WPS7479

Policy Research Working Paper 7479

Shock Waves: Managing the Impacts of Climate Change on Poverty

Background Paper

Households and Heat Stress

Estimating the Distributional Consequences of Climate Change

Jisung Park
Stephane Hallegatte
Mook Bangalore
Evan Sandhoefner

WORLD BANK GROUP
Development Economics
Climate Change Cross-Cutting Solutions Area
November 2015

Abstract

Recent economic research documents a range of adverse welfare consequences from extreme heat stress, including health, labor productivity, and direct consumption disutility impacts. Without rapid adaptation, climate change will increase the burden of heat stress experienced by much of the world's population in the coming decades. What will the distributional consequences of this added heat stress be, and how might this affect optimal climate policy? Using detailed survey data of household wealth in 690,745 households across 52 countries, this paper finds evidence suggesting that the welfare impacts of added heat stress caused by climate change may be regressive. Specifically, the analysis finds that poorer households tend to be located in hotter locations across and within countries, and poorer individuals are more likely to work in occupations with greater exposure to the elements not only across but also within countries. These findings—combined with the fact that current social cost of carbon estimates do not include climate damages arising from the productivity impacts of heat stress—suggest that optimal climate policy, especially when allowing for declining marginal utility of consumption, involves more stringent abatement than currently suggested, and that redistributive adaptation policies may be required to reduce the mechanical inequities in welfare impacts arising from climate change.

This paper was commissioned by the World Bank Group's Climate Change Cross-Cutting Solutions Area and is a background paper for the World Bank Group's flagship report: "Shock Waves: Managing the Impacts of Climate Change on Poverty." It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The authors may be contacted at jisungpark@fas.harvard.edu.

Households and Heat Stress: Estimating the Distributional Consequences of Climate Change

By: Jisung Park*, Stephane Hallegatte**, Mook Bangalore**, Evan Sandhoefner†

Keywords: heat stress, labor productivity, climate change, poverty, exposure

JEL: E24, Q54, Q50, I32

*Economics Department, Harvard University: jisungpark@fas.harvard.edu
** Climate Change Group, The World Bank Group, shallegatte@worldbank.org
mbangalore@worldbank.org
†Harvard College: evansandhoefner@college.harvard.edu

Authors would like to thank Geoffrey Heal, Marianne Fay, Laura Bonzanigo, and Samuel Stolper, Tom Pullum, Ruilin Ren, and Clara Burgert as well as participants of the World Bank Poverty and Climate Change conference for valuable comments and feedback. A portion of this research was funded by the Harvard Environmental Economics Program, the National Science Foundation (GRFP), and the Faculty of Arts and Sciences at Harvard University, as well as by the Office of the Chief Economist of the Climate Change Group of the World Bank Group.

I. Introduction

What will the distributional welfare impacts of climate change be? Despite its importance for climate policy, this is a question for which there is as yet relatively little empirical evidence.

Recent work documenting significant welfare impacts of temperature stress on the human body – operating through health, productivity, and consumption disamenities – raises the question of whether and to what extent the increased heat stress from a warmer world will occur in such a way that systematically biases certain socioeconomic groups over others.

The distributional consequences of climate damages informs at least two policy decisions. First, the within- and across-country distribution of climate damages will affect the decisions regarding *climate mitigation*, informing in particular the question of how much mitigation is desirable. Second, irrespective of future mitigation decisions, understanding the ways in which climate change may affect the world's most vulnerable populations will be crucial in enabling policy makers to target adaptation investments toward the right geographies and technologies.

Previous research has indicated substantial heterogeneity in climate-related economic impacts, with a suggestion of poorer regions such as South Asia and Sub-Saharan Africa bearing outsized impacts proportional to their respective national income levels (Nordhaus 2011; Hsiang and Jina, 2014). However, much of this work focuses on impacts as they operate through agriculture or storms.

A wave of recent research explores the climate-welfare impact as they operate through thermal stress of human beings, and suggests that temperature-productivity relationships may comprise a substantial share of the overall welfare burden (Heal and Park, 2015). The focus of this literature so far has been on establishing causal inference and average effect magnitudes. There is very little work on the distributional dimensions of added extreme heat stress arising from climate change.[1]

This study attempts a first pass at addressing this question, by using detailed data on household wealth in developing countries. Combining household wealth data from the Demographic and Health Surveys (DHS) for 52 developing countries with weather data from the Climatic Research Unit (CRU), this paper provides a provisional distributional breakdown of heat-related climate impacts both across and within countries in the present, as an informative proxy for what we might expect from climate change in the future.

We find that, 1) poorer households are more likely to be engaged in occupations with greater potential heat exposure (e.g. agriculture, unskilled manual labor), and that, 2) for the vast

[1] Hsiang (2011), Dell, Jones, and Olken (2013; 2014), and Heal and Park (2014) show that hotter-than-average years tend to reduce per capita income in hot and poor countries, and go on to suggest that, without convergence in adaptation levels, poorer countries would suffer larger impacts from extreme heat stress due to climate change.

majority of hot countries – those with average annual temperatures above 25˚C – poorer households tend to be located in hotter (more marginal) areas within each country. While, on the whole, the aggregate relationship between heat and household wealth is negative and suggestive of highly regressive impacts, there is substantial heterogeneity in this relationship by local climate, suggesting that, in some cold countries, moderate warming may have a progressive welfare impact due to the fact that poorer households are located in places subject to more extreme cold stress. Further research regarding both the expected changes in exposure – for instance, projected changes in extreme heat and extreme cold days at the local level – as well as the extent and evolution of adaptive capacity is sorely needed.

The paper is organized as follows. Section 2 provides background information and a brief review of the literature on temperature stress and human welfare. Section 3 provides a conceptual framework motivating the empirical analysis. Section 4 describes the data. Section 5 provides a descriptive analysis. Section 6 provides the empirical strategy. Section 7 discusses primary results. Section 8 concludes.

II. Background

An emerging empirical literature suggests significant causal impacts of thermal stress on welfare-relevant outcomes in a variety of contexts.[2] Whereas previous studies linking environmental conditions like climate (temperature) to economic output have been unable to attribute causality due to omitted variables problems (or, when experiments have been conducted in lab-settings that are of limited welfare-relevance) a key methodological innovation in recent years has been the use of panel data to identify the causal impacts of temperature stress, controlling for important correlates such as institutions or human capital (Dell, Jones, Olken, 2014).

These quasi-experimental analyses find impacts of extreme heat events – for instance, days with temperatures above 25°C – on economic outcomes such as labor productivity or local output (Hsiang, 2011; Sudarshan et al, 2014; Dell, Jones, Olken, 2014). By leveraging high-frequency variation in weather (e.g. annual or daily average temperature and precipitation) these studies allow researchers to estimate the causal impact of extreme temperature on economic output,[3] controlling for location-specific unobservables such as institutional features or baseline firm productivity.

The recent literature emphasizes three damage channels in particular: (1) health impacts; (2) consumption impacts; and (3) production impacts of extreme temperature stress.

---

[2] See Heal and Park (2015) for a review of the recent literature documenting the micro- and macro-economic impacts of temperature stress.

[3] There are also a growing number of studies that identify causal impacts of weather variation on other economic outcomes such as agricultural output, energy demand, exports, conflict, and migration. For an excellent review of this burgeoning literature, see Dell, Jones, Olken (2014).

Health impacts

Building on a longstanding epidemiological case-study literature,[4] recent empirical work using panel methods find that heat waves can trigger large-scale mortality responses even in rich countries with high levels of electrification. In the US, for example, an additional day with mean temperature above 32°C (90°F) leads to an increase in annual age-adjusted mortality of about 0.11 percent (Deschenes and Greenstone, 2014).[5] Not surprisingly, the impact of temperature stress on health seems to vary across the age distribution, with infants and the elderly experiencing generally higher risk (Graff Zivin and Schrader, 2015).

Consumption Impacts

Moderate climates can be a consumption amenity which affect individual's utility directly as well as the marginal utility associated with forms of consumption that are affected by climatic conditions (e.g. dining outdoors, going to the park). A longstanding hedonic pricing literature documents substantial willingness to pay (WTP) for milder climates (Hoch and Drake, 1987; Maddison, 2003). There is a well-established pattern of residential sorting by WTP for climate amenity which suggests that mild climates (for instance, having fewer extreme heat and cold days) are a normal consumption good (Sinha and Cropper, 2013). In effect, individuals are willing to accept lower wages for any given job-locational amenity bundle in areas that have more temperate climates.

Valuations of climate amenities have placed projected welfare losses due to climate change in the range of 2-5% of total income (Albouy et al, 2011; Sinha and Cropper, 2013). For the most part, the hedonic valuation of climate as a consumption amenity has focused on developed economy contexts, due primarily to data availability.

Production Impacts

Emerging evidence across a range of experimental and quasi-experimental studies suggests that heat events have an adverse causal impact on economic production, at least in the short run. Such impacts are relatively novel to the climate and development economics literature, but seem to be of non-trivial welfare significance.[6]

[4] Health impacts from extreme heat stress are well-documented in the epidemiological case study literature (Kovats and Hajat, 2008). Hotter regions are also associated with grater heat-related mortality and morbidly burdens, and even lower rates of physical exercise (Center for Disease Control and Prevention, 2010).

[5] A day with mean temperature below 20° F is associated with an increase in annual mortality of roughly 0.07 to 0.08 percent. While mortality impacts arise from both hot and cold days, there seems to be greater non-linearity in response for heat than for cold.

[6] For the most part, current social cost of carbon estimates do not incorporate these channels in damage estimates (Tol, 2009).

There is now strong evidence of reductions in labor supply, firm- and individual-level production, and macroeconomic output at the regional and national level in response to extreme heat events (Heal and Park, 2015).

For instance, Zivin and Neidell (2014) find that, in industries with high exposure to climate, workers report lower time spent at work as well as lower time spent on outdoor leisure activities on hot and cold days.[7] At temperatures over 100˚F, labor supply in outdoor industries drops by as much as one hour per day compared to temperatures in the 76-80°F range.

Similarly, firm- and individual-level studies have documented significant output and labor productivity declines due to heat stress. Sudarshan et al (2014) find plant-level productivity declines among Indian manufacturers, even when controlling for region, firm, and individual-specific factors.[8] Hot days above 25˚C cause lower productivity in manufacturing plants, with a magnitude of roughly minus 2.8% per ˚C.[9]

Even in relatively capital-intensive industries in developed economies such as the US, extreme heat seems to affect production non-trivially. In a study of automobile manufacturing plants in the US over the period 1994-2010, Cachon, Gallino et al. (2012), find that hot days are associated with lower output across the board. At the extreme, a week with six or more days above 90°C reduces that week's production by about 8%.[10]

Finally, extreme heat has been shown to reduce macroeconomic output indicators as well. Hsiang and Deryugina (2014) and Park (2015), find that years with more hot days are associated with lower local income and payroll per capita, controlling for location-specific unobservables and time-trends. Hsiang and Deryugina (2014) suggest that, in the average US county, a day with temperatures above 29˚C (84˚F) lowers annual income by roughly 0.065%, which amounts to -23.6% lower productivity on a hot day versus an optimal day (15˚C or 59˚F). Average productivity of individual days declines roughly linearly by 1.5% for each 1˚C (1.8˚F) increase in daily average temperature beyond 15˚C (59˚F). Park (2015) finds similar results using US annual payroll data,

[7] While Zivin and Neidell do not show this, intuitively one might think that extreme temperature and weather events lead to a reduced average flow intensity of economic activity if measured at a high enough level of aggregation.

[8] Sudarshan et al (2014) are able to show that the effect is driven mostly through reduced worker productivity while working, as opposed to missed days of work due, for instance, to disrupted sleep during warm nights.

[9] Similarly, Adhvaryu et al (2013) show that manufacturing worker efficiency at the plant level declines substantially on hotter days, an effect that is driven primarily by on-the-job task productivity decline as opposed to increased absenteeism. Even earlier work by Niemelä et al. (2002) examines the productivity of call center workers in different ambient temperatures and finds that, above 22 degrees C, each additional degree C is associated with a reduction of 1.8 percent in labor productivity.

[10] While their study design is unable to fully disentangle the contributions of task productivity decline and missed days of work, or to test for the extent of air conditioning by plant, the results suggest that, even in relatively capital intensive industries of relatively well-adapted economies, the productivity impacts of extreme temperature may be non-trivial.

and finds that highly exposed industries such as construction, mining, or transportation experience impacts that are roughly twice as large as those that occur primarily indoors.[11]

On average, these studies suggest a per-degree-C point impact magnitude of around minus 1% to 3%, although there is some evidence that the impacts are smaller in developed economies such as the United States and firms or regions with higher levels of air conditioning.[12] While there is as yet limited research regarding the heterogeneity in temperature driven impacts across different levels of occupational exposure to heat stress (e.g. indoor/outdoor), intuition and anecdotal evidence (for instance, from agriculture, or in the realm of time use decisions[13]) suggests that there may be important differences in impact magnitudes by occupation.

Interestingly, those studies that are able to use daily temperature data find significant impacts from extreme heat days, much like the impact of killing degree days in the agricultural literature (Schlenker and Roberts, 2006; Butler and Huybers, 2013; Burke and Emerick, 2014). This may suggest that the heat-related welfare impacts from climate change primarily from the incidence of extreme heat day events, rather than from the mean-shift of average annual temperatures per se. This is relevant in the context of distributional implications, specifically in projecting the incidence of effective extreme heat stress due to climate change across different regions (e.g. already hot places vs temperate or cold places), as discussed in more detail below.

