidizes housing protection with more resources going to larger houses (i.e., richer households), this policy response could increase inequality. As another example, a recent study points to lower global impacts of temperature change on poverty in the longer term—suggesting household adaptation to gradual warmer temperature over time (Dang, Nguyen, and

[5] For more focused discussion, in Figure 1 we present one-directional arrows indicating the directions of impacts. But the impacts can be multi-directional. For example, poverty reduction is observed to bring beneficial impacts on economic growth in the longer term (Thorbecke and Ouyang, 2022).

Trinh, 2023). But this study also finds some evidence for more impacts on inequality in the longer term.

But more importantly, this framework helps highlight the fact that not all climate change impacts on poverty and inequality are expected to be mediated by economic growth (Hallegatte *et al.*, 2017), or any single sector alone. It would be important to investigate the final impacts of climate change on poverty and inequality, which are generated as a sum total through all these different channels. Furthermore, the existing literature has mostly focused on the impacts of temperature change on short-term poverty. Indeed, existing studies do not distinguish between various forms of poverty dynamics, such as chronic and transient poverty. We attempt to fill these gaps with new estimates on the global impacts of temperature change on both chronic and transient poverty.

2.2. Data and Empirical Models

We review recent studies and pay special attention to data and empirical models in this section. We focus on questions whether studies use household consumption (income) surveys as the main sources of data, whether they use panel data, whether recent studies use big data (e.g., satellite data) more often, and whether studies analyze data that are more disaggregated than the country level. Regarding empirical models, we review studies that employ cross sectional models, panel data models, as well as non-parametric and simulation techniques.

2.2.1. Data

- ✓ Are household consumption (income) surveys the main sources of data?

While household surveys appear to be the standard data sources for climate change studies, it is useful to review this question and limitations with household surveys before we discuss the new data sources employed in recent studies. Indeed, existing studies examining the effects of climate change and natural disasters on poverty often rely on household consumption surveys as a dominant source of data. This is true both for single-country (e.g., Akter and Mallick, 2013; Arouri *et al.*, 2015; Bangalore *et al.*, 2018) and cross-country analyses (Azzarri and Signorelli, 2020; Carter *et al.*, 2007). A notable advantage of most living standards measurement study (LSMS)-type household surveys is that they provide comprehensive data on household consumption levels, enabling researchers to construct poverty indicators that directly align with the study's objectives (Wong and Brown, 2011; Jakobsen, 2012). In single-country analyses, the scope of the survey can be more closely tailored to specific regional or national contexts, providing nuanced understanding of the poverty situation. These studies often employ the headcount poverty rate and the Gini coefficient to measure inequality, which can be estimated using household surveys.[6]

While single-country studies often focus on specific events or circumstances within a country, their findings are typically limited in generalizability. In contrast, cross-country studies attempt to overcome this limitation by comparing and contrasting experiences across a range of countries. This broader perspective can shed light on patterns and relationships that might not be apparent within a single-country context, thereby offering findings with greater generalizability. However, assembling comparable data across multiple countries presents a significant challenge due to variations in data collection methods, definitions of key variables, and data quality among different nations. As a result, many studies often rely on standardized databases on poverty and inequality such as the World Bank's PovcalNet database, later transitioned into the Poverty and Inequality Platform (PIP), which offer estimates for inequality and poverty under various poverty lines or the United Nations University's World Income

[6] While most studies primarily rely on the Gini coefficient (Cappelli *et al.*, 2011; Tol, 2021; Paglialunga *et al.*, 2022; Pleninger, 2022), other inequality indexes are also estimated based on household surveys such as income ratios, Theil index, or Palma ratio to analyze inequality in more depth (Keerthiratne and Tol, 2018; Diffenbaugh and Burke, 2019). Beyond income poverty and inequality, recent studies also follow a lack of basic needs approach and examine other welfare aspects including food, education, healthcare, and social protection (e.g., Paavola, 2017; González *et al.*, 2022; Rana *et al.*, 2023).

Inequality Database (WIID) (Azzarri and Signorelli, 2020; Cappelli *et al.*, 2021; Paglialunga *et al.*, 2022).[7]

Still, a major limitation with household surveys is that such surveys are often not frequently collected, particularly in poorer countries due to resources and logistical constraints. A 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 a 10 percent increase in a country's household consumption is associated with almost one-third (i.e., 0.3) more surveys, indicating the paradoxical fact that poorer countries with a stronger need for poverty reduction also face a more demanding challenge of poverty measurement given their smaller numbers of surveys.

Furthermore, many studies exploring the impacts of natural disasters on poverty and inequality traditionally rely on household surveys that collected data on extreme events (Datt and Hoogeveen, 2003; Khandker, 2007; Bui *et al.*, 2014; Arouri *et al.*, 2015; Karim, 2018). While these surveys, usually based on respondents' recollections, provide direct insights into how households are affected by and respond to disasters, the accuracy of such data can be subject to recall bias and other inherent errors associated with self-reported information. In addition, many (older) surveys do not provide GIS information that accurately geo-locates households. Consequently, recent studies have increasingly turned to other sources of data that offer the geographical and temporal granularity needed to provide better and timely analysis of climate change and natural disasters that we discuss below.

✓ Are panel data often used?

The analysis of climate change and natural disasters' effects on poverty and inequality has evolved in tandem with advancements in data collection and processing. Early studies often

[7] For more details of the PIP database, see: https://pip.worldbank.org/home.

rely on cross-sectional survey data due to the constraints of data availability (Adger, 1999; Datt and Hoogeveen, 2003; Carter *et al.*, 2007; Lal *et al.*, 2009). Cross-sectional studies observe a set of units (e.g., households or individuals) at a single point in time, allowing researchers to make comparisons and draw conclusions about prevalence of poverty and inequality. However, cross-sectional data comes with inherent limitations. It only provides a snapshot view of poverty across units at one point in time but does not offer insights into changes over time or the dynamics that drive these changes. This lack of temporal perspective can lead to omitted variable bias and severely limit causal inferences. Recognizing these limitations, many studies have turned to panel data, which observes the same units across multiple time points (Giesbert and Schindler, 2012; Rodriguez-Oreggia *et al.*, 2012; Yamamura, 2015; Keerthiratne and Tol, 2018; Baez *et al.*, 2020; Sedova *et al.*, 2020; Sohnesen, 2020; Cappelli *et al.*, 2021). Panel data allows researchers to track changes over time and explore the temporal dynamics of poverty and inequality; consequently, it also offers a more in-depth understanding of the effects of climate change and natural disasters, which often have a longitudinal nature themselves.

However, the use of panel data is subject to several barriers. In particular, tracking the same households (individuals) over a long period is expensive and poses logistical challenges, especially where households migrate or live in remote locations. In particular, attrition—where households drop out of the panel for various reasons—is a well-known issue affecting the quality of panel data and would require considerable resources investment and advanced survey strategies to address (Schoeni *et al.*, 2013). As an example, the attrition rate in the panel Russia Longitudinal Monitoring Survey (RLMS) is already 40 percent in the first 10 years after it was fielded, but sharply increases to more than 70 percent after another 10 years (Kozyreva *et al.*, 2016). These challenges can be amplified in poorer countries (or conflict situations), where both resources and data collection capacity are limited. Given these challenges, alternative data imputation methods have been proposed to construct synthetic panels from repeated cross sections that allow richer analysis of poverty dynamics (Dang *et al.*, 2019; Dang and Lanjouw, 2023). But since there are few applications of these imputation methods for studying the impacts of climate change (see, e.g., Nakamura *et al.*, 2023), more studies in different contexts would be useful.

Recent studies have utilized administrative data, which typically offers better census-type coverage and longer-run panel data, especially in wealthier countries where such data is readily available. For instance, Duque *et al.* (2018) use administrative data from Colombia to examine how early-life exposure to adverse weather conditions and subsequent human capital investments via conditional cash transfers (CCTs) affect children's long-term outcomes. Focusing on school performance, Park (2022) exploits student-level administrative data from a public school district in the U.S. to examine how hot temperatures impact high-stakes exam performance and subsequent educational attainment. Similarly, Heyes and Saberian (2019) analyze U.S. immigration judges' decisions, demonstrating a link between outdoor temperature and immigration adjudications. Yet, while administrative data offer multiple advantages over household survey data such as accuracy, representativeness, and longer panel data, it is still rarely used in poorer countries due to weaker statistical capacity (Dang *et al.*, 2023b), which could range from fewer resources to less established data infrastructure. This explains the limited analysis of administrative data for poorer countries, particularly in the context of poverty and inequality.