To summarize the literature to date:

Building on the longstanding cross-sectional fact that hotter countries tend to be poorer (Sachs et al, 2001; Horowitz, 2001), and that hotter municipalities within some countries tend to be poorer (Acemoglu and Dell, 2012), recent quasi-experimental research suggests that temperature stress exerts a causal impact on economic outcomes. While it is as yet unclear how much of the impact can be attributed to institutional correlates (Acemoglu, Johnson, and Robinson, 2001), or other geographically correlated factors such as agricultural productivity (Gallup et al, 2001), the emerging picture is one of non-trivial welfare impacts, arising from a combination of health effects, consumption disamenities, and production impacts.

But some important puzzles remain. It is still unclear whether the primary impacts (along all three channels) are from heat, or whether both heat and cold matter. For instance, is there an

[11] Park suggests furthermore that the magnitude of these extreme heat day impacts vary by level of average heat exposure, which may suggest scope for adaptive investments that could offset some of these impacts in the medium to long run.

[12] As noted above, these point estimates may be biased predictors of the labor productivity impacts of future climate change, due to the possibility of long-run adaptation. Adaptations may be as simple as reductions in labor effort or hours (especially during particular times of the day) or investment in air conditioning equipment. Of course, such seemingly simple adaptations may be prohibitively costly or effectively unavailable in many developing country contexts. An air conditioner is of no use if electric infrastructure fails at precisely the times of day when its cooling services are most in need.

[13] Graff Zivin and Neidell (2013, 2014)

optimal temperature zone for human economic activity? How will the geographic and economic distribution of such zones evolve with future climate change?

It is also unclear whether the within-country gradients in WTP for the climate amenity by income levels holds true across countries as well. Greenstone and Jack (2013) point out that WTP for environmental quality in the form of lower pollution certainly seems to track income. It is as yet unclear whether the same can be said for environmental quality in the form of thermal comfort – from both a consumption and production standpoint.

Perhaps most importantly from a policy perspective, the literature has so far focused primarily on establishing the existence and magnitude of a causal effect. It has devoted decidedly less attention to the distributional dimensions of policy measures designed to reduce current or future heat stress – by means of global climate mitigation or local climate adaptation. This is the puzzle we seek to address in this paper.

III. Conceptual Framework

It is well known that policy decisions about climate change cannot ignore distributional equity issues (Arrow, Cropper et al. 2014). This is especially true given the fact that climate change is a global public goods problem whose effects span the entire globe, and affect multiple generations.

The primary objective of this analysis is to assess the possible distributional consequences of climate change through temperature impacts, to inform climate policies (e.g., how much and how to reduce emissions?) and development and poverty-reduction policies (e.g., can climate change represent a significant obstacle to poverty reduction? Can it threaten the long-term prospects of some economic activities?). Of course, by focusing on the impacts of extreme heat stress, we are limiting the scope of analysis to one particular set of mechanisms through which climate damages could manifest. As such, the implications should be interpreted in the broader context of damage heterogeneity along other dimensions such as sea-level rise, storm intensity, or agricultural yield decline.

We abstract away also from the choice of policy mechanism – whether it comprises a price mechanisms such as a carbon tax, a quantity mechanism such as cap-and-trade, or direct mandates.[14] The relevant dimension of the policy problem is that, from a global social planner's perspective, there exists some optimal level of mitigation that balances the costs of mitigation with the benefits, in terms of damages avoided, of doing so.

This section provides a simple conceptual framework to fix ideas, and to serve as a guide to empirical analysis.

[14] For a detailed account of the economics of instrument choice, see Goulder and Parry (2008).

Distributional Equity and Climate Policy

Distributional equity both across and within generations has been an important and contentious feature of climate policy design (Nordhaus, 1996; Stern, 2006; Weitzman, 2009).

Debates surrounding the correct discount rate focus primarily on the issue of *inter*-generational equity:[15] the realized distribution of costs and benefits between current and future generations.[16] We will abstract away from this issue of inter-temporal discounting for the purposes of this analysis.

Another important issue is that of *intra*-generational equity, which involves the ways in which costs and benefits of climate policy are distributed across individuals in any given generation, for instance, between developed and developing countries, or between wealthy and impoverished individuals within countries.

From the perspective of development economics, an emphasis on poverty alleviation implies some form of theoretical preference for intra-generational equity, whether it is made explicit or not. Within a public economics framework, this often assumes either a) a social welfare function that puts additional emphasis on the consumption of poorer individuals (e.g. log utility, which features diminishing marginal returns to consumption, an input to utility); and/or b) favored weighting of the realized utility of poorer individuals in aggregating individual welfare to the societal level (e.g. progressive welfare weighting on part of a global or national social planner). From a normative ethics standpoint, there may be a wide range of ethical paradigms that justify such social preferences a priori, such as Rawlsian Utilitarianism.

Thus, regardless of specific philosophical positions, and abstracting from specific country contexts, a wide range of considerations makes the distributional dimensions of the climate damage function important for policy analysis.

From a policy perspective, it is useful to ask the following questions:

- For a given amount of global warming, how much of the welfare impacts of temperature stress – operating through health, consumption disamenities, and/or production impacts – can we expect to accrue on rich and poor households respectively?
- Are there reasons to expect that the impacts of warming will be regressive, exacting disproportionately large damages on poorer households and individuals?

[15] There are at least three relevant components of the discount rate in the climate change context: (1) the pure rate of time preference, (2) the consumption discount rate (a measure of diminishing marginal utility of consumption), and (3) the assumed future growth rate of consumption.

[16] For a review of recent research on the issue of intertemporal discounting in the context of climate change, see Arrow et al (2014).

- Or, conversely, are there reasons to expect the impacts to be progressive, reducing the welfare of richer households and individuals disproportionately?

To fix ideas let us assume that household utility is a function of *c*, a vector of household consumption of goods and services, which depends on household's wealth. Over time, households generate wealth through a number of channels, the aggregation of which comprises total income for household *i* in any given period *t*:

$$Y_i = \sum_{t=1}^{T} y_{i,t} = \sum_{j=1}^{J} \alpha_{j,i}\beta_{j,i}$$

Here, *J* denotes the full set of possible livelihood-generating activities available to household *i*, and α is a vector of assets, which may include human capital (education, health, labor hours) or physical capital (equipment, land, livestock). The term β_j represents the productivity of any given asset, *j*.

A subset $L \subset J$ of these production activities involves human labor, which may be subject to temperature-related productivity or health shocks. Specifically, labor productivity depends on *T*, the ambient temperature (specifically, the wet-bulb globe temperature, which is inclusive of humidity), human and health capital, H, and $K \in J$ the level of adaptive capital (e.g. air conditioning, clothing, and electric infrastructure):

$$\beta_i(T_i, K_i, H_i(T_i))$$

Depending on the social planner's preferences for equity (e.g. Rawlsian, Utilitarian), the welfare weights $\theta_1 \ldots \theta_N$ will place greater or lesser emphasis on the utility of those individuals toward the bottom of the consumption/income distribution.

The specification of the utility function itself $u_i(c)$ will also affect the progressivity or regressivity of any climate-policy decision, to the extent that it may or may not put a higher emphasis on consumption by poorer individuals. This suggests that optimal mitigation stringency would be increasing in the progressivity of climate damages (i.e. the impacts of mitigation policy sufficiently *re*gressive). In other words, if poorer households and individuals suffer equal or proportionally larger damages than richer households and individuals, then optimal climate mitigation would entail more abatement, ceteris paribus.[17]

[17] Note that even if the consumption impacts from warming are distributed perfectly homogenously across income groups, if we assume that marginal utility of consumption declines with level of income or wealth, then the social planner would want to choose a level of total mitigation stringency that is stronger than would otherwise be the case.

The distributional impacts of an increase in global average surface temperatures ($\bar{\bar{T}}$), and, as corollary, of a policy aimed at mitigating global temperature rises, will then depend on a few important factors.

First, it will depend on the covariance between the realized incidence of additional temperature stress in the locality of household *i* due to global warming, (ΔT_i), and household *i's* income or wealth levels; that is, (1) the covariance between the mapping from global climate change $(\Delta\bar{\bar{T}})$ to the incidence of local temperature shocks (ΔT_i) and the level of household wealth $(\mathrm{Y_i})$: $\mathrm{cov}(\Delta T_i / \Delta\bar{\bar{\mathrm{T}}}\ , Y_i)$. Let us call this *geographic exposure bias.*

Second, it will depend on the degree to which income generating activities for household i are subject to productivity and health impacts of temperature stress: that is, the covariance between occupation-specific temperature sensitivities and the total income or assets of those households with individuals engaged in temperature-sensitive occupations, $cov(\frac{d\beta_l}{dT}, y_i)$. Let us call this *occupational exposure bias*.

1) Geographic Exposure Bias

Will areas with poorer households experience greater increased heat exposure from climate change?

The answer seems ambiguous a priori.

On the one hand, climate models suggest that a given amount of average global warming will lead to greater annual average temperature increases at higher latitudes, which tend to be more sparsely populated, and often are home to richer economies. For instance, +2˚C global mean surface temperature increase will likely lead to substantially more than +2˚C annual mean surface temperature increase in high-latitude countries like Canada or New Zealand, and less than +2˚C in low latitude countries such as Ghana or Indonesia (Stocker et al, 2013).

On the other hand, to the extent that tropical climates often feature high humidity levels, a smaller incremental increase in temperatures may translate into larger increases in realized extreme temperature exposure for individuals in lower latitudes. Moreover, it is possible that average warming at the climatic level masks substantial heterogeneity in the manifestation of such warming at the level of local weather events.

If, as the literature suggests, the bulk of the damages from heat stress arise from extreme heat days – the increased incidence of tail events in the local weather distribution as opposed to mean-shifts in the overall climate distribution – then lower latitudes may experience greater overall increases in *realized heat exposure* for any given level of *average warming* (Heal and Park, 2015).

Indeed, the literature suggests non-linearity in temperature impacts per degree of added heat stress, and that the most noticeable labor productivity impacts occur beyond some heat threshold (between 25°C and 32°C). Most studies using daily weather variation suggest that the majority of damages occur on extreme heat days (days with temperatures above 25°C). This is true in the context of mortality responses (Deschenes and Greenstone, 2013), labor supply responses (Graff-Zivin and Neidell, 2013), and individual- and regional output responses (Cachone et al, 2012; Sudarshan et al, 2013; Park, 2015).

Given the likelihood that any variation in ${\Delta T_i}/{\Delta \overline{\overline{T}}}$ will depend on the initial climate – that is, whether a household is situated in hot or cold average climates – it may thus be useful to understand the covariance structure between household wealth and average climates. Thus, we seek to understand the covariance structure between household wealth and average (current) exposure to temperature stress $(\overline{T_i})$: that is, $cov(\overline{T_\iota}, Y_i)$, where we use household wealth as a proxy measure for income.

2) Occupational Exposure Bias

Poorer households may be more likely to engage in work that is more exposed to the elements, $cov\left(|\frac{d\beta_l}{dT}|, y_i\right) > 0$, in which case we would expect even uniform warming to result in outsized welfare losses for poorer households due to the higher likelihood of heat-related health and productivity impacts. Conversely, it may be the case in some countries that relatively affluent households are employed in sectors more susceptible to heat exposure: $cov\left(|\frac{d\beta_l}{dT}|, y_i\right) > 0$.

Exposed sectors may include outdoor work intensive sectors such as agriculture or construction, as well as transportation (e.g. rickshaw drivers) and manual labor intensive industries where air conditioning is missing or inadequate. And workers in these sectors are not only economically vulnerable but often experience the highest mortality rates after a heatwave. For instance, after the May 2015 heatwave in India, in the state of Andhra Pradesh, which experienced the most severe impacts, a majority of 900 reported victims were elderly or low-income workers (Al Jazeera, 2015; Vice News, 2015).

Understanding the covariance structure between household wealth and occupational exposure to temperature stress is thus an additional factor that may determine the distributional impacts of heat stress arising from climate change.[18]

[18] Note that it is also possible that manual labor and outdoor work intensive occupations pay lower wages on average. According to the US Bureau of Labor Statistics, the average construction laborer makes 25 percent less than the median US worker, and laborers in Farming, Fishing, and Forestry occupations make 48 percent less.

In addition to these two dimensions, the distributional welfare consequences of global warming may depend on many other factors which are important but beyond the scope of this study. They include the covariance between the realized incidence of additional extreme heat events in the locality of household *i* (T_i) and household *i's* endowment of physical capital – especially forms of capital that can help households adapt to increased heat stress (e.g. electricity and air conditioning). Other possible covariates of interest may include the age and health status of individuals in poorer and richer households; the covariance between expected temperature stress and changes in prices of particular necessity goods; the covariance between expected temperature stress and other climate stressors that may affect non-labor outcomes, including agricultural productivity; the covariance between expected temperature stress and institutional settings (in settings where work hours are more flexible, the impacts of temperature-related productivity shocks may be reduced relative to settings with rigid wage contracts).

Given the data available, we focus on geographic and occupational exposure bias. Exploration of the other dimensions listed above are left for future research.