- ✓ Do recent studies use big data (e.g., satellite data) more often than previous studies?

The rise of big data, together with progress in geographic information system (GIS) technology, has greatly expanded the range of data sources available for studies on climate change, particularly natural disasters. An alternative to household surveys is to use global disaster databases such as the Emergency Events Database (EM-DAT), which provides comprehensive data on the occurrence and impacts of over 22,000 mass disasters worldwide since 1900 (Yamamura, 2015; Cappelli *et al.*, 2021). Another source of disaster data is DesInventar, which provides records of disaster at the country level from 1980 (Rodriguez-Oreggia *et al.*, 2012; Keerthiratne and Tol, 2018). The advantage of such databases is their wide coverage and the standardization of disaster data, enabling cross-country comparisons. However, they often lack detailed local-level data, which can be crucial for understanding variations in disaster impacts within countries. Moreover, these databases predominantly focus on large-scale disasters, potentially excluding smaller, localized disasters that can have a substantial cumulative impact on poverty and inequality.[8] The reliance on official reports or media coverage for disaster validation may also underrepresent disasters in areas with less robust reporting systems. These limitations highlight the importance of incorporating additional data sources to provide a more comprehensive understanding of disaster impacts.

Another nuanced approach in the study of disaster impacts combines traditional survey techniques with geospatial and localized risk information (i.e., footprint data). Geo-referencing is employed to further validate self-reported exposure data, thus combining ground truth with computational models. Such methodologies aim to generate a more intricate understanding of localized risks and household experiences, and therefore bring a multidimensional perspective that blends traditional and high-tech methods. Specifically, recent studies use community flood maps and satellite imagery to identify flood risks or use self-reported survey data that were validated with a newly developed flood map, offering a more complex understanding of households' experiences during flood events (Erman *et al.*, 2019; Erman *et al.*, 2020). A particularly significant development is the use of reanalysis data, which combines satellite observations, ground measurements, and statistical models to offer near-global coverage of

[8] To be included in EM-DAT, a disaster must meet at least one of the following criteria: 10 or more people reported killed, 100 or more people reported affected, declaration of a state of emergency, or a call for international assistance.

climate variables (Giesbert and Schindler, 2012; Diffenbaugh and Burke, 2019; Azzarri and Signorelli, 2020). In particular, Rentchler *et al.* (2022) combine different data sources on flood, population, and poverty to provide more granular assessment of exposure to flood risks and poverty.

Combining various data sources is especially valuable for providing critical weather information in remote and inaccessible areas where ground-based networks are limited.[9] While satellites can capture a broad spectrum of data simultaneously, satellite data comes with its own set of limitations. For instance, these records typically cover a shorter time span than station-based data, owing to the relatively recent deployment of satellite technologies. Furthermore, the data require complex processing to account for non-climatic factors, such as variations in satellite orbits and the need for instrument calibration.

✓ Do studies analyze data that are more disaggregated than the country level?

While most existing studies analyze country-level data, using such data has certain drawbacks. Country-level data can mask significant disparities within countries, such as regional variations in weather conditions, exposure to natural disasters, and levels of poverty and inequality. This issue can be particularly pronounced in developing countries, which are often located in tropical areas with diverse weather conditions and disaster risks. Consequently, important intra-country variations can be obscured when data is aggregated at the national level. In response to this limitation, a growing number of studies have begun to exploit subnational data. These studies observe more pronounced effects of climate change on economic growth and poverty at this more granular level (Damania *et al.*, 2020; Kalkuhl and Wenz, 2020; Dang *et al.*, 2023b). This shift towards more localized analyses underscores the need for more disaggregated,

[9] Temperature and rainfall data are primarily sourced from ground-based weather stations, which are valued for their long-term records and high precision (Jones and Olken, 2010; Dell *et al.*, 2012). However, station-based data often has uneven geographic distribution, resulting in coverage gaps particularly in poorer countries or regions where there is limited infrastructure to support these stations (Dell *et al.*, 2014).

region-specific data and further highlights the potential of new data sources in shedding light on the intricate relationships between climate change, poverty, and inequality.

2.2.2. Empirical Models

Previous studies often rely on three primary types of econometric models to examine the economic effects of climate change and natural disasters: cross-sectional models, panel models, and long differences models. The first two models have been used to evaluate the effects on poverty and inequality (Arouri *et al.*, 2015; Azzarri and Signorelli, 2020; Paglialunga *et al.*, 2022), while the last model has been used recently on other outcomes such as agriculture, health, and labor reallocation (Burke and Emerick, 2016; Obradovich *et al.*, 2018; Liu *et al.*, 2023).

Cross-sectional models offer the starting point where the relationship between climate change and poverty (inequality) is commonly formulated as

$$Y_i = \alpha_{CS} + \beta_{CS} T_i + \gamma_{CS} P_i + \varepsilon_i \tag{1}$$

In such models, the dependent variable (Y_i) typically represents a socio-economic indicator, such as poverty (inequality), in a specific location (i) during a given period. These models factor in variables like annual temperature (T_i) and precipitation (P_i) (Azzarri and Signorelli, 2020).[10]

A potential omitted variable bias is an inherent challenge in Equation (1), which refers to a situation where unobserved correlations between temperature and other factors like technological changes or labor productivity, could influence the outcome variable. To

[10] While rainfall is not the central focus of our review, it is worth noting that a substantial body of literature has applied similar models to explore the impacts of (various metrics of) rainfall on different outcomes. For example, previous studies have used total annual precipitation (Damania *et al.*, 2020), rainfall deviations from the historical means (Corno and Voena, 2023), and extreme rainfall events exceeding specific thresholds (Shah and Steinberg, 2017). Each of these measures provides a distinct lens through which the multifaceted impacts of rainfall can be understood.

overcome this limitation, researchers use panel models. Panel models often take the following form

$$Y_{i,t} = \alpha_{FE} + \beta_{FE} T_{i,t} + \gamma_{FE} P_{i,t} + \mu_i + \lambda_t + \epsilon_{i,t} \tag{2}$$

These models employ fixed effects for both location (μ_i) and year (λ_t), providing control for unobserved time-invariant factors and temporal changes that may affect the dependent variable ($Y_{i,t}$) (Paglialunga *et al.*, 2022). Notably, Equation (2) assumes that climatic variables have linear effects. To test the robustness of this assumption, some studies have proposed variations improvements, such as introducing quadratic temperature terms, controlling for temperature change, or further examining interactive effects between temperature levels and changes (Kalkuhl and Wenz, 2020).

Yet, to better address potential non-linear effects of climate change, other studies propose a temperature-bin approach that allows for a more flexible function of temperature by dividing it into designated bins (Chen and Gong, 2021; Mullins and White, 2020)

$$Y_{i,t} = \alpha_{TB} + \sum_{j=1}^{k} \beta_{TB} T_{i,j} + \gamma_{TB} P_{i,t} + \theta_i + \vartheta_t + \nu_{i,t} \tag{3}$$

A criticism of panel models, however, is that while such models can identify short-term effects of climatic changes, they do not capture long-run effects, particularly if these effects are mediated through household adaptation or intensify over time. To address this, long differences models aiming at analyzing gradual changes in the outcome variable and climatic variables between time periods are often employed (Burke and Emerick, 2016; Chen and Gong, 2021; Wing *et al.*, 2021)

$$\Delta Y_i = \alpha_{LD} + \beta_{LD} \Delta T_i + \gamma_{LD} \Delta P_i + \omega_{i,t} \tag{4}$$

Robustness checks for the long-differences model include alternative specifications such as different period-average definitions, further controlling for geography or resource endowment covariates, and employing additional model specifications similar to those in panel models.[11]

Beyond empirical estimation, a simulation-based approach is also popular for forecasting climate change impacts (Hsiang *et al.*, 2013; Burke *et al.*, 2015; Moore and Diaz, 2015). The method typically involves constructing a theoretical model, which is subsequently calibrated with actual data to simulate potential future outcomes under various climate scenarios. The most common practice in the economics literature involves using estimates from historical data and empirical models, as detailed in Equations (1)-(4), to project future climate change impacts (Burke and Emerick, 2016; Kalkuhl and Wenz, 2020; Newell *et al.*, 2021). The estimating model can be simplified as

$$Y_{future} = f(X_{current}, X_{predicted}) \tag{5}$$

where X include climatic variables such as temperature, rainfall, and other relevant socio-economic indicators that are used to predict the future outcomes like poverty rates, inequality, and economic growth.