The specific empirical questions we take to the DHS data may be summarized as follows:

1) *Geographic Exposure Bias*:
   What is the cross-sectional relationship between household wealth and extreme heat exposure within countries?
2) *Occupational Exposure Bias:*
   What is the cross-section relationship between household wealth and occupational exposure to heat stress within countries?

IV. Data

Household-level Wealth and Occupation Data and Cluster-level Geographic Identifiers (DHS)

The DHS is a household survey that provides nationally representative and standardized data on health, population, and a limited number of socioeconomic variables in developing countries, administered by ICF International and hosted by the United States Agency for International Development (USAID). One of these socioeconomic variables is a household-level "wealth index", which is computed based on each household's ownership of a standard set of assets, housing construction materials, and quality of water access and sanitation facilities.[19] DHS also includes a limited set of household characteristics including size of household (number of occupants), whether or not the household is located in an urban or rural setting, which we use as a vector of household specific controls.

[19] DHS wealth scores are especially valuable in this context because many of the poorest countries lack reliable government-collected income data.

Also included in more recent waves of DHS surveys is a geographic identifier. This identifier provides the coordinate location of the survey cluster. There are typically 500-1000 survey clusters in a country, with each cluster containing around 25 households. To guarantee anonymity of the interviewed households, the geographical locations of the clusters have been randomly allocated by DHS within a radius from the real location of maximum 2 km for urban areas, and 5 km for rural areas.

DHS data is available for over 90 countries from over 300 surveys (numerous rounds are conducted within the same country). Of this, surveys in 52 countries contain *both* a geographic identifier at the survey cluster level and a wealth index at the household level, conditions necessary to estimate where poorer households and richer households live within a country (this is an estimate since the survey clusters are offset, for full details and limitations of the method, see Appendix A). Thus, our sample contains DHS household survey data from 52 countries, with the most recent survey in each country selected. The year in which the survey data was collected varies somewhat by country (between 1994 and 2013), but the vast majority (75%) in our sample are surveys conducted after 2008. Our final sample consists of household wealth scores from 690,745 households (which also contain coordinates of the survey cluster) in 52 countries covered by the DHS.

We extract household wealth scores for the universe of survey respondents. DHS provides each household with a wealth score, with the distribution of scores within a country ranging from about -200,000 (asset poorest households) to +200,000 (asset richest households), with a median of zero. We express this score as percentiles of the country-specific wealth distribution (for ease of interpretation), and use wealth quintiles – defining the poor as the bottom 20 percent in terms of wealth index.

The wealth index provided by the DHS has been used previously to represent poverty (Barros et al., 2012; Fox, 2012; Ward and Kaczan, 2014). However, it should be considered as an estimate of "structural" poverty, since asset indices take a long time to change, as opposed to measures like income or consumption, which are more "stochastic" measures of poverty. Additionally, due to the relative nature of the index, defensible comparisons between countries are challenging, and understanding within-country results in terms of real variables (dollars, for example) can be difficult.[20] Wealth scores are thus reported as percentiles of the country-specific wealth distribution, and the results we show below compare poor and non-poor households *within* the 52 countries.

Occupational Exposure Data

[20] Adjusting income data, which is a flow variable that is often a derivative of recorded market activities, for cross-country differences in purchasing power is hard enough (Deaton and Heston, 2010). Creating purchasing power-corrected wealth indices for poor households in developing countries is a tall order that we do not attempt here.

A subset of 47 of the 52 countries in our sample, which represent roughly 74% of the households in the full sample, contain occupational information. We use this information to examine the relationship between household wealth and likelihood of climatic exposure at work.[21] DHS occupational information includes occupation codes for the survey respondent as well as for the partner for married households, sometimes down to very specific categories: e.g. “Okada rider”, “Poultry farmer”, or “Dock Worker”.

While the degree of specificity in occupations varies by country, DHS provides 9 aggregated parent categories for all 47 countries in this subsample. The aggregated occupation categories are: “professional/technical/managerial”, “clerical”, “sales”, “agricultural”, “household and domestic”, “services”, “skilled manual”, “unskilled manual”, and “army”.

This leaves us with 510,600 households for whom we have information on temperature, wealth, and occupational characteristics, as well as the demographic controls listed above.

Temperature Data (CRU)

We match households to local weather variables by using the cluster level geographic coordinates provided in the DHS surveys (all households within each cluster have the same coordinates; there are about 25 households per cluster). Average monthly temperature and precipitation data is taken from the Climatic Research Unit (CRU) at the University of East Anglia. CRU provides time-series reanalysis data on month-to-month weather at a high spatial resolution (0.5 degree x 0.5 degree grid cells), which is averaged over the period 1950-2013 at the grid cell level. For each coordinate location, we extract the climate data from CRU on temperature and precipitation.

For the econometric analysis, we use climate data for the year 2013, the year in which most of the DHS surveys were conducted. For the poverty exposure bias analysis, we use the range of climate data from 1960-2013.

Our preferred measure of heat exposure is average temperature of the hottest month. The primary results reported here – namely a strong negative correlation between household wealth and warmer temperature in hot countries, as well as a strong positive correlation between household wealth and warmer temperatures in cold countries – are robust to alternative classifications of temperature, including monthly high temperatures, coldest month temperatures, as well as average annual temperatures. Our preferred specification controls for average monthly precipitation and elevation.

[21] We were unable to obtain complete occupational data for Cambodia, Angola, Uganda, Mali, or Bangladesh.

V. Descriptive Analysis – Poverty exposure bias for temperatures

To investigate the exposure of poor and non-poor households to high temperatures within the 52 countries we define a "poverty exposure bias" (PEB) that measures the fraction of poor people exposed, compared to the fraction of all people exposed per country. When estimating the number of people exposed (and not exposed), we incorporate DHS data on household size and also use household weights to ensure the representativeness of our results. We compute the PEB as follows:

$$\text{Poverty Exposure Bias}_i = \frac{\text{Share of poorest quintile exposed}}{\text{Share of all quintiles exposed}} - 1$$

If the PEB is greater than 0, poor people are more exposed to high temperature stress than average; if the PEB is less than zero, poor people are less exposed. For instance, if within a country 25% of the population in quintile 1 are exposed to high temperatures and 20% of the entire population is exposed, the PEB would be 0.25. Since the wealth index is comparable only within and not between countries, the PEB we calculate in this paper is an estimate of whether poor people are more or less exposed compared to the entire population *within* a specific country.

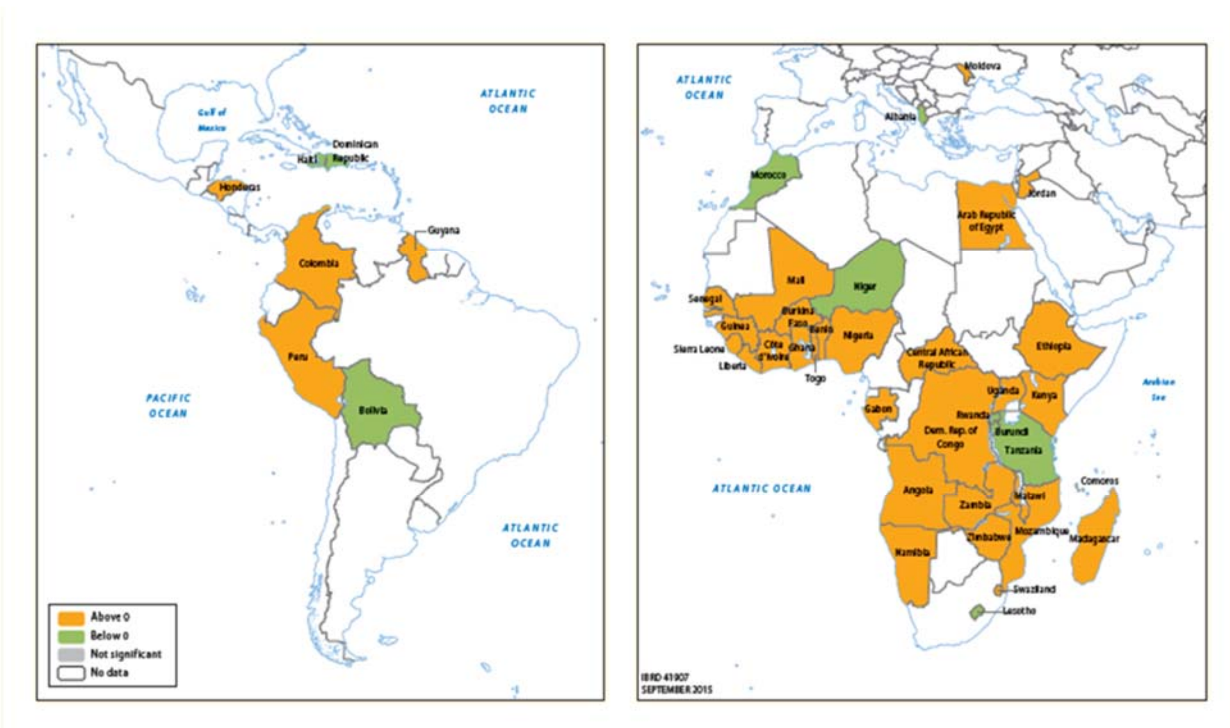
This PEB metric has recently been applied to floods and droughts (Winsemius et al., 2015). While for floods defining exposure is fairly straightforward (either a household is in a flood zone or not), for droughts and temperatures, defining exposure is not as direct. Here we define the exposure to heat waves in a way that is comparable with the approach followed for floods and droughts in Winsemius et al. (2015).

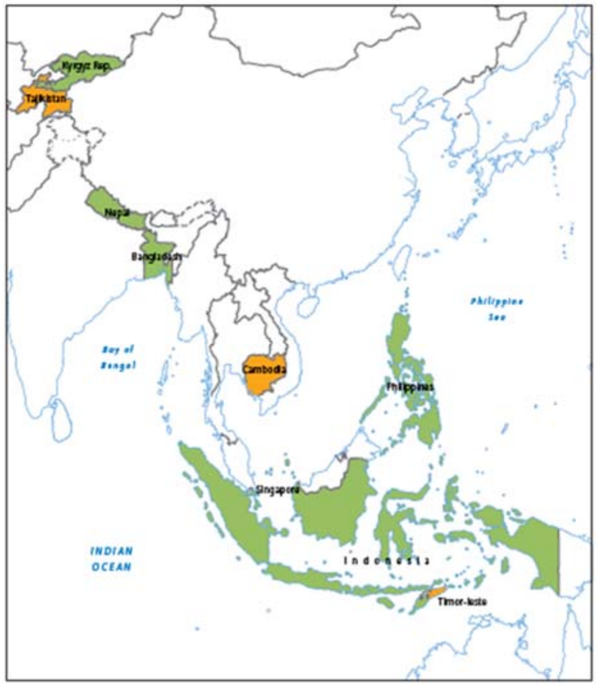
First, we obtain the maximum monthly temperature from CRU from 1960-2013 for each household in the sample (all of the 690,000+ households). This provides us a distribution of extreme monthly temperatures for each household, which is used to assess the risk of high temperature. With this distribution, we then calculate the number of months a household experienced a temperature above the 98^{th} percentile of country-month temperatures in its countries. For instance, if the 98^{th} percentile of temperature in Nigeria over the considered period (1960-2013) is 30 degrees C, and household in Nigeria experiences a temperature of 31 degrees C, we mark that household as experiencing a "hot" month. Across the sample of 1960 to 2013, we calculate the number of "hot" months each household experiences.

If the total number of "hot" months a household experiences is more than 2% of all months from 1960-2013 (that is, if the household experiences more "hot" months than the average in the country), then that household is classified as being *over-exposed* to high temperatures. If the household experiences less "hot" months than is expected, that household is classified as *under-exposed*.

This provides us with each household as being (over-)exposed or not. Within each country, we also know whether the household is poor (if the household is in Quintile 1 of the wealth index). Based on this information, we calculate the PEB to high temperatures in each of the 52 countries. We find that 37 out of 51 countries exhibit a positive PEB (that is, poor people are more over-exposed to high temperature than the average). In population terms, this represents 56% of the analyzed population (the fraction is small because large countries such as Bangladesh, the Philippines and Indonesia have a negative PEB). These results can be found in Map 1 and the full estimates of the PEB are provided in Appendix B.

The results suggest that in three-fourths of the countries analyzed, poor people reside in areas that are more exposed to extreme temperature stress. In Africa in particular, 28 out of 34 countries exhibit a positive PEB to high temperatures, including most countries in western and southern Africa. In Latin America the results are more mixed, with half of the analyzed countries exhibiting a positive PEB. In Asia, five out of eight countries exhibit a negative PEB, suggesting poor people are less exposed than non-poor people to high temperatures.





Map 1. Among the 52 countries we analyze, poor people in most countries are more exposed to higher temperatures than the average population.

The literature reviewed earlier in this paper suggests that there is an "optimal zone" for temperature, and as a result in some cold countries it may be desirable to settle in areas which are hotter. For this reason, in countries with cooler climates, we may find an over-exposure of non-poor people in hotter areas.

Indeed, we find that many of the 37 countries that exhibit a poverty exposure bias for temperature are already hot. If we plot the PEB against a country's average annual temperature from 1961 to 1999 (to represent average climate), we find that hotter countries have a higher exposure bias (Figure 1). At the same time, cooler countries exhibit a smaller bias, and in some cool countries, a negative bias. This occurs because, in these cool countries, nonpoor people tend to settle in areas with higher temperatures because they are climatically more desirable.

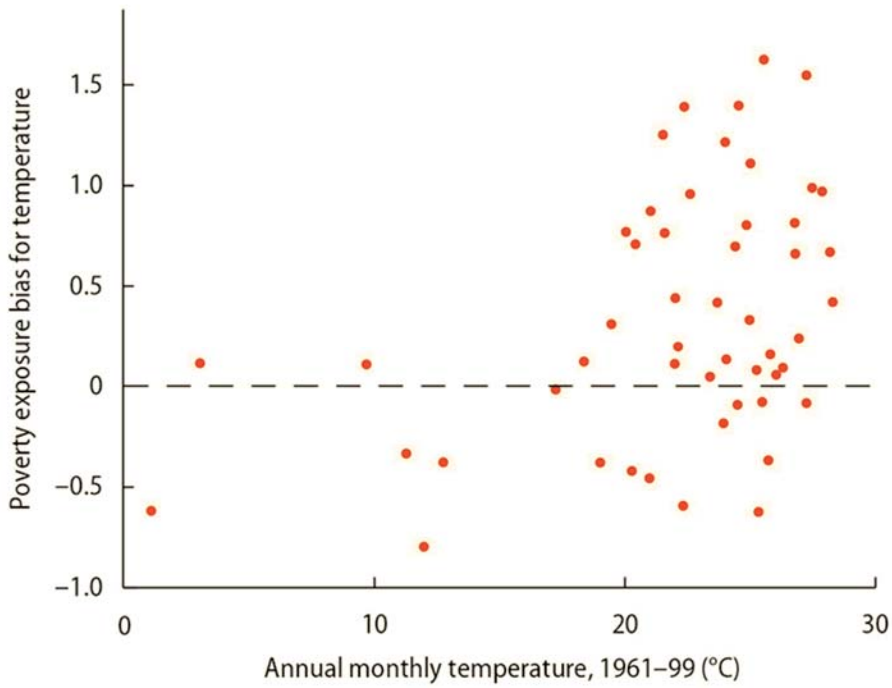


Figure 1: Poor people in hotter countries live in hotter areas, but less so in cooler countries.

These descriptive analyses suggest the sorting of poor and non-poor households within a country to be non-random, but based at least in part on sub-national trends in temperature within a country. This dynamic between poverty, occupation, and high temperatures is explored further using econometric analysis below.

VI. Empirical Strategy

Here, we do not try to isolate the impact of temperature on output or welfare or to establish a causal relationship between climate and wealth. Instead, we start from the assumption that higher temperatures will be detrimental, especially where temperatures are high already, and we assess the distribution of impacts by investigating whether poor people will be more exposed to these impacts because of their localization or occupation.

Household Wealth and Temperature

We estimate possible heterogeneity in climate-induced heat stress first by estimating the cross-sectional relationship between household wealth and today's temperature stress. For the cross-section analysis, we use temperature data for 2013, the year in which most of the surveys have been conducted. We use a multiple OLS regression framework in which household wealth scores are regressed on temperature as well as a vector of demographic and climatic controls.

We begin by fitting a global pooled OLS of household wealth percentiles on average temperature:

$$\mathrm{Y_i} = \beta_0 + \beta_1 T_i + \theta X_i + \epsilon_i \quad (1)$$

Here, $\mathrm{Y_i}$ denotes household i's wealth score, expressed as percentiles of the sample wealth distribution of that household's home country; T_i denotes the hottest month temperature experienced in 2013 of household i; X_i denotes a vector of household-specific controls for urban/rural status, household size, elevation, humidity, and average monthly precipitation; and ϵ_i denotes a household-specific error term.

Because wealth scores are not comparable across countries, our preferred specification is to run 52 parallel regressions for each of the countries in our sample. The average number of households is approximately 13,313 per country.

Specifically, we run the following linear model for each country:

$$\mathrm{Y_{ij}} = \beta_{0j} + \beta_{1j} T_{ij} + \theta_j X_{ij} + \epsilon_{ij} \quad (2)$$

$\mathrm{Y_{ij}}$ denotes household i's wealth score, expressed as percentiles of the sample wealth distribution of country j; T_{ij} denotes the hottest month temperature experienced in 2013 of household i in country j; X_{ij} denotes a vector of household-by-country-specific controls for urban/rural status, household size, elevation, humidity, and average monthly precipitation; and ϵ_{ij} denotes a household-, country-specific error term. This results in 52 separate β_{1j} coefficients, which summarize the geographic exposure bias within any given country.

To the extent that poorer households tend to be located in hotter environments – that is, $\beta_{1j} < 0$ – this would suggest that the (negative) labor productivity impacts from future climate change might fall along regressive lines.[22]

Alternatively, $\beta_{1j} > 0$ would suggest possible progressivity in heat-related impacts (assuming these impacts are negative).

Optimal Temperature Zones for Economic Activity?

The recent literature on temperature and human physiology, productivity, and WTP for climate amenities, (documented above) provides additional informative priors for this analysis. If it is the case that extreme temperatures per se are what affect human welfare – that is, not only heat stress but cold stress as well – then one would expect heterogeneity in this relationship by average climate zone, similar to the effects observed by Park and Heal (2013).

In countries with relatively warm average climates, warmer regions would correspond to areas subject to greater extreme heat stress and its attendant negative impacts on labor productivity,

[22] Once again, this assumes additionally that already hot places will experience more hot days per degree C of overall global warming. Of course, if cold places turn out to experience a greater increase in hot days per degree C of overall global warming, the reverse may be true.

labor supply, health, and climate as consumption amenity. Conversely, in relatively cold countries, warmer places would correspond to milder places – that is, areas that are subject to less extreme cold stress and the negative impacts that it may entail.[23]

In countries that span hot and cold climates (e.g. Chile) or feature large seasonal temperature swings (e.g. countries with large desert or tundra environments) the relationship between warmer summer temperatures and welfare would be less straightforward, possibly non-linear. Regions within these countries may be subject to both extreme heat stress and cold stress, and thus moving to an incrementally warmer climate would have an ambiguous effect on overall temperature exposure, since it may reduce cold stress but increase heat stress, and vice versa for moving to a marginally colder climate.

Thus, we stratify our analyses by average climate ("hot" vs "cold") to assess whether, in a linear model, the sign of β_{1j} depends on whether increasing temperature corresponds to a movement away from or toward the optimal temperature zone. As can be seen in the tables below, the primary result – of poorer households being located in more "marginal" climates – is robust to various cutoff classifications and temperature criteria (e.g. hottest month temperature, coldest month temperature, average annual temperature).

Finally, we run a quadratic specification in temperature, in particular for countries that have wide intra-annual temperature ranges (e.g. countries with minimum and maximum average monthly temperatures that vary by more than 10˚C) to assess the possibility of an optimal temperature zone. The quadratic specification takes the following form:

$$\mathrm{Y_{ij}} = \beta_{0j} + \beta_{1j}T_{ij} + \beta_{2j}T_{ij}^2 + \theta_j X_{ij} + \epsilon_{ij} \qquad (2)$$

A positive coefficient on β_{1j} and a negative coefficient on β_{2j} in this instance would correspond to a concave (single-peaked) relationship between temperature (hottest month, average month, and coldest month) and wealth; a positive coefficient on both β_{1j} and β_{2j} would suggest a convex relationship.

To summarize the empirical predictions:

- For hot countries, $\beta_{1hot} < 0$ would suggest that poorer households tend to be located in hotter climates, and that, as such, the health, production, and amenity impacts of future warming may fall along regressive lines. Conversely, $\beta_{1hot} > 0$ in hot countries would suggest that poorer households tend to be located in milder climates, and that the

[23] In this framework, one can think of the stock of household wealth as representing the accumulation of many years of flow income, which in turn may be influenced by climatic factors such as temperature. Of course, the lack of panel data at the household level prevents causal identification, which means that the relationships that we find are almost certainly confounded by omitted variable bias. However, the consistency of the temperature-wealth relationship is remarkable, as illustrated below.

health, production, and amenity impacts of future warming may fall along progressive lines.

- For cold countries, the reverse would be true. That is, $\beta_{1cold} < 0$ would suggest that poorer households are located in milder climates, implying regressive impacts. $\beta_{1cold} > 0$ would imply the opposite: that poorer households are located in colder/more marginal climates, implying progressive impacts given the assumptions above.
- For temperate countries with wide intra-annual temperature ranges or a wide range of hot and cold climate regions within the country, $\beta_{2temperate} < 0$ would suggest that the relationship between household wealth and temperature is single-peaked: i.e. that poorer households tend to live in more marginal climates and are subject to more heat and/or cold stress. Conversely, $\beta_{2temperate} > 0$ would suggest the opposite: that richer households tend to be located in more extreme climates.

Household Wealth and Occupational Exposure

As an additional method of assessing the extent to which poorer households may suffer outsized welfare losses from climate-induced heat exposure, we estimate the exposure-bias of poorer households arising from occupational choice.

Specifically, we construct an indicator variable denoting whether or not a household has at least one member engaged in an "exposed occupation". We define "exposed occupation" to include agriculture, unskilled manual labor, and military occupations. We also run a specification in which the "exposed occupation" variable does not include agricultural occupations. The interpretation of the analysis depends non-trivially on how this variable is defined, something we discuss in further detail in the following section.

We fit a logistical regression for the subset of countries (described above) which contain information on household occupations:

$$\mathrm{Prob}\big(I_{\mathrm{ij}} = 1\big) = \Phi(\gamma_{0j} + \gamma_{1j}Y_{ij} + \theta_j X_{ij} + \epsilon_{ij}) \quad (3)$$

Where $\mathrm{Prob}(I_{\mathrm{ij}} = 1)$ denotes the probability that the indicator variable for exposed occupation is equal to one, and $\Phi(\dots)$ is the cumulative standard logistic distribution function. Y_{ij} denotes the wealth percentile of household *i* in country *j*; X_{ij} denotes a vector of household-by-country-specific controls for urban/rural status, household size, elevation, humidity, and average monthly precipitation; and ϵ_{ij} denotes a household-, country-specific error term.

The empirical predictions from this model can be summarized as:

- For all countries, $\gamma_{1j} > 0$ would imply that poorer households tend to be more likely to engage in occupations that are more exposed to the elements, and that any given amount of warming would, ceteris paribus, exact a greater welfare loss on the poor within any given country. This would suggest regressive impacts of climate change-induced warming.

- Conversely, $\gamma_{1j} < 0$ would suggest the opposite: progressive impacts of climate change-induced warming.

VII. Results

Household Wealth and Temperature

We find that, on average, poorer households tend to be located in more marginal climates, controlling for rural/urban status, size of household, as well as elevation, humidity, and average precipitation. This relationship is most striking in countries that are situated in hot climates with average annual temperatures above 20˚C.

Interestingly, there is a positive association between warmer temperatures and household wealth percentiles in countries that occupy relatively cold climates, which is consistent with models of optimal temperature for human activity (production and consumption amenities).

Pooled Sample Estimates

Pooling all 690,745 households in our sample, the baseline regression (equation 1) yields a positive relationship between hottest month temperature and household wealth. On average, a one degree Celsius increase in hottest month temperature is associated with a +0.13 percentile increase in household wealth within any given country, significant at a p-value of 0.01 (Table 1). This raw estimator is likely mechanically biased, however, by the fact that, while the pooled sample contains both very hot and very cold countries, the vast majority of the countries and households in our sample are hot tropical nations.

Table 1

Household Wealth Percentiles and Hottest Month Temperature All Households and countries						
Household Wealth Percentile (within country)	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
Avg Temp of Hottest Month (˚C)	.1335793	.0081037	16.48	0.000	.1176963	.1494623
Household Size	.1801929	.0103446	17.42	0.000	.1599179	.2004679
Urban dummy	34.04134	.058225	584.65	0.000	33.92722	34.15546
Altitude	.0007082	.0000323	21.91	0.000	.0006448	.0007716
Cloud cover	.0823544	.002364	34.84	0.000	.077721	.0869878
Average annual precipitation	-.0001654	.0004729	-0.35	0.727	-.0010922	.0007614
Constant	24.73837	.3166964	78.11	0.000	24.11765	25.35908

Number of obs = 690,745
R-squared = 0.3350

Restricting to households in hot climates – those with average annual temperatures above 20C – yields a rather different result. Households in hotter (more marginal) environments tend to be significantly poorer on average – measured in terms of their relative location within the country-specific wealth distribution (Table 2; Figure 2, below). On average, households in places that feature +1˚C warmer summer temperatures (hottest month average temperature) are -0.56 percentiles lower on the own-country wealth distribution.[24] Urban households are richer on average, as would be expected, as are those with larger families. Average monthly precipitation is positively correlated with household wealth, consistent with the notion that in primarily agricultural environments, more rainfall is associated with higher yields.

[24] Restricting further to hot countries that have significant within-country temperature variation (greater than 5C across all regions within the country), we see a sharper relationship.