The simulation approach is forward-looking and allows for predictions into the future under various scenarios. It also offers flexibility in incorporating diverse factors and complex interactions. However, two key limitations of most simulation studies are the assumptions that the impacts of warming due to one degree increase in one place (i.e., what they measure in the past when using mostly weather variations) would be the same everywhere else (i.e., what they try to predict in the future, which is a global increase in temperature), and that future impacts will be similar in magnitude to impacts in the past. When these assumptions do not hold, estimation results are likely biased and miss impacts that are of a systemic nature (e.g., a

[11] Variants of the long-differences model include stacking long-term data into intervals (e.g., decades) to examine the long-term effects of disasters on economic outcomes (see, for example, Boustan *et al.*, 2020). Another example is triple-differences models that make use of variation in multiple weather shocks across different channels such as space, time, and cropping cycles (Baez *et al.*, 2020).

collapse in major ecosystems or physical systems) or linked to absolute thresholds (e.g., physiological limits).

It is useful to note that future impacts of climate change on income, inequality, or poverty does not depend only on the nature and magnitude of climate change impacts, but socioeconomic contexts also matter (Kelly and Adger, 2000; Hallegatte and Rozenberg, 2017). Future socioeconomic contexts (and household vulnerability) are extremely uncertain and driven by socioeconomic and technological trends, as well as policies and collective action. For example, the share of farmers engaged in small-scale agriculture, or the number of households lacking improved water and sanitation, can significantly influence population vulnerability to poverty. Most empirical studies do not adequately capture these socioeconomic factors, and assume unchanged vulnerability over time. This limit underscores the need for future research to integrate these elements for a more comprehensive understanding of the complex relationship between climate change, disasters, and poverty.

3. Impacts on Poverty and Inequality

3.1. Poverty

A large body of literature has examined the impacts of climate change—but mostly through disasters—on poverty, both from individual empirical studies and literature reviews.[12] However, due to data limitations, not all studies have been able to quantify these effects on poverty (Hallegatte and Rozenberg, 2017). This section summarizes the key findings from several sample empirical studies that have successfully quantified these impacts.

In Vietnam, Arouri *et al.* (2015) explore the effects of storms, floods, and droughts on household welfare, finding that all three types of disasters reduce per capita expenditure by around 1.5%, 4.4%, and 3.5%, respectively and increase the probability of poverty for

[12] For a recent review of the literature, see Hallegatte *et al.* (2020).

households in flood-affected communes by 1.8 percentage points. Another study by Bui *et al.* (2014) for the same country estimates that poverty would have decreased by 2.7 percentage points if households had not been exposed to natural disasters. Analyzing data from Mexico during 2000-2005, Rodriguez-Oreggia *et al.* (2013) highlight significant adverse effects of natural disasters on both human development and poverty, with an increase in poverty of between 1.5% and 3.7%. Notably, floods and droughts are the most devastating. Similar results are found in Argentina by González *et al.* (2022) where they find that a variety of natural disasters from 1970 to 2010 contributed to more multi-dimensional poverty.

On a global scale, combining household surveys from 24 Sub-Saharan African countries, Azzarri and Signorelli (2020) find that flood shocks result in a 35% decrease in total and food per-capita consumption and a 17-percentage point increase in extreme poverty. Azzarri and Signorelli (2020) also predict that increases in rainfall and temperature, and consequently the incidence of disasters across Western and Central Africa, could result in dramatic increases in extreme poverty rates by up to 30 percentage points. Analyzing a new global, subnational database on poverty across 134 countries, Dang *et al.* (2023a) find strong and statistically significant global effects of both higher and lower temperature on poverty, with a one-degree Celsius (i.e., 1°C) annual increase in temperature causing 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). But this study also finds smaller impacts in the longer term, suggesting household adaptation to gradual warmer temperature over time.

Other studies simulate the future effects of climate change and disasters on poverty. For example, using a CGE model to explore how future climate scenarios would affect economic growth and poverty in Zambia, Thurlow *et al.* (2012) find that even small changes in climate expected by 2025 can increase the absolute number of poor people by 32,000 over 10 years, while also yielding variable impacts on GDP growth depending on the climate scenario. Meanwhile, Hallegatte and Rozenberg (2017) forecast that the number of people in extreme poverty due to climate change could reach between 35 million and 122 million by 2030, depending on the severity of climate impacts and the socioeconomic context and trends (e.g., pace of demographic transition, changes in economic structure, evolution of the skill premium, or the progress in providing universal access to basic infrastructure services).

Overall, previous studies consistently indicate a negative impact of various types of natural disasters on household income, expenditure, and poverty levels across different geographical regions. Furthermore, simulation studies all point to potentially severe impacts of climate change on global poverty, particularly in Africa, further emphasizing the urgency of addressing this pressing issue. However, directly comparing these estimates proves difficult, given the diverse measures of poverty used across the studies. This highlights the necessity for a harmonized database to facilitate more meaningful comparisons and better understanding of climate change impacts.

3.2. Inequality

A number of empirical studies have evaluated the global impacts of climate change on inequality, with more recent studies finding negative impacts. In particular, Yamamura (2015) finds that while natural disasters have increased income inequality in the short-term (5 years), this effect disappears in the long term (10 years). A recent study by Song *et al.* (2023), on the other hand, find catastrophic natural disasters to have negative relationships with inequality, as measured by the Gini index, in both the short and long run. Diffenbaugh and Burke (2019) similarly argue that global warming has significantly increased economic inequality between countries. Their findings reveal that global warming has reduced per capita GDP by 17-31% at the poorest four deciles, contributing to a wealth gap that is 25% larger than in a world without global warming. Similarly, Paglialunga *et al.* (2022) find a 1% increase in temperature to correspond to a 0.5-point increase in the Gini index. Cevik and Jalles (2023) focus more on the difference in the climate change effects across countries and find the impacts to be seven times greater in developing countries. Gilli *et al.* (2023) analyze country-level income deciles data and find rising temperature to have most negative impact on the poorest deciles within countries. Analyzing more disaggregated subnational inequality data across 134 countries, Dang *et al.* (2023a) similarly find that a 1°C rise in temperature leads to 0.8 and 1.4 percent increases in the Gini and Theil indices, respectively.

Yet, single-country studies often find mixed evidence of climate change impacts on income inequality. For instance, Bui *et al.* (2014) demonstrate that natural disasters can have a significant impact on income distribution in Vietnam, particularly in regions with larger rural populations and agricultural workforces. Other within-country studies, however, present a more complex picture, highlighting uneven climate change impacts across different income levels within the same country. Pleninger (2022) finds that in the United States, the short-term effects of natural disasters primarily affect middle income population groups, leaving overall income inequality unchanged. This finding aligns with Otrachshenko and Popova's (2021) study for Russia showing that extreme hot temperatures negatively impact regional GDP per capita but do not significantly affect income inequality. However, both studies confirm the variation in vulnerability among income levels and regions, with the poor regions being more susceptible to disasters.

Some studies even highlight potential reductions in inequality following climate-related events. For example, Keerthiratne and Tol (2018) document a decrease in the Gini coefficient by 0.01 points in the aftermath of natural disasters in Sri Lanka. This reduction appears to be driven not by an increase in the income of poorer households, but rather by a decrease in the income of richer households. This finding adds another layer of complexity to our understanding, highlighting that climate change impacts on inequality can vary greatly depending on country-specific socioeconomic and environmental contexts.

3.3. Other Outcomes/ Channels

Studies that explicitly examine the mechanisms linking climate change and disasters with poverty and inequality are still relatively few, perhaps due to data limitations. The handful of studies that explore these mechanisms often converges on a few key themes, with agriculture standing out as a primary driver (Azzarri and Signorelli, 2020; Paglialunga *et al.*, 2022). Climate change impacts tend to be amplified in countries with large rural populations or a high proportion of the workforce in agriculture. Such demographic characteristics not only exacerbate the vulnerability of these populations to climate change but also enhance the potential for climate change to aggravate inequality.

Extreme climatic events may have differing impacts depending on the rural-urban context. While rising temperatures seem to exacerbate inequality more in largely rural countries (or regions), extreme precipitation events are associated with increased disparities in predominantly urban areas. Paglialunga *et al.* (2022) show that precipitation deviation can trigger flood risks in urban areas, damaging infrastructure and overloading drainage systems. Such events can disrupt food availability and inflate prices, disproportionately affecting the urban poor who rely more on markets for food. Combining household surveys with climatic datasets, our analyses of Chile, Colombia, and Indonesia, Nakamura *et al.* (2023) find that while households in large metropolitan areas are more likely to escape from poverty, climate shocks such as extreme rainfalls and high flood risks significantly reduce upward mobility, thus offsetting such benefits of urban agglomerations.

In terms of adaptation mechanisms, social safety nets such as unemployment insurance can mitigate the negative impacts of natural disasters on income (Pleninger, 2022). However, these measures may fall short in the face of multiple or severe disasters occurring within short timeframes. This indicates that the capacity to adapt and mitigate climate change effects is a critical factor in determining how these events influence poverty and inequality.

In summary, understanding the mechanisms that link climate change and disasters with poverty and inequality is a multifaceted endeavor. While we have gained substantial insights from the focus on agriculture, numerous mechanisms remain relatively unexplored. These might include conflict, migration, and changes in labor productivity, which are promising areas for future research.[13]

4. New Estimates for Chronic and Transient Poverty

4.1. Data and Analytical Framework

Our empirical analysis relies on data from the Subnational Poverty and Inequality Database (SPID), a recently introduced global database mapping poverty and inequality on a subnational scale (Dang *et al.*, 2023a; Nguyen *et al.*, 2023). SPID is compiled from the Global Monitoring Database (GMD), an extensive repository of household survey data managed by the World Bank. The database derives from official national household income and consumption surveys, incorporating over 1,594 subnational units from 134 countries and spanning the period from 2003 to 2019 with most observations starting from 2010. Typically, a subnational unit aligns with a state or province (that is, first-level administrative boundaries - ADM1), but can also represent a cluster of regions, as determined by the specific household surveys' sampling approach.

[13] For example, climate change and related disasters could lead to an increase in conflict over increasingly scarce resources (Burke *et al.*, 2009; Koubi, 2019), which in turn could exacerbate poverty and inequality. Migration, both within and across borders, is another possible response to climate change and disasters (Gröger and Zylberberg, 2016; Missirian and Schlenker, 2017), which could either mitigate or exacerbate inequality depending on the socio-economic characteristics of the migrants and the receptiveness of the destination regions. Climate change impacts on labor productivity, especially in sectors that are highly dependent on physical labor and weather conditions could have far-reaching effects on income distribution and poverty (Somanathan *et al.*, 2021).

The key measure of SPID includes the (headcount) poverty rates estimated for each subnational unit using the daily poverty lines of \$2.15, \$3.65, and \$6.85 and the relevant household income (consumption) surveys based on the GMD. That is, these poverty rates are calculated at the subnational level using household-level data and the specified poverty lines. The database also provides a multidimensional poverty index for a comprehensive perspective on poverty assessment. For assessing inequality, the SPID offers the Gini and Theil indexes (at the subnational unit level), which are the most common metrics for evaluating income inequality. All measurements are adjusted to real values using 2017 PPP dollars.

To examine the effects of warmer temperature on chronic poverty, we integrate the SPID data with the ERA5 satellite reanalysis data from the European Centre for Medium-Range Weather Forecasts Reanalysis 5 (ECMWF). The ERA5 offers hourly assessments of multiple climate-related variables across an approximate 0.25 longitude by 0.25 latitude degree resolution grid, with data accessible from 1979 onwards. In line with previous studies, we compile the gridded data at the regional level by determining area-weighted averages (i.e., averaging all grid cells within a given region) (Kalkuhl and Wenz, 2020).

4.2. Temperature effects on poverty

Our review so far has considered the effects of temperature on both poverty and inequality due to their inherent connection. In the following empirical analysis, we narrow our focus to explore the link between temperature and poverty. This choice is driven by our interest in examining poverty dynamics, an area that has not been extensively covered in current studies. For a deeper look into the effects of temperature on inequality, readers can refer to more detailed analysis presented in Dang *et al.* (2023). We start with the analysis of temepraturе effects on contemporary poverty in this section and present new estimates on poverty dynamics in the subsequent section.

We present the results of the effects of warmer temperature on contemporary poverty in Table 1. Our main focus is the headcount poverty rate at the subnational unit level, using the \$3.65/day or \$6.85/day poverty thresholds.[14] To further highlight the differences between estimates using country-level data versus using subnational unit level data, we aggregate the subnational unit level data to the country level.[15] We begin with an examination at the country-level (Panel A), followed by the localized analysis at the subnational level (Panel B). We employ two models: the fixed-effects model and the long differences model, as shown in Equations (2) and (4). In each panel, the results of the fixed-effects panel model are presented in Columns (1) and (3), with the results of the long differences model in Columns (2) and (4).[16] Across both panels, the findings reveal strong evidence of the negative effects of rising temperature on poverty, regardless of the poverty measures used.

Furthermore, the estimates derived from the subnational-level analysis (Panel B) exhibit stronger magnitudes compared to the country-level analysis (Panel A). Results of the equality tests confirm that these variations between the two levels of analysis are significant, indicating that an analysis based on country-level data may underestimate the effects of increased temperatures. This finding is consistent with that in another study using different poverty data (Dang *et al.*, 2023a) and aligns with earlier research that has identified stronger effects of temperature on economic growth at the subnational level (e.g., Damania *et al.*, 2020; Kalkuhl and Wenz, 2020).

We then turn our focus to the subnational analysis to interpret the estimation results. Specifically, Column (1) of Panel B illustrates that a 1˚C increase in temperature corresponds to a 7.2 percentage point increase in poverty, translating to a 61.5% increase in poverty given

[14] We also check the robustness of our findings using alternative measures of poverty in the Appendix.
[15] Alternatively, we also use country-level data from the World Development Indicator (WDI) database. Our findings remain consistent (see Table A4 in the Appendix).
[16] For the long differences model, we measure poverty and weather variables as the differences between 2010 and 2019.

an average poverty rate of 11.7%. The results of the long differences model are also significant and consistent with previous findings. However, the coefficient estimates from the long differences model are relatively less pronounced, with a 1˚C increase in temperature being associated with 1.6 percentage points (or 13.7%) increase in poverty. The t-tests at the bottom of Panel B indicate that the differences between the two approaches are statistically significant.

The difference between the two specifications may arise from the difference between (i) short-term vulnerability, which links short-term weather fluctuations to poverty, including transient poverty in response to extreme weather, and (ii) a longer-term and more systemic vulnerability, which links changes in climate conditions to poverty, and especially chronic poverty. Part of this difference originates from the mechanisms through which weather and climate affect people and activities, but possibly also from households' long-term adaptation in response to longer-term temperature change. The role of household adaptation in reducing the negative effects of temperature on various outcomes, such as economic production, agriculture, and human capital, has already been highlighted in empirical studies (e.g., Chen and Gong, 2021; Graff Zivin *et al.*, 2018; Kalkuhl and Wenz, 2020).

While our main interest lies on the effects of temperature on poverty, we also find mixed evidence regarding the impacts of rainfall on poverty, which align with findings from previous studies on economic growth (Dell *et al.*, 2012; Damania *et al.*, 2020; Kotz *et al.*, 2022). The varying effects of rainfall might be attributed to its different outcomes on the economy. Adequate rainfall can benefit agricultural regions by enhancing crop yields, potentially alleviating poverty. Conversely, excessive rainfall can result in flooding, damaging infrastructure and agriculture, which could exacerbate poverty conditions. We further examine different functional forms of the rainfall variable in Table A5 (Appendix A). These include the squared term of rainfall (Columns (1) and (2)), deviations from long-term averages of rainfall (Columns (3) and (4)), and particularly high rainfall amounts, defined as being above certain percentiles (Columns (5) to (8)). Again, our results on the effects of temperature remain consistent while the effects of rainfall appear inconclusive.

4.3. Temperature effects on poverty dynamics

Chronic poverty

We turn next to investigate climate change impacts on chronic poverty. Chronic poverty, characterized by prolonged and persistent poverty conditions, can have severe and lasting consequences on individuals and communities, affecting multiple generations and hindering overall socio-economic development. Addressing chronic poverty is therefore essential for sustainable poverty reduction, as transient poverty alleviation measures might not effectively target the root causes of long-term poverty.