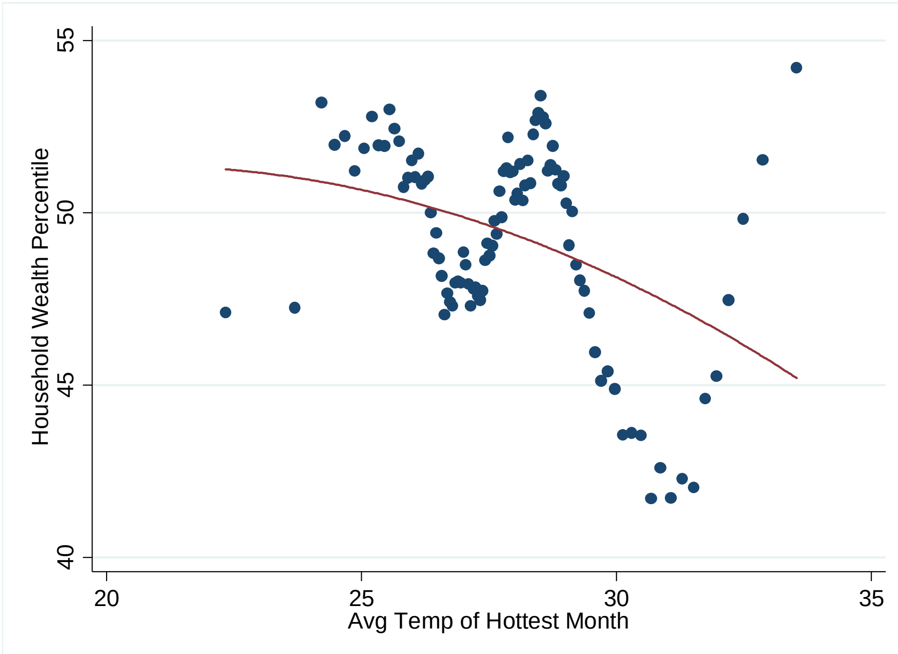


Figure 2: Household wealth percentile and average hottest month temperature, hot countries only (avg temp>20˚C). Controls for precipitation, elevation, household size, temperature range and urban/rural included.

Table 2

Household Wealth Percentiles and Hottest Month Temperature
Households in Hot Climates (avg annual temperature >20˚C)

Household Wealth Percentile (within country)	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
Avg Temp of Hottest Month (˚C)	-.5618505	.0158178	-35.52	0.000	-.5928529	-.5308481
Household Size	.2748562	.0113446	24.23	0.000	.2526212	.2970912
Urban dummy	33.29254	.0677116	491.68	0.000	33.15983	33.42526
Altitude	-.0016699	.0000902	-18.52	0.000	-.0018466	-.0014932
Cloud cover	.0947017	.0026809	35.33	0.000	.0894472	.0999561
Average annual precipitation	-.0176307	.0005912	-29.82	0.000	-.0187895	-.0164719
Constant	46.1357	.5285159	87.29	0.000	45.09982	47.17157

Number of obs = 532,693
R-squared = 0.3247

Similarly, restricting to households in colder climates – average annual temperatures below 15˚C – yields a strong positive association between temperature and wealth (Table 3). A +1˚C increase in summer temperatures (hottest month average temperature) is associated with +0.68 percentiles higher position on the own-country wealth distribution. This is consistent with the notion that the role of warmer temperature may depend on climatic context. Running the same linear specification with coldest month temperature as the independent variable yields an even steeper slope (Figure 3 below). This may suggest that, for colder countries, the level of cold stress is a more relevant margin of welfare impact.

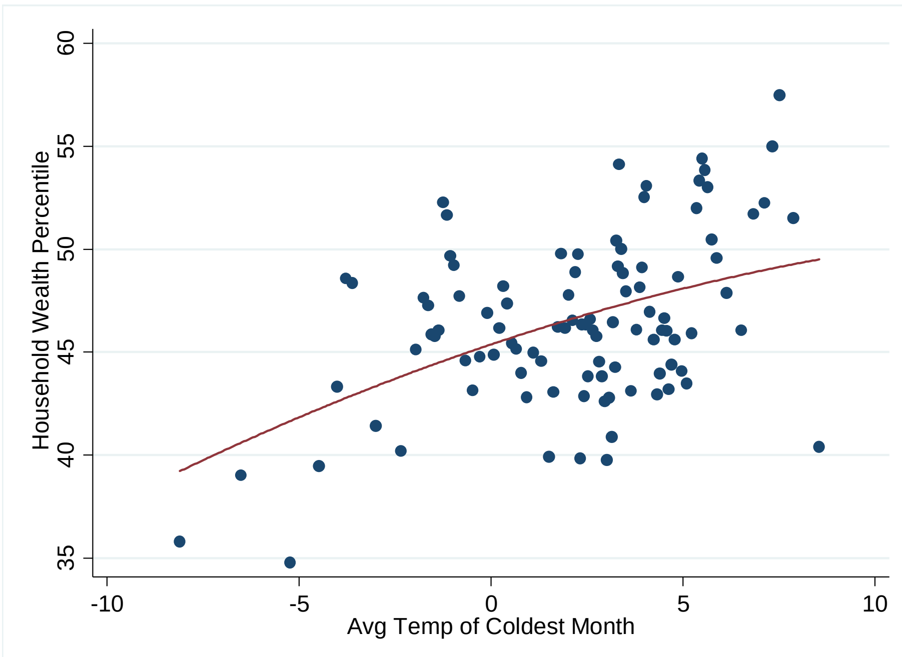


Figure 3: Household wealth percentile and average coldest month temperature, cold countries only (avg temp<15˚C). Controls for precipitation, elevation, household size, temperature range and urban/rural included.

Table 3

Household Wealth Percentiles and Hottest Month Temperature
Households in Cold Climates (avg annual temperature <15˚C)

Household Wealth Percentile (within country)	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
Avg Temp of Hottest Month (˚C)	.682565	.0172055	39.67	0.000	.6488422	.7162879
Household Size	-.2898152	.0368943	-7.86	0.000	-.3621281	-.2175022
Urban dummy	41.54639	.1640677	253.23	0.000	41.22482	41.86796
Altitude	-.0004443	.0000482	-9.22	0.000	-.0005388	-.0003499
Cloud cover	-.3453785	.0087651	-39.40	0.000	-.362558	-.3281989
Average annual precipitation	.0280246	.0028037	10.00	0.000	.0225293	.0335199
Constant	44.54621	.8686438	51.28	0.000	42.84367	46.24875
Number of obs = 62,671 R-squared = 0.5224						

Looking at households located in highly variable climates – average intra-annual monthly average temperature variation of more than 10˚C – we find a single-peaked relationship between wealth percentile and hottest month temperature: $\beta_1 > 0$ & $\beta_2 < 0$ (Table 4). This pattern persists with various cutoffs for temperature variability. This calculation suggests that the wealth level starts to decrease when the average temperature of the hottest month exceeds 30˚C.

As mentioned previously, the fact that wealth scores are defined in relative terms specific to each country makes meaningful cross-country comparisons of magnitudes challenging. Thus, our preferred specification estimates country-specific coefficients for the relationship between household wealth percentile and temperature.

Table 4

Household Wealth Percentiles and Hottest Month Temperature
Households in Temperate/Variable Climates (seasonal variation in monthly avg temp>10˚C)

Household Wealth Percentile (within country)	*Coef.*	*Std. Err.*	*t*	*P>t*	*[95% Conf.*	*Interval]*
Avg Temp of Hottest Month (˚C)	*2.203624*	*.1091334*	*20.19*	*0.000*	*1.989725*	*2.417524*
Avg Temp of Hottest Month (˚C) – Squared	*-.0365271*	*.0021138*	*-17.28*	*0.000*	*-.0406701*	*-.0323841*
Household Size	*-.5164057*	*.0261461*	*-19.75*	*0.000*	*-.5676516*	*-.4651598*
Urban dummy	*32.73719*	*.1377886*	*237.59*	*0.000*	*32.46713*	*33.00725*
Altitude	*.0011107*	*.0000403*	*27.55*	*0.000*	*.0010317*	*.0011897*
Cloud cover	*-.0185756*	*.0057596*	*-3.23*	*0.001*	*-.0298644*	*-.0072868*
Average annual precipitation	*.0434736*	*.0015622*	*27.83*	*0.000*	*.0404118*	*.0465355*
Constant	*3.251478*	*1.511665*	*2.15*	*0.031*	*.2886407*	*6.214315*
Number of obs = 130,413						
R-squared = 0.3267						

Country-Specific Estimates

Running the baseline regression for each of the 52 country sub-samples yields a pattern that is consistent with the idea of an optimal temperature zone (Table A, Appendix). Out of the 52 countries surveyed, 22 exhibit a significant negative relationship between temperature and household wealth, 12 exhibit a statistically insignificant relationship, and 18 show a significant positive relationship.

The vast majority of those countries exhibiting negative relationships are tropical countries with hot average climates such as Ghana, Zimbabwe, or the Arab Republic of Egypt. For the majority of countries in our data set with average annual temperatures above 20˚C, $\beta_{1hot} < 0$ (significant at p<0.01), which suggest that poorer households tend to be located in hotter, more marginal climates. A similar result is obtained if one uses average hottest month temperature as the "climate" variable.

To focus on the impact of very extreme heat arising from global warming, one may wish to isolate the subsample of unambiguously hot countries, for whom relatively high temperatures within the country will almost certainly be associated with greater heat exposure, as opposed to possibly being correlated with reduced cold exposure. Looking at the 22 hottest countries in our sample with average temperatures above 25C, we note that 13 have significant negative relationships.[25] As a matter of comparison, the United States has an average annual temperature of about 11°C, and an average hottest monthly temperature of 21°C. The fact that some notable hot and poor countries like Bangladesh or Indonesia feature *positive* relationships between household wealth and heat exposure, however, suggests there might be important dimensions of heterogeneity across omitted characteristics, calling for further investigation.

For the majority of cold countries in the data set – countries with average annual temperatures below 20˚C, or coldest monthly average temperatures below 15 degrees C – the opposite is true. That is, $\beta_{1cold} > 0$ for 8 of the 12 countries in our data set with average annual temperatures below 20˚C.[26] For cold countries with average annual average temperatures below 15˚C, all 6 of 6 feature $\beta_{1cold} > 0$.[27]

This might suggest that, in cold countries, wealthier households self-select into warmer regions due to a higher WTP for milder climates, or that households in more marginal (colder) regions have lower wealth due to greater cold stress. It could, of course, also be a function of other correlates such as institutions. We discuss these possibilities in more detail below.

The magnitudes of β_1 vary considerably across countries and climates, but are in some cases very large and in general are consistent with previous work documenting across- and within-country gradients in income by temperature. For countries with average temperatures below 15˚C, the average significant regression coefficient is 0.68 percentiles per degree C. For countries with average temperatures above 20˚C, the average significant regression coefficient is -0.9 percentiles per degree C. For extremely hot countries – say, those with average temperatures above 25˚C – the average significant regression coefficient is approximately -2.1 percentiles per degree C.

Country Case Study: Nigeria (Hot)

[25] Notable exceptions include Indonesia, Bangladesh, Cote D'Ivoire, Gabon, Liberia, and Haiti. These countries, however, on average feature very compressed average temperature distributions, with hottest month temperatures within each country exhibiting very little variation. For instance, the standard deviation in average hottest month temperatures for Indonesia and Bangladesh are 0.78 C and 0.98 C respectively. One possible explanation may involve landlockedness and distance to coasts or ocean-navigable ports, which is a variable that is not included in our regressions but have been shown to be important predictors of economic productivity (Sachs and Warner, 2001).

[26] Running the linear specification for these countries with coldest month temperature as the independent variable yields consistently stronger relationships.

[27] It is worth noting that there are relatively few cold countries in general, in part because the poor countries of interest are predominantly hot, in part because there are simply not that many nation states that are located exclusively in cold areas of the world.

Taking Nigeria as a representative case study, we see a strong negative relationship between heat stress and household wealth in the following scatterplot (with data points binned by percentile of the temperature distribution, Figure 4).

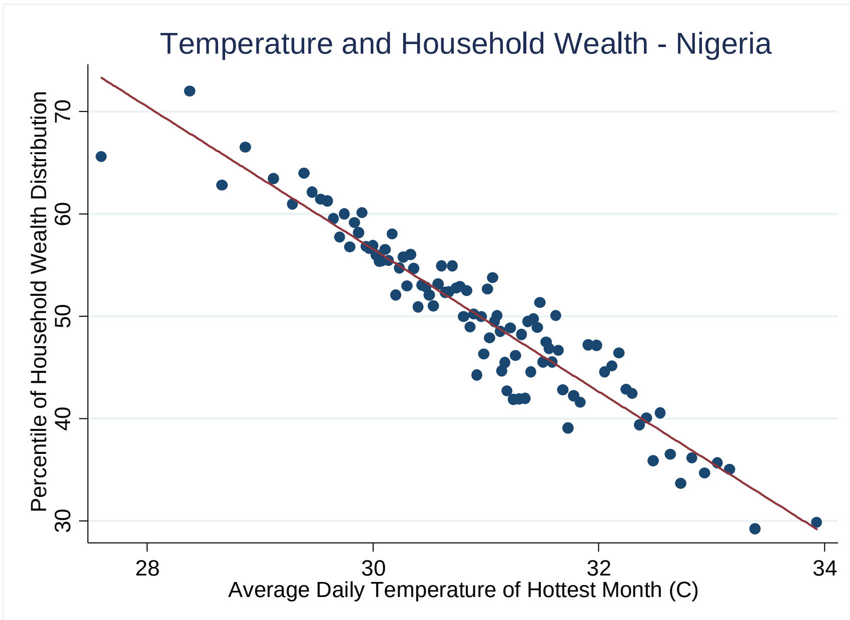


Figure 4: Average hottest month temperature and Nigerian household wealth by temperature bin. Controls for precipitation, elevation, household size, and urban/rural included.