We present our analysis of the effects of warmer temperatures on chronic poverty using three measures: (i) the number of times each subnational unit is in poverty (i.e., the subnational unit's mean consumption per individual in 2017 falls beneath the $3.65/day or $6.85/day poverty thresholds) from when it was first observed until it was last observed in the SPID database; (ii) the share of time that a subnational unit is in poverty during the same period. The measures are then regressed on temperature and rainfall variables using the same period of measurement.[17] Alternatively, we also employ a third measure, which is the average poverty rate using a window of 5-year period, conditional on each subnational unit having at least two data points during a particular period.[18] We then apply a fixed-effects model for the last measure. These three measures offer different but complementary aspects (i.e., absolute and

[17] We also include the number of data points we have for each subnational unit in the database to control for potential differences due to data availability for each subnational unit.

[18] For example, a subnational unit with data available from 2010 to 2019 was divided into two 5-year periods, with poverty and weather variables being averaged during each period.

relative measures) of the intensity of poverty depth that a subnational unit can fall into during the specified period. We discuss another measure of chronic poverty below.[19]

Our analysis, presented in Table 2, consistently reveals negative effects of hotter temperatures on the three measures of chronic poverty, irrespective of the poverty threshold or the measure of chronic poverty employed. For example, using the first measure, a 1°C increase in temperature corresponds to a 2.3 percentage point (or 6.4%) increase in the number of poverty incidences at the $3.65/day threshold. Similarly, the second measure reveals an increase of 1.1 percentage points (or 6.3%) in the proportion of times a subnational unit is in poverty for the same temperature increase. The third measure, which looks at the average poverty rate over 5-year periods, shows a robust effect of warmer temperatures on chronic poverty. Notably, the effects of rainfall on chronic poverty are mixed.[20] These results underline the severity of the adverse effects of rising temperatures on chronic poverty and underscore the need for targeted interventions to mitigate these effects.

Finally, we delve into a more detailed examination of the effects of hotter temperature across regions. This part of our analysis leverages the temperature bin approach (Equation 3), offering a more flexible functional form of temperature, as shown in Figure 2. We specify temperature as a series of indicator variables corresponding to 3˚C bins, where coefficients can be interpreted as the relative effects of falling within a particular bin compared to a reference "comfortable" bin (that is, 15-18˚C). We classify extreme hot weather as temperature being above 27˚C, and extremely cold weather as temperature being below 6˚C. Figure 2 highlights that rising temperature tends to exacerbate chronic poverty, particularly in poorer regions such as Sub-Saharan Africa. (For this exercise, we measure chronic poverty as the number of times each subnational unit is in poverty). We also observe adverse effects of colder temperature,

[19] See Fusco and Van Kerm (2023) for a recent review on chronic poverty measures.

[20] It could be the case that non-linear effects of rainfall, or variations in rainfall over time, explain the mixed effects on the outcomes. However, other studies that analyze disaggregated data find negative impacts of rainfall on economic growth (Damania *et al.*, 2020; Kotz *et al.*, 2022).

predominantly in Europe and Central Asia.[21] These insights correspond with several studies that find negative effects of cold weather on aspects such as productivity, health, and economic growth (Cook and Heyes, 2020; Dell *et al.*, 2012; Deschênes and Moretti, 2009).

Transient poverty

Unlike chronic poverty, transient poverty is characterized by short-term fluctuations in poverty status, often due to temporary shocks or income volatility. Understanding transient poverty is therefore crucial for assessing how individuals and communities cope with short-term disruptions caused by climate change and weather shocks, which could have long-term implications if not effectively managed. For better comparison with earlier results, we employ three related measures of poverty: (1) chronically poor, (2) transiently poor, and (3) generally poor. Specifically, we classify a subnational unit as "chronically poor" if it falls below the poverty threshold in both periods within a 5-year window, conditional on having at least two data points during that period. Conversely, a subnational unit is considered "transiently poor" if it falls below the poverty threshold in either (but not both) of the two periods within the same 5-year window. Finally, a subnational unit is classified as "generally poor" if it is either chronically poor or transiently poor—that is, it falls below the poverty threshold in either of the two periods. While this new definition of chronic poverty is somewhat simpler than those employed for Table 2 (and it is most similar to the measure for the share of time that a subnational unit is in poverty during a specified period), it allows for better comparison with transient poverty and general poverty.

[21] We provide additional heterogeneity analyses in Appendix A. For Figure A2, we use the World Bank's income classifications and divide our sample into two groups: firstly, the low income and lower-middle income countries, and secondly, the upper-middle income and high-income nations. The figure consistently reveals the negative effects of hotter temperatures on chronic poverty. In addition, the effects of colder temperatures are also discernible, but predominantly within the high-income bracket. In Figure A3, we present the estimates of hotter temperature on chronic poverty, adjusted for real GDP per capita on a country-by-country basis. This underscores poor countries' strong exposure to warming temperatures, with African countries such as Togo, Malawi, and Uganda being particularly vulnerable.

Our findings, summarized in Table 3, demonstrate negative effects of hotter temperatures on poverty, and these effects are robust across various measures of poverty. These results are reassuringly consistent with those based on different definitions of chronic poverty shown in Table 2. For example, a 1°C increase in temperature is associated with a 1.6 percentage point increase in chronic poverty at the $3.65/day threshold. The coefficient estimate is stronger when using the poverty line of $6.85/day. We also find negative effects of temperature change on transient poverty, and that the effects on transient poverty are much less pronounced than (i.e., around one-fifth) those on chronic poverty, as confirmed by the equality test for the higher poverty line. Similar to previous analyses, the impacts of rainfall are mixed, generally showing a negative correlation with chronic poverty and a positive but weaker correlation with transient poverty. Overall, these results underscore the need to better distinguish chronic and transient poverty for more effective policy advice.

4.4. Robustness tests

We assess the robustness of our results by examining them through different measures and specifications. We start with the results of contemporary poverty, using different model specifications for the panel and long difference models. The results are presented in Table A1 (Appendix). First, we show that our estimates remain stable regardless of the inclusion of country specific time trends (Column 1). Another issue to address is the potential misspecification of the functional form of temperature. Consequently, in Columns (2) and (3), we employ alternative functional forms of temperature, incorporating quadratic and cubic temperature terms. Results of these exercises provide further support to our main findings. Additionally, we explore different variants of the long differences model using alternative choices for the window length, specifically 4-year and 5-year period. Columns (4) and (5) confirm that our findings are not affected by these alternative window lengths.

Subsequently, we perform further tests in Table A2 (Appendix) to ensure the robustness of our results against different temperature measures. We conduct these tests by employing (i) log of temperature (Column 1); (ii) 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 when temperature exceeds 28°C (Column 3); (iv) excluding regions where temperature exceeds this level (Column 4); and (v) employing temperature shock, defined as the difference between actual temperature and long-term temperature being greater (less) than 2 (-2) standard deviations (Column 5). The outcomes of these tests show little deviation from our baseline specification. We also conduct alternative measurements of temperature bins for Figure 2 by dividing the temperature distribution within each region into deciles, with the 60th percentile serving as the baseline group. The results presented in Figure A1 (Appendix A) indicate that the effects of extreme weather remain consistent with those observed in Figure 2.

Finally, we examine alternative chronic poverty measures. Specifically, we define chronic poverty using the poverty line of $2.15/day (both number of incidences and proportion of incidence), and we also measure the average poverty rate using various window lengths (4-year and 5-year windows). For this test, we employ the fixed-effects model as outlined in Equation (2). The results shown in Table A3 (Appendix A) reaffirm our previous findings.

5. Conclusion

We offer an updated and comprehensive review of recent studies on climate change on poverty and inequality, paying special attention to studies' data sources as well as empirical methods. Our findings suggest that while studies generally find negative impacts of climate change on poverty, especially for poorer countries, there is less agreement on its impacts on inequality. We further analyze a recent global database at the subnational unit level that is constructed from official national household income and consumption surveys for more than 1,594 subnational units from 134 countries and spanning the period from 2003 to 2019. Our results suggest that temperature change has larger impacts over the short-term than over the long-term and more impacts on chronic poverty than transient poverty. These results are robust to various measures of chronic poverty and are more pronounced for poorer countries. These findings are relevant for policy advice and highlight the importance of tackling chronic poverty to more effectively reduce poverty.

Our findings also help emphasize the need of collecting better-quality data, which include panel household survey data (e.g., to better monitor poverty mobility patterns), more disaggregated data (e.g., to more accurately estimate climate change impacts), more use of administrative data in poorer countries, and better integration of different data sources to address their respective limitations. Data imputation methods may also offer promising alternatives in contexts where actual panel data are unavailable. Our analysis suggests that promising future research can further identify the specific channels through which climate change impacts poverty and inequality. It is also useful to better quantify the long-term impacts of climate change on various forms of poverty and inequality, including multi-dimensional aspects.

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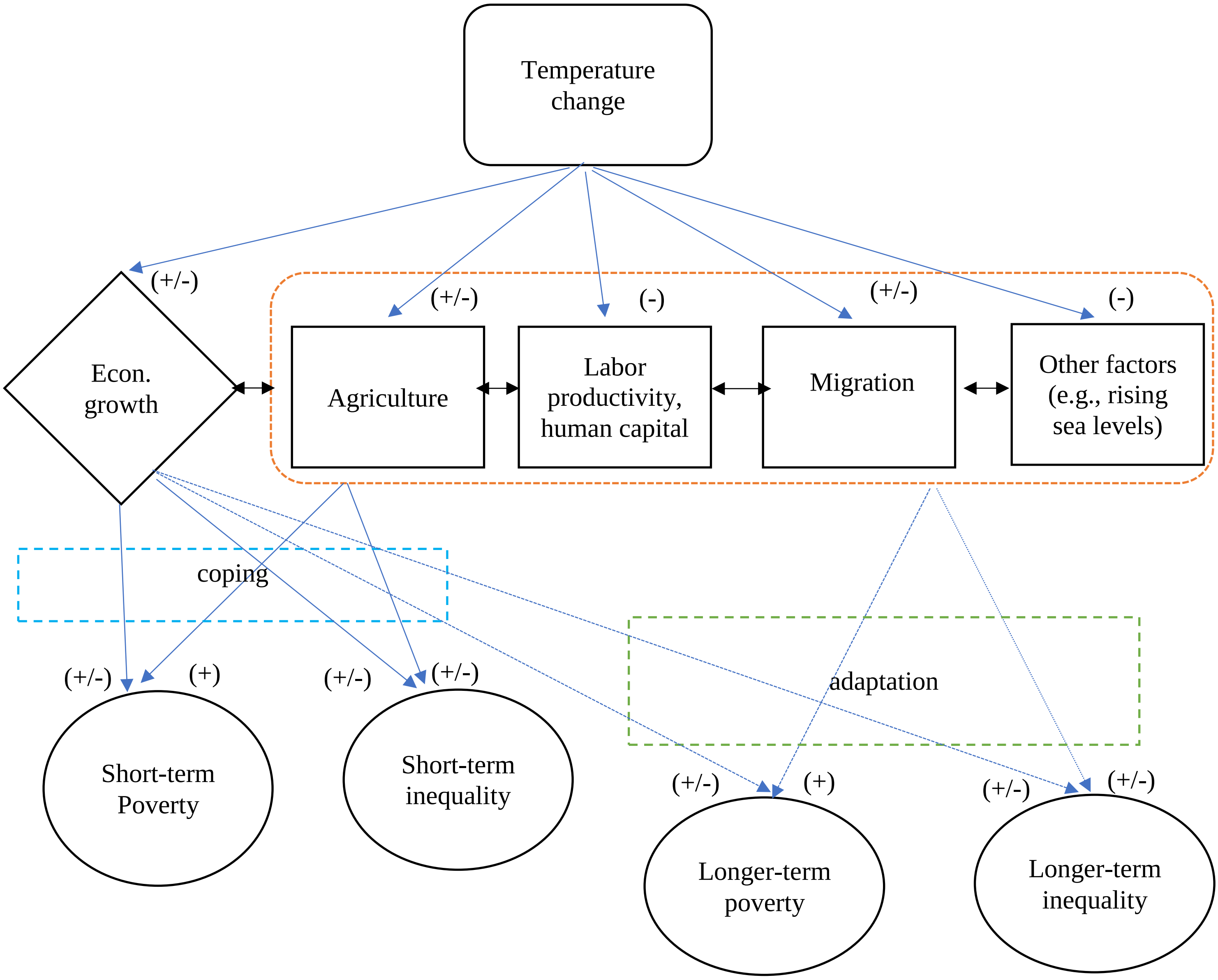
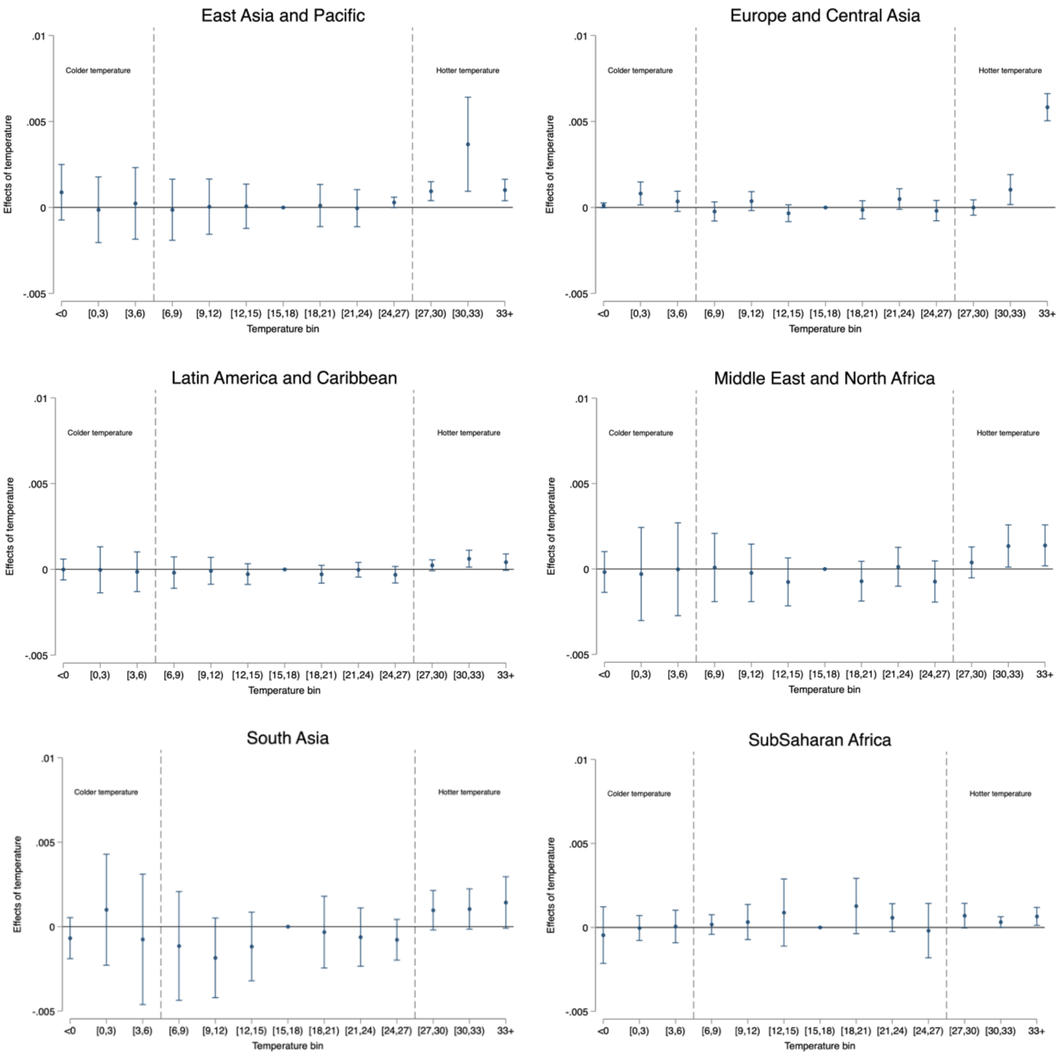
Figure 1: Temperature Change Impacts on Poverty



Notes: The positive and negative impacts of temperature change on poverty and inequality are shown using the plus (+) and minus (-) signs. Both signs (+/-) indicate mixed impacts.

Figure 2: Effects of temperature on chronic poverty by region



Notes: The figures show the point estimates and their 95% confidence intervals of temperature bins using regression with rainfall and subnational fixed effects. Robust standard errors are clustered at the subnational level. Chronic poverty is measured by the number of times each subnational unit is in poverty. The reference temperature bin is [15,18). Hotter temperature and colder temperature are defined as temperature being in the top decile (i.e., greater than 27°C) and bottom decile (i.e., less than 6°C) of the temperature range, respectively.