Among the 38,144 households surveyed, households located in places that are exposed to greater degrees of heat stress within the country have systematically lower levels of aggregate wealth, once again, controlling for size of household, whether or not the household is located in an urban or rural setting, and other climatic factors such as average precipitation.[28] Households located in a grid cell with 1 degree Celsius warmer summer temperature tend to be 6.2 percentiles poorer on average. Nigeria is a hot country with an average temperature of 27.3 degrees C (81.2 degrees F), and as such, one would expect that future climate change would increase heat stress for most if not all households, since most households already reside in areas that are subject to more heat stress than cold stress.

Country Case Study: Lesotho (Cold)

Lesotho illustrates the opposite effect: a positive relationship between temperature and wealth. Among the 9,226 households surveyed, a one degree Celsius warmer hottest month temperature is associated with a 4.3 percentile higher household wealth score. Lesotho is a relatively cold country, with average annual temperatures in the low teens (14.4 degrees Celsius,

[28] Similar scatterplots for various other countries are presented in the Appendix.

or roughly 60 degrees Fahrenheit), and winter month temperatures dropping well below freezing. So one would expect the relatively warmer households to be closer to the human thermoregulatory optimum, and as such suffer fewer cold-related diminutions to labor supply and labor productivity. On average, households in a 1C warmer climate have 4 percentile higher wealth score (Figure 5).

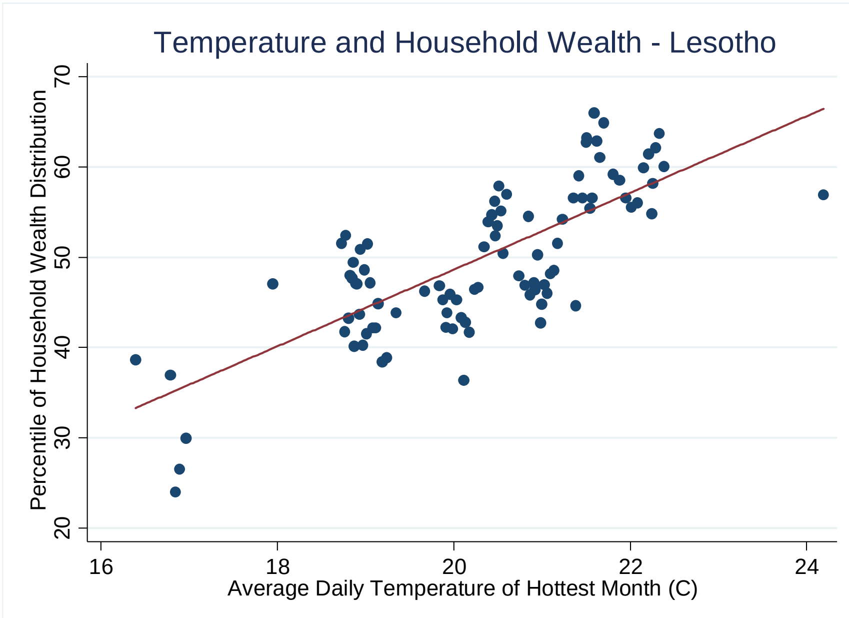


Figure 5: Average hottest month temperature and household wealth by temperature bin for Lesotho. Controls for precipitation, elevation, household size, and urban/rural included.

Household Wealth and Occupational Exposure

Turning to occupations, we find that, on average, workers in poorer households tend to be engaged in occupations that are more likely to be exposed to temperature stress, controlling for rural/urban status, size of household, as well as elevation and average precipitation. This is driven primarily by the prevalence of agricultural occupations in poorer households.

We find a clear negative relationship between exposure likelihood and household wealth in all 47 countries for which occupational data are available. In a simple logit regression of an exposure dummy on household wealth percentile, all resulting coefficients are negative and significant at $p<0.01$. Detailed regression results are presented in the Appendix, Table B. As shown in Table C of the same Appendix, there is no clear relationship between the likelihood of occupational exposure and temperature stress; that is, no clear evidence suggesting that households in hotter climates are more or less likely to work in occupations with greater exposure to the elements.

Agricultural occupations account for the vast majority of highly exposed occupations, comprising approximately 38.2% of total respondent's occupations in the 47 countries for which occupational data are available. Unskilled manual labor accounts for 7.77%, and the army makes up 0.22% of responses.

Limiting to Non-Agricultural Occupations

Rural-urban migration and transition out of agriculture are key features of economic development and demographic transition, trends that are likely to continue in many developing economies. As such, one might want to know how occupational exposure bias operates in contexts in which agriculture is not the primary source of employment for the economy. To do this, we redefine the "exposed occupation" dummy to exclude agricultural occupations, focusing primarily on unskilled manual labor occupations.

In a logit regression of this non-agricultural exposure dummy on household wealth percentile, we find that 16 of the total 47 countries to exhibit a significant negative relationship; whereas 23 exhibit a significant positive relationship. This suggests that in just over half of the sampled countries, there is a positive relationship between wealth and likelihood of working in unskilled manual labor.[29] Detailed regression results are presented in the Appendix, Table D.

There are ex ante reasons to suspect that these results may exhibit heterogeneity based on a country's development level. In very poor countries, unskilled manual labor may be a desirable alternative to agriculture, suggesting a positive relationship. In relatively more developed countries, unskilled manual labor is less desirable compared to skilled work, suggesting a negative relationship.

As a first pass at exploring this intuition, we group countries by their World Bank income level classifications: low, lower-middle, and upper-middle.[30] Out of the 39 countries in our sample which feature some statistically meaningful relationship between wealth and (non-agricultural) occupational exposure, 17 are classified as low-income, 17 as lower-middle-income, and 5 as upper-middle-income.

Among the low-income countries, 82% feature a positive relationship between household wealth and non-agricultural occupational exposure, whereas only 41% and 40% of lower-middle-income and upper-middle-income countries exhibit positive relationships respectively. This suggests that structural factors may be important to consider in future work that seeks to model the distributional welfare impacts of heat stress over the long term.

[29] Only a handful of countries made use of the "army" category in their occupational reporting, so non-agricultural exposure is accounted for almost entirely by unskilled manual labor.
[30] The World Bank also provides a high-income category, but no such countries are present in our data set.

Country Case Study: Nigeria

Nigeria illustrates the typical relationship between household wealth and occupational exposure for a relatively low income country. With a per capita income of roughly \$3,203 USD (2014) in market exchange rate, Nigeria is a lower middle-income country, with the majority of households engaged in agriculture or manual labor (>51%). Even within Nigeria, it is the poorest households that are more likely to be engaged in manual work that occurs primarily outdoors. Households in Nigeria exhibit a negative relationship between household wealth and occupational temperature exposure, with a logistical regression coefficient of -0.04, significant at the 99% confidence level. This yields the following regression equation:

$$E_{Nigeria} = \frac{1}{e^{0.04138Y_{i,Nigeria}-1.597} + 1}$$

Where *E* represents probability of occupational exposure from 0 to 1, and $Y_{i,Nigeria}$ represents household wealth in percentile units.

Thus, a household in the 40th percentile of the wealth distribution has a 48.5% chance of being occupationally exposed, whereas a household in the 60th percentile has a 29.2% chance (Figure 6).[31]

[31] A more detailed look at the subcategories making up unskilled manual labor in Nigeria reveals that okada riders (commercial motorcycles for hire) account for about 78%, with butchers adding about 19% and 9 other categories comprising the remainder. Detailed tables for these occupational breakdowns are included in the Appendix, Section E.

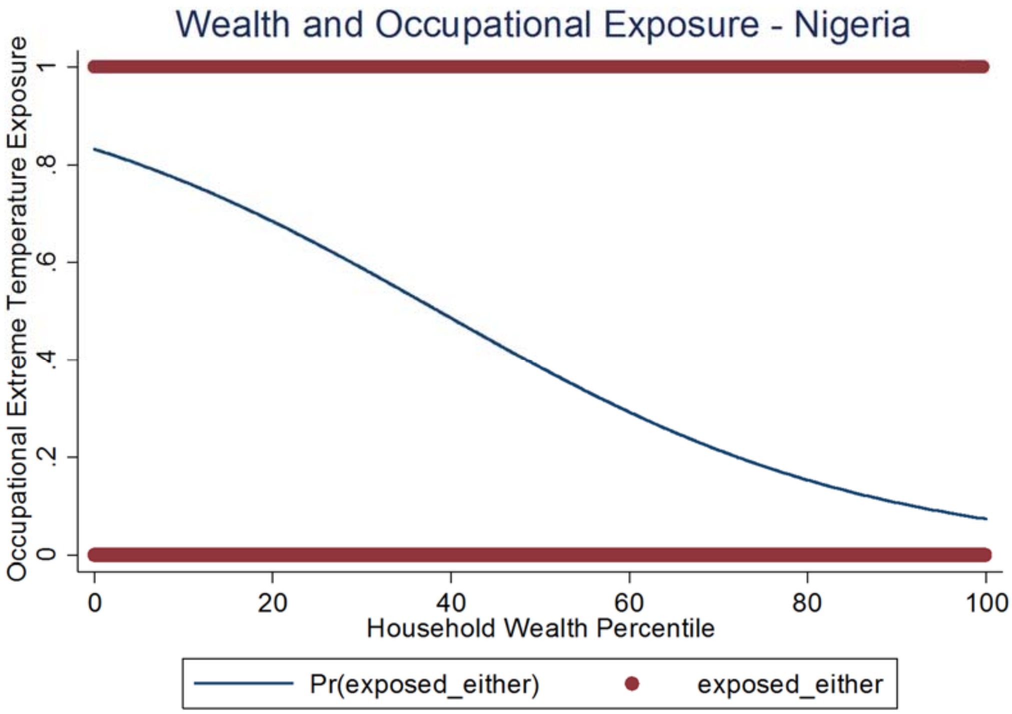


Figure 6: Occupational extreme temperature exposure and household wealth in Nigeria, values fitted by logistical regression. Dummy is 1 if either parent is exposed, 0 if neither.

Limitations

However, it must be noted that the temperature and occupational analyses presented above have a number of limitations, which we point out below. As a result, our analyses should only be seen as a first attempt at examining the dynamics between high temperatures and poverty at the household-level, with more research to follow.

The first limitation is that in the econometric analysis, we only use temperature data from 2013. As a single point in time, it is therefore possible that the temperatures experienced for 2013 may be different from longer-term trends. Future work should focus towards using a longer time series data.

Importantly, we considered only the temperature, while the effect of climate conditions on productivity and amenities work through multiple interacting metrics. For instance, the same temperature level has very different health and performance implication depending on the humidity level (Pal and Eltahir, 2015). Future work using higher resolution data and multiple variables to measure temperature stress would be an improvement.

Further, the lack of more robust set of controls means policy-relevant heterogeneity analyses are left on the table. This includes the role of built infrastructure, electricity access, and access to healthcare facilities which may reduce acute health impacts, but cannot be gleaned from this analysis (see below). Other useful controls include data on human capital.

Additionally, the interaction with other environmental stressors may be important to differentiate, especially if climate change and air quality vectors are not completely correlated in the future. Productivity impacts in hot areas may arise from ozone or carbon-monoxide as well as temperature. Future analyses that can control for average ozone or carbon monoxide levels would help researchers understand the ways in which exposure to climate extremes and low air quality interact.

And finally, because the wealth scores are relative within countries, it is difficult to derive meaningful, policy-relevant parameter estimates of the extent of exposure bias that is generalizable across countries. It is also impossible to ascertain the relative contribution of climate change to increasing heat stress in hot places versus reducing cold stress in cold places.

Other factors that may be important in ascertaining distributional welfare burdens

Access to Physical Capital

Poorer households are likely to have lower adaptive capacity for a variety of reasons. Even if they are aware of means to mitigate heat-related impacts, they may be constrained from employing them on various margins. They are less likely to have regular access to electricity, which is vital when it comes to mitigating heat stress. Poorer individuals may also tend to live in more vulnerable housing (lower housing quality); and for example, in developed countries, live on the top floor of houses without centralized air conditioning. More generally, poorer households will be less able to smooth consumption in the face of income shocks that may arise from unusually hot summers.

Income and electricity rates have been documented as being the primary drivers of AC adoption (Biddle, 2008). This is a statement about the rate of change in adaptive technology uptake. The implication, then, is that poorer areas – which often also have low rates of electrification – will likely adapt more slowly to the onset of climate change-related heat stress, exacerbating underlying inequalities in adaptive capacity. Given the geographic distribution of low-income individuals (i.e. the fact that, on average, populations in already hot regions tend to be poorer), a further implication is that climate change may endogenously make lower-income areas relatively less likely to adopt AC technology, exacerbating the rate of income inequality growth.

Demographic factors

It is possible that demographic factors matter. Elderly and very young populations are on average more severely affected by temperature stress, which means that a given degree of warming may result in greater realized exposure for these individuals (Kovats and Hajat 2008;

Graff Zivin and Shrader, 2015). In terms of direct health consequences of thermal stress, it is well established that the very young and the very old will bear an outsized share of the burden.

In general, demographic trends suggest that poorer countries will likely have a lower proportion of elderly individuals in the immediate future, but perhaps have higher densities of children and infants. However, there is significant uncertainty in the timing of climate-change-induced heat impacts, which means that it is difficult to assess even to a rough approximation which way the exposure bias may run ex ante. More research is clearly needed on this topic.

VIII. Conclusion

This paper examines empirically the geographical and occupational exposure of poor and non-poor households to heat stress, using data from household surveys and climate measurements at the sub-national level. We find that poorer households tend to be located in hotter locations across and within countries, and poorer individuals are more likely to work in occupations with greater exposure to the elements not only across but also within countries. This suggests the impacts arising from global warming – at least as they pertain to direct thermal stress of human beings – may be regressive.

However, we also find some evidence to suggest that part of the negative (and regressive) impacts of climate change may be offset by the fact that, in cold parts of the world, poorer populations tend to live in the more marginal (colder) environments, and that these populations may benefit from moderate warming.

There is, of course, a difference between mean-shifts in the climate distribution and changes in the incidence of extreme heat and cold days, which seem to be more relevant for welfare. These results are also of course limited only to the context of thermal stress of human agents, so abstracts away from damages to crops, and damages arising from flooding, storms, disease vectors, etc. Our results also have a number of limitations (including the low resolution of the climate data, the fact that our survey coordinates are offset, the use of only a limited set of controls, and that we only use 2013 for the econometric analysis). More research is needed including these aspects.

References

Acemoglu, Daron, and Melissa Dell. "Productivity Differences Between and Within Countries." American Economic Journal: Macroeconomics (2010): 169-188.

Acemoglu, D., et al. (2001). The colonial origins of comparative development: an empirical investigation, National bureau of economic research.

Albouy, David, et al. Climate amenities, climate change, and American quality of life. No. w18925. National Bureau of Economic Research, 2013.

Al Jazeera (2015). Poor bear brunt as India heatwave death toll tops 1,000. http://www.aljazeera.com/news/2015/05/poor-bear-brunt-india-heatwave-death-toll-tops-1000-150527092228109.html.

Arrow, K. J., et al. (2014). "Should Governments Use a Declining Discount Rate in Project Analysis?" Review of Environmental Economics and Policy: reu008.

Attanasio, O. and M. Székely (1999). "An asset-based approach to the analysis of poverty in Latin America."

Barros, A. J. D., Ronsmans, C., Axelson, H., Loaiza, E., Bertoldi, A. D., França, G. V. A., Bryce, J., Boerma, J. T. and Victora, C. G.: Equity in maternal, newborn, and child health interventions in Countdown to 2015: a retrospective review of survey data from 54 countries., Lancet, 379(9822), 1225–33, doi:10.1016/S0140-6736(12)60113-5, 2012.

Bi, P., et al. (2011). "The effects of extreme heat on human mortality and morbidity in Australia: implications for public health." Asia-Pacific journal of public health: 1010539510391644.

Burke, M. and K. Emerick (2013). "Adaptation to climate change: Evidence from US agriculture." University of California, Berkeley. http://www. ocf. berkeley. edu/~ kemerick/burke_emerick_2013. pdf

Butler, Ethan E., and Peter Huybers. "Adaptation of US maize to temperature variations." Nature Climate Change 3.1 (2013): 68-72.

Cachon, G., et al. (2012). "Severe weather and automobile assembly productivity." The Wharton School, University of Pennsylvania. http://opim. wharton. upenn. edu/~ cachon/pdf/weather_1015. pdf.

Carter, M. R. and C. B. Barrett (2006). "The economics of poverty traps and persistent poverty: An asset-based approach." The Journal of Development Studies 42(2): 178-199

Centers for Disease Control and Prevention (CDC). "State indicator report on physical activity, 2010." Atlanta, GA: US Department of Health and Human Services (2010).

Deaton, Angus, and Alan Heston. "Understanding PPPs and PPP-based National Accounts." American Economic Journal: Macroeconomics (2010): 1-35.

Dell, M., et al. (2009). Temperature and income: reconciling new cross-sectional and panel estimates, National Bureau of Economic Research.

Dell, M., et al. (2012). "Temperature shocks and economic growth: Evidence from the last half century." American Economic Journal: Macroeconomics 4(3): 66-95.

Deryugina, T. and S. M. Hsiang (2014). Does the Environment Still Matter? Daily Temperature and Income in the United States, National Bureau of Economic Research.

Deschênes, O. and M. Greenstone (2007). Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US, National Bureau of Economic Research Cambridge, Mass., USA.

Fisk, W. J., Price, P., Faulkner, D., Sullivan, D., Dibartolomeo, D., Federspiel, C., ... & Lahiff, M. (2002). Worker productivity and ventilation rate in a call center: Analyses of time-series data for a group of workers. Lawrence Berkeley National Laboratory.

Fox, A. M.: The HIV-poverty thesis re-examined: poverty, wealth or inequality as a social determinant of HIV infection in sub-Saharan Africa?, J. Biosoc. Sci., 44(4), 459–80, doi:10.1017/S0021932011000745, 2012.

Gallup, J. L., et al. (1999). "Geography and economic development." International regional science review 22(2): 179-232.

Goulder, Lawrence H., and Ian WH Parry. "Instrument choice in environmental policy." Review of Environmental Economics and Policy 2.2 (2008): 152-174.

Greenstone, M. and B. K. Jack (2013). Envirodevonomics: A research agenda for a young field, National Bureau of Economic Research.

Grether, W. (1973). "Human performance at elevated environmental temperatures." Aerospace Medicine 44(7): 747-755.

Hallegatte, Stéphane. "Strategies to adapt to an uncertain climate change." Global Environmental Change 19, no. 2 (2009): 240-247.

Heal, G. and J. Park (2013). Feeling the heat: Temperature, physiology & the wealth of nations, National Bureau of Economic Research.

Hoch, Irving, and Judith Drake. "Wages, climate, and the quality of life." Journal of Environmental Economics and Management 1.4 (1974): 268-295.

Horowitz, J. K. (2009). "The income–temperature relationship in a cross-section of countries and its implications for predicting the effects of global warming." Environmental and resource economics 44(4): 475-493.

Kovats, R. S. and S. Hajat (2008). "Heat stress and public health: a critical review." Annu. Rev. Public Health 29: 41-55.

Maddison, David. "The amenity value of the climate: the household production function approach." Resource and Energy Economics 25.2 (2003): 155-175.

Mankiw, N. G. and M. Weinzierl (2009). The optimal taxation of height: A case study of utilitarian income redistribution, National Bureau of Economic Research.

Mendelsohn, R., et al. (1994). "The impact of global warming on agriculture: a Ricardian analysis." The American Economic Review: 753-771

Nordhaus, William D., and Zili Yang. "A regional dynamic general-equilibrium model of alternative climate-change strategies." The American Economic Review (1996): 741-765.

Nordhaus, William D. "Geography and macroeconomics: New data and new findings." Proceedings of the National Academy of Sciences of the United States of America 103.10 (2006): 3510-3517.

Nordhaus, William D. Estimates of the social cost of carbon: background and results from the RICE-2011 model. No. w17540. National Bureau of Economic Research, 2011.

Pal, Jeremy S., and Elfatih A. B. Eltahir. 2015. "Future Temperature in Southwest Asia Projected to Exceed a Threshold for Human Adaptability." Nature Climate Change advance online publication (October). doi:10.1038/nclimate2833.

Park, J. (2015). "Will We Adapt? Temperature Shocks, Labor Productivity, and Adaptation to Climate Change in the United States 1986-2012."

Park, J. and G. Heal (2015). "Temperature Shocks and Labor Productivity: Evidence from the United States."

Sachs, Jeffrey D., and Andrew M. Warner. "Fundamental sources of long-run growth." The American Economic Review (1997): 184-188.

Schlenker, W., et al. (2005). "Will US agriculture really benefit from global warming? Accounting for irrigation in the hedonic approach." American Economic Review: 395-406.

Seppanen, O., et al. (2006). "Effect of temperature on task performance in office environment." Lawrence Berkeley National Laboratory.

Sherwood, S. C. and M. Huber (2010). "An adaptability limit to climate change due to heat stress." Proceedings of the National Academy of Sciences 107(21): 9552-9555.
Sinha, Paramita, and Maureen L. Cropper. The value of climate amenities: Evidence from us migration decisions. No. w18756. National Bureau of Economic Research, 2013
Solow, R. M. (1956). "A contribution to the theory of economic growth." The quarterly journal of economics: 65-94.
Stern, Nicholas Herbert. Stern Review: The economics of climate change. Vol. 30. London: HM treasury, 2006.
Stocker, T. F., et al. (2013). Climate Change 2013. The Physical Science Basis. Working Group I Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change-Abstract for decision-makers, Groupe d'experts intergouvernemental sur l'evolution du climat/Intergovernmental Panel on Climate Change-IPCC, C/O World Meteorological Organization, 7bis Avenue de la Paix, CP 2300 CH-1211 Geneva 2 (Switzerland).
Tol, R. S. (2009). "The economic effects of climate change." The Journal of Economic Perspectives: 29-51.
Vice News (2015). Poor People Are Most Affected as Hundreds Die in Blistering Indian Heatwave. https://news.vice.com/article/poor-people-are-most-affected-as-hundreds-die-in-blistering-indian-heatwave.
Ward, J. and Kaczan, D.: Challenging Hydrological Panaceas: Water poverty governance accounting for spatial scale in the Niger River Basin, J. Hydrol., 519, 2501–2514, doi:10.1016/j.jhydrol.2014.05.068, 2014.
Weitzman, Martin L. "On modeling and interpreting the economics of catastrophic climate change." The Review of Economics and Statistics 91.1 (2009): 1-19.
Winsemius, H., B. Jongman, T. Veldkamp, S. Hallegatte, M. Bangalore, and P. J. Ward. 2015. "Disaster Risk, Climate Change, and Poverty: Assessing the Global Exposure of Poor People to Floods and Droughts." Background paper prepared for World Bank Report "Shock Waves: Managing the Impacts of Climate Change on Poverty".
World Bank (2015). Climate Data (Climate 4 Development). Washington, DC: World Bank
Zivin, J. G. and M. Neidell (2014). "Temperature and the allocation of time: Implications for climate change." Journal of Labor Economics 32(1): 1-26.

Appendix

Appendix A: Spatial wealth data sets and DHS surveys

DHS surveys cover a wide range of developing countries, and contain geographic points at the cluster level. There are 52 surveys in the DHS program that contain both GPS information at the cluster level and poverty indicators; these are the countries for which we overlay the temperature data.

For each household, the DHS provides the wealth index factor score (typically from -200,000 for the poorest households to +200,000 for the richest, with the median at 0). For the econometric analysis, we normalize this factor score to include only positive numbers (for ease of interpretation), without changing each household's relative position with regarding to the factor score. For the poverty exposure bias analysis, quintiles have been calculated taking into account household weights, and have been provided in the raw DHS data. We employ this quintile classification for our analysis at the national-level.

One issue with DHS surveys – and almost all other household surveys – is that they have not been designed to be representative at small spatial scales. At best, they are representative at the spatial scale of a large province or area. Furthermore the process used to select the surveyed households is not always reported explicitly, and often has to account for cost- considerations that can bias the sample. We are well aware of this limit, and it implies that results should be interpreted with caution. The fact that we are working on a large sample of 52 countries compensates for the limit of the analysis at the country level.

Another major limitation is that the geographic information is not as precise as the household wealth data. First, the coordinates provided by DHS are only at the cluster level, and thus all households in the same cluster are represented spatially with the same set of coordinates. Second, these coordinates have been offset (to guarantee anonymity of the interviewed households), by 2km in urban areas and 5km in rural areas, creating a bias in our matching of household to temperature.

Appendix B: Full results for the poverty exposure bias to high temperatures.