Table 1: Effects of temperature on poverty

Dependent variable:	Poverty $3.65/day		Poverty $6.85/day	
	Fixed-effects model	Long differences model	Fixed-effects model	Long differences model
	(1)	(2)	(3)	(4)
Panel A: Country-level analysis				
Temperature	0.007***	0.004***	0.022***	0.015***
	(0.002)	(0.001)	(0.004)	(0.002)
Rainfall	-0.0002	0.0002	-0.0002	-0.0001
	(0.0002)	(0.0004)	(0.0005)	(0.0006)
Country & Year FEs	Yes	No	Yes	No
Mean poverty	0.059	0.059	0.210	0.210
Observations	461	134	461	134
Equality test (Panel vs. long differences)	p = 0.150		p = 0.030	
Panel B: Subnation-level analysis				
Temperature	0.072***	0.016***	0.051**	0.028***
	(0.023)	(0.001)	(0.023)	(0.001)
Rainfall	-0.006**	-0.013***	0.014***	-0.005
	(0.003)	(0.002)	(0.004)	(0.004)
Subnational & Year FEs	Yes	No	Yes	No
Mean poverty	0.117	0.117	0.267	0.267
Observations	4,958	1,594	4,958	1,594
Equality test (Panel vs. long differences)	p = 0.000		p = 0.000	
Equality test (country vs. subnational)	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Number of countries	134	134	134	134
Number of regions	1,594	1,594	1,594	1,594

Notes: Robust standard errors in parentheses. Standard errors are clustered at the country level (Panel A) and subnational level (Panel B). Poverty and weather variables in the long-differences model are measured by the difference between 2010 and 2019. The long differences estimation is based on cross-sectional data with a smaller sample size compared with panel data. The equality test p-values show the t-test between the panel FE results vs. the long differences results, and the country analysis results vs. the subnational analysis results. *** p<0.01, ** p<0.05, * p<0.1.

Table 2: Effects of temperature on chronic poverty

	Poverty \$3.65/day		Poverty \$6.85/day		Poverty \$3.65/day	Poverty \$6.85/day
	Number of incidences	Proportion of incidence	Number of incidences	Proportion of incidence	Average poverty rate	
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature	0.023***	0.011***	0.067***	0.019***	0.027***	0.027***
	(0.003)	(0.001)	(0.005)	(0.002)	(0.008)	(0.008)
Rainfall	0.092***	0.048***	-0.332***	0.011	0.075***	0.046***
	(0.020)	(0.009)	(0.041)	(0.012)	(0.012)	(0.012)
Subnational & Year FEs	No	No	No	No	Yes	Yes
Mean dependent var.	0.361	0.176	0.894	0.351	0.132	0.290
Observations	1,262	1,262	1,262	1,262	278	278

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

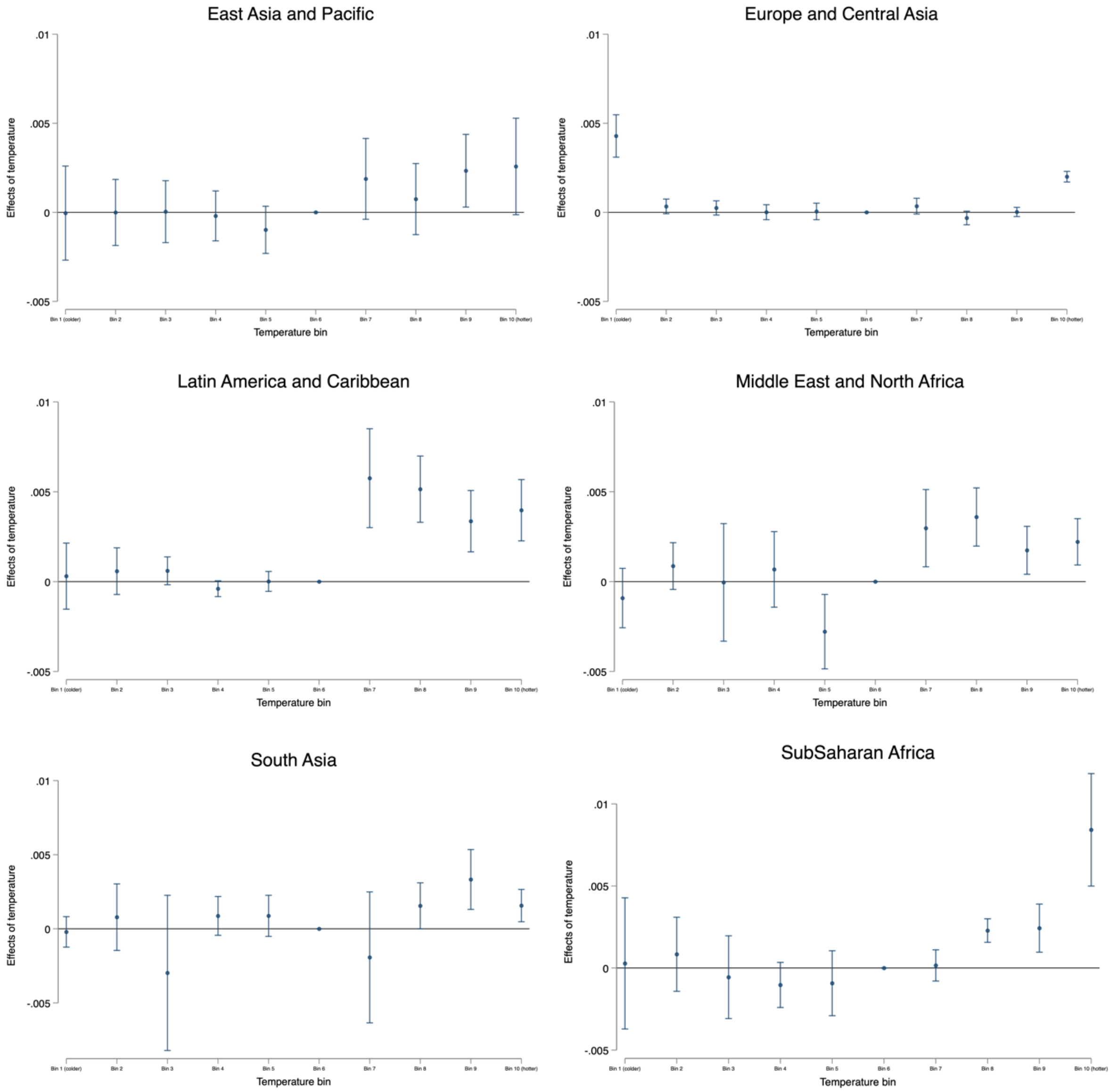
Table 3: Effects of temperature on transient vs. chronic poverty

	Poverty $3.65/day			Poverty $6.85/day		
	Chronically poor	Transiently poor	Generally poor	Chronically poor	Transiently poor	Generally poor
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature	0.016***	0.012***	0.028***	0.036***	0.007**	0.043***
	(0.003)	(0.002)	(0.003)	(0.005)	(0.003)	(0.005)
Rainfall	-0.007***	-0.004**	-0.011***	0.002	0.004*	0.007
	(0.002)	(0.002)	(0.003)	(0.004)	(0.002)	(0.004)
Equality test (Chronically poor vs. transiently poor)	p = 0.224			p = 0.000		
Subnational & Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Mean dependent var.	0.041	0.021	0.063	0.139	0.039	0.178
Observations	935	935	935	935	935	935

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

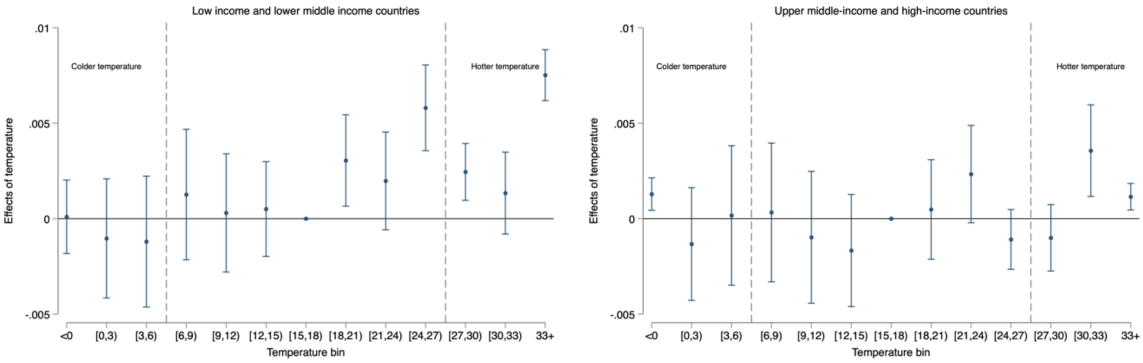
Appendix A: Additional Tables and Figures

Figure A1: Effect of temperature on chronic poverty by region – Alternative bin approach



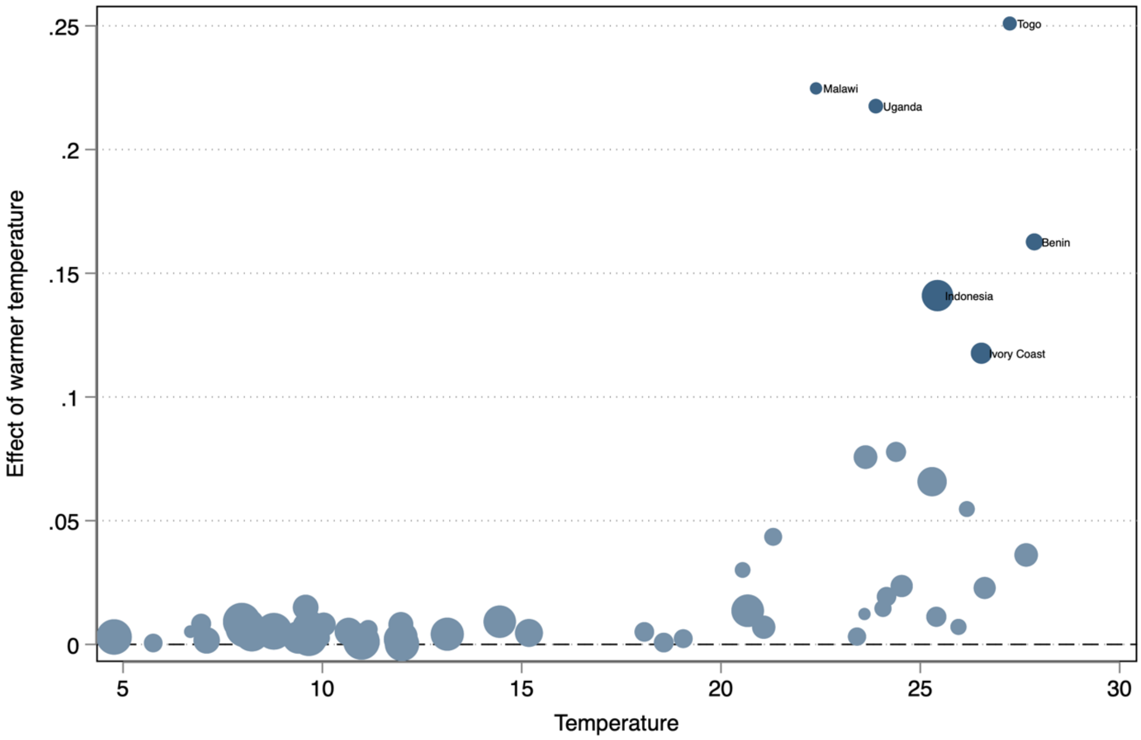
Notes: The figure shows the point estimates and their 95 percent confidence intervals of temperature bins using regression with rainfall and subnational fixed effects. Robust standard errors are clustered at the subnational level. Chronic poverty is measured by the number of times each subnational unit is in poverty. Temperature bins are identified by dividing regional average temperature into deciles with the temperature bin in the 6th decide being the reference group. Hotter temperature and colder temperature are defined as temperature being in the top decile (i.e., bin 10) and bottom decile (i.e., bin 1) of the temperature range, respectively.

Figure A2: Effect of temperature on chronic poverty by income group



Notes: The figure shows the point estimates and their 95 percent confidence intervals of temperature bins using regression with rainfall and subnational fixed effects. Robust standard errors are clustered at the subnational level. Chronic poverty is measured by the number of times each subnational unit is in poverty. The reference temperature bin is [15,18). Hotter temperature and colder temperature are defined as temperature being in the top decile (i.e., greater than 27°C) and bottom decile (i.e., less than 6°C) of the temperature range, respectively.

Figure A3: Effect of temperature on chronic poverty across countries adjusted by real GDP



Notes: Chronic poverty is measured by the number of times each subnational unit is in poverty. The figure shows the point estimates of temperature and the country dummies using regression with control variable and subnational fixed effects. Each country's marker is proportional to its real GDP per capital using the World Development Indicator (WDI) database (i.e., a larger size indicates a higher GDP per capita level).

Table A1: Robustness tests – Alternative specifications

	Fixed-effects model			Long differences model	
	Adding country-specific linear time trend	Adding temperature squared term	Adding temperature cubic term	4-year average	5-year average
	(1)	(2)	(3)	(4)	(5)
Temperature	0.072***	0.082***	0.091***	0.017***	0.016***
	(0.024)	(0.030)	(0.029)	(0.001)	(0.001)
Temperature squared		0.000	0.001**		
		(0.000)	(0.000)		
Temperature cubic			-0.000		
			(0.000)		
Control for rainfall	Yes	Yes	Yes	Yes	Yes
Subnational & Year FEs	Yes	Yes	Yes	No	No
Mean poverty	0.117	0.117	0.117	0.227	0.224
Observations	4,604	4,958	4,958	2,310	1,726

Notes: Poverty is measured using the poverty line of \$3.65/day. Robust standard errors in parentheses. Standard errors are clustered ats the subnational level. 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: Robustness tests – Alternative measures of temperature

	Poverty \$3.65/day				
	Log temperature	Temperature from CRU	Number of days temperature above 28	Dropping subregions with temperature above 28	Temperature shock
	(1)	(2)	(3)	(4)	(5)
Temperature	0.155***	0.090***	0.001**	0.072***	0.019***
	(0.041)	(0.027)	(0.000)	(0.023)	(0.004)
Control for rainfall	Yes	Yes	Yes	Yes	Yes
Subnational & Year FEs	Yes	Yes	Yes	Yes	Yes
Mean poverty	0.117	0.117	0.117	0.117	0.117
Observations	4,958	4,927	4,105	4,724	4,958

Notes: Results of fixed-effects model. Robust standard errors in parentheses. Standard errors are clustered at the subnational level. 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: Robustness tests – Alternative measures of chronic poverty

	Poverty $2.15/day (Number of incidences)	Poverty $2.15/day (Proportion of incidence)	Average poverty rate – 4-year	Average poverty rate – 5-year
	(1)	(2)	(3)	(4)
Temperature	0.004***	0.002***	0.015***	0.021***
	(0.001)	(0.001)	(0.004)	(0.003)
Control for rainfall	Yes	Yes	Yes	Yes
Subnational & Year FEs	Yes	Yes	Yes	Yes
Mean dependent var.	0.079	0.039	0.119	0.091
Observations	1,262	1,262	642	1,008

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Country-level analysis using alternative data from WDI

Dependent variable:	Poverty $3.65/day		Poverty $6.85/day	
	Fixed-effects model	Long differences model	Fixed-effects model	Long differences model
	(1)	(2)	(3)	(4)
Temperature	0.016***	0.011***	0.023***	0.014***
	(0.002)	(0.001)	(0.003)	(0.001)
Rainfall	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Country & Year FEs	Yes	No	Yes	No
Observations	1,847	420	1,846	420
Equality test (Panel vs. long differences)	p = 0.000		p = 0.000	

Notes: Robust standard errors in parentheses. Standard errors are clustered at the country level. Poverty and weather variables in the long-differences model are measured by the difference between 2010 and 2019. The long differences estimation is based on cross-sectional data with a smaller sample size compared with panel data. The equality test p-values show the t-test between the panel FE results vs. the long differences results. *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Alternative measures of rainfall

Poverty:	$3.65/day	$6.85/day	$3.65/day	$6.85/day	$3.65/day	$6.85/day	$3.65/day	$6.85/day
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Temperature	0.074***	0.048**	0.078***	0.049**	0.070***	0.054**	0.069***	0.055**
	(0.024)	(0.023)	(0.024)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Rainfall	-0.009*	0.020***						
	(0.005)	(0.006)						
Rainfall squared	0.000	-0.000***						
	(0.000)	(0.000)						
Rainfall deviation			-0.006**	0.006**				
			(0.002)	(0.002)				
Rainfall > 90th percentile					-0.001	0.007		
					(0.006)	(0.007)		
Rainfall > 95th percentile							0.006	0.010
							(0.010)	(0.011)
Subnational and Year FEs	0.057	0.054	0.058	0.051	0.056	0.049	0.056	0.050
Observations	4,958	4,958	4,958	4,958	4,958	4,958	4,958	4,958

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