Country name	Poverty exposure bias for temperature
Albania	-0.333
Angola	1.251793
Bangladesh	-0.07701
Benin	0.988184
Bolivia	-0.45717
Burkina Faso	0.668089
Burundi	-0.42028

Cambodia	0.239931
Cameroon	1.396431
Central African Republic	0.803523
Colombia	0.696162
Comoros	1.215704
Congo (Kinshasa)	0.133276
Cote d'Ivoire	0.091555
Dominican Republic	-0.18336
Egypt	0.198946
Ethiopia	1.391134
Gabon	1.109011
Ghana	1.546153
Guinea	1.625395
Guyana	0.158178
Haiti	-0.09212
Honduras	0.046851
Indonesia	-0.36818
Jordan	0.122819
Kenya	2.264893
Kyrgyzstan	-0.61815
Lesotho	-0.79582
Liberia	0.081452
Madagascar	0.440403
Malawi	0.112495
Mali	0.421567
Moldova	0.109866
Morocco	-0.01598
Mozambique	0.418412
Namibia	0.77016
Nepal	-0.37713
Niger	-0.08275
Nigeria	0.81481
Peru	0.31108
Philippines	-0.62428
Rwanda	-0.37742
Senegal	0.970137
Sierra Leone	0.057704
Swaziland	0.708064
Tajikistan	0.115736

Tanzania	-0.59295
Timor-Leste	0.332469
Togo	0.660964
Uganda	0.957571
Zambia	0.763263
Zimbabwe	0.871651

Table A: Summary of Main Results

Household Wealth Percentile and Hottest Month Temperature
By Climate Region

Country	β_j (percentiles per degree C) [SE]	P-value	Avg Annual Temperature (˚C)	Avg Hottest Month Temperature (˚C)	Avg Coldest Month Temperature (˚C)	Development Group Classification
Niger	-0.58062775 [1.1198932]	0.60458	29.3	34	24	Low
Burkina Faso	-2.0106396 [0.69863937]	0.00417	28.8	33	25	Low
Mali	0.21126458 [0.96721856]	0.82721	28.4	33	24	Low
Cambodia	-4.8617459 [1.636353]	0.00309	28	30	24	Low
Benin	-6.5054552 [0.57889932]	4.06E-27	27.9	30	26	Low
Ghana	-6.5128295 [0.67608657]	8.16E-20	27.5	30	25	Lower-Middle
Togo	-3.5405888 [0.58073089]	3.64E-09	27.3	30	25	Low
Senegal	-4.1714673 [0.36340022]	3.58E-26	27.3	30	24	Lower-Middle
Nigeria	-6.2331911 [0.59049823]	1.33E-24	27.3	31	24	Lower-Middle
Cote d'Ivoire	2.4138272 [0.67177564]	0.00038	26.6	29	25	Lower-Middle
Philippines	2.0976112 [0.37809252]	4.03E-08	26.6	28	25	Lower-Middle
Indonesia	2.2627246 [0.58108183]	0.0001	26.5	27	26	Lower-Middle
Sierra Leone	-5.871334 [1.2680002]	4.91E-06	26.5	29	25	Low
Gabon	8.947171 [0.90808164]	3.99E-20	26.1	28	24	Upper-Middle
Guinea	-3.542454 [0.69010222]	5.22E-07	26.1	29	24	Low
Liberia	19.29442 [2.2276259]	2.55E-16	26	28	24	Low
Guyana	9.3444326 [1.8301401]	5.88E-07	25.9	28	25	Lower-Middle
Central African Republic	-4.3704593 [0.87091193]	1.08E-06	25.5	28	23	Low
Comoros	-14.770104 [2.61593]	4.69E-08	25.3	27	23	Low

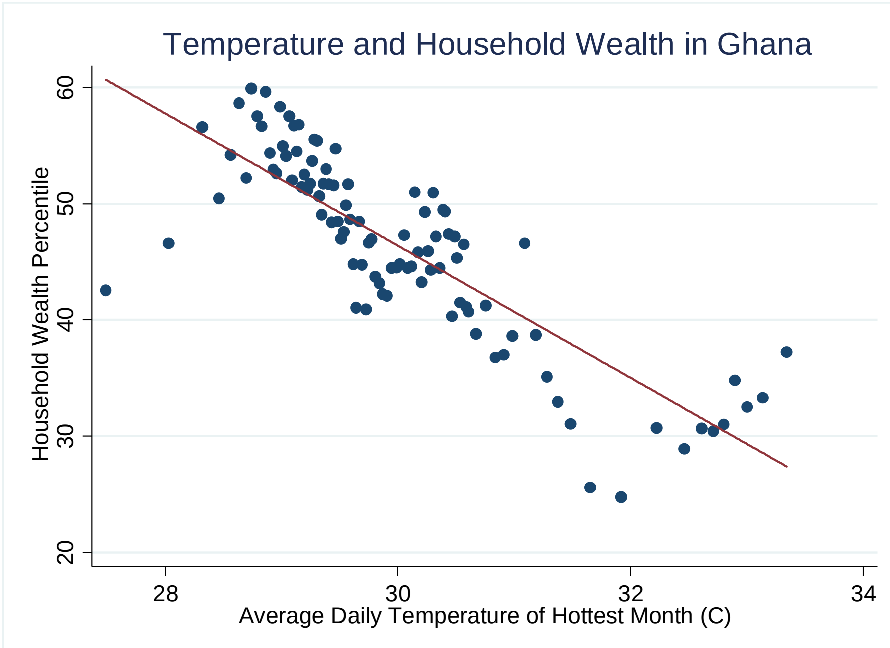
Cameroon	-0.90331903 [0.16047154]	2.88E-08	25.2	28	23	Lower-Middle
Timor-Leste	-8.5372101 [2.0562427]	4E-05	25.1	26	24	Lower-Middle
Dominican Republic	1.0241545 [0.56838777]	0.07216	24.9	27	23	Upper-Middle
Bangladesh	4.8173452 [0.98622937]	1.34E-06	24.9	29	17	Lower-Middle
Haiti	5.5383516 [0.83052343]	8.27E-11	24.8	27	23	Low
Mozambique	0.29501742 [0.47521627]	0.53497	24.2	27	20	Low
Congo (Kinshasa)	-2.052182 [0.54903613]	0.00021	23.9	25	22	Low
Honduras	0.69436635 [0.2814719]	0.01379	23	25	21	Lower-Middle
Tanzania	-0.21843565 [0.49381811]	0.65846	23	25	20	Low
Uganda	-2.6570787 [0.44017472]	3.74E-09	23	25	21	Low
Egypt	-2.5078512 [0.31992168]	9.73E-15	22.4	29	14	Lower-Middle
Angola	1.812745 [0.67091265]	0.00743	22.4	25	19	Upper-Middle
Malawi	0.16359438 [0.47660903]	0.73151	22.3	26	18	Low
Zambia	-1.2433808 [0.64204155]	0.05373	21.7	25	17	Lower-Middle
Madagascar	-2.7611615 [0.34269114]	5.00E-15	21.7	24	18	Low
Namibia	1.0346204 [0.45712779]	0.02408	21.2	25	16	Upper-Middle
Kenya	-1.8865034 [0.52049087]	0.00033	21	24	19	Lower-Middle
Colombia	-1.2073289 [0.0625475]	4.80E-80	20.9	22	20	Upper-Middle
Burundi	1.3502724 [0.6113885]	0.02782	20.8	23	19	Low
Zimbabwe	-3.2243243 [0.42443163]	2.45E-13	20.6	24	15	Low
Swaziland	-1.0508171 [0.6122296]	0.08727	20.5	25	16	Lower-Middle
Nepal	0.95396568 [0.24575053]	0.00013	20	26	11	Low
Ethiopia	-1.0409564 [0.24797496]	3.1E-05	19.5	22	17	Low
Rwanda	2.8716341 [0.75597578]	0.00017	19.3	21	17	Low
Jordan	6.3264029 [1.1963511]	1.60E-07	18.5	26	10	Upper-Middle

Morocco	-0.7556784 [0.4048611]	0.06262	17.8	26	11	Lower-Middle
Peru	0.38618239 [0.08156083]	2.47E-06	16	19	14	Upper-Middle
Albania	0.86707462 [0.47103403]	0.06632	14.6	25	6	Upper-Middle
Lesotho	4.27286 [0.62661087]	3.68E-11	14.4	20	8	Lower-Middle
Bolivia	0.10595015 [0.07628625]	0.16519	14.1	17	10	Lower-Middle
Tajikistan	-0.83329432 [0.32930191]	0.01185	11.8	24	-2	Lower-Middle
Moldova	-1.3669285 [1.500654]	0.36292	10.9	22	-3	Lower-Middle
Kyrgyzstan	1.1468391 [0.25611554]	1.1E-05	7.11	20	-8	Lower-Middle

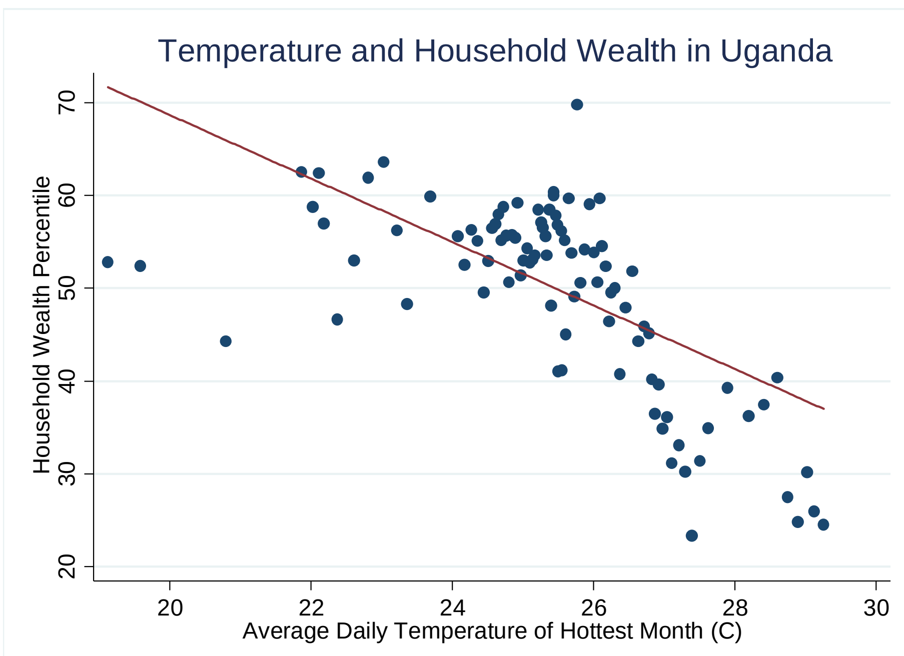
OLS linear regression of household wealth percentile on hottest monthly temperature, controlling for household size, urban/rural status, altitude, and precipitation (equation 1).

Sorted by average annual temperature. Green denotes statistically significant; Red denotes statistically insignificant.

Temperature and Household Wealth in Representative Hot Countries

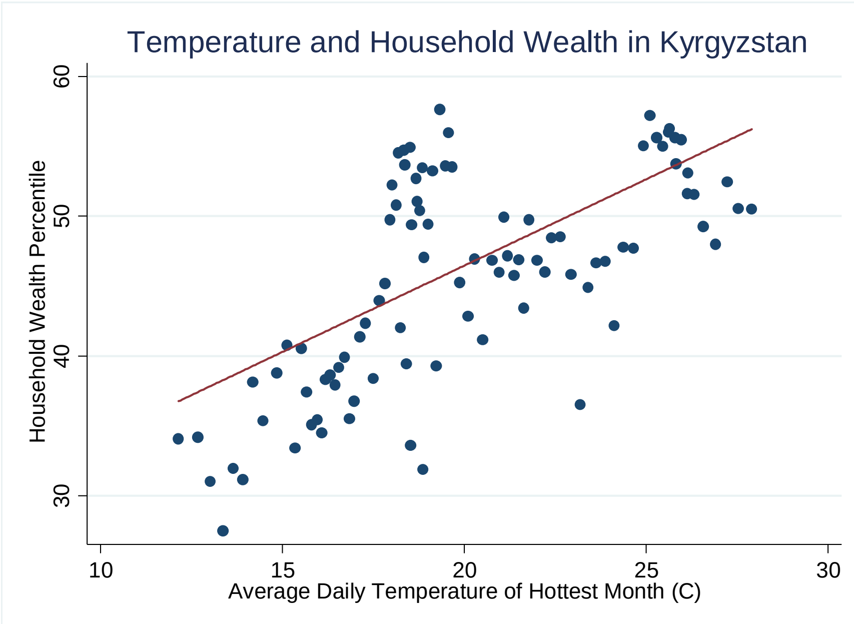


Controls: household size, urban/rural status, altitude, and precipitation.

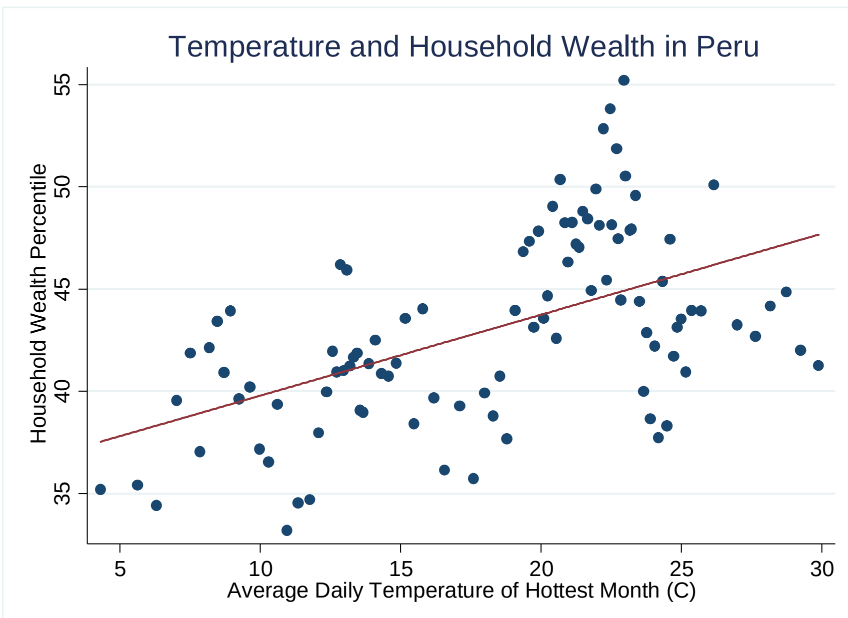


Controls: household size, urban/rural status, and precipitation.

Temperature and Household Wealth in Representative Cold Countries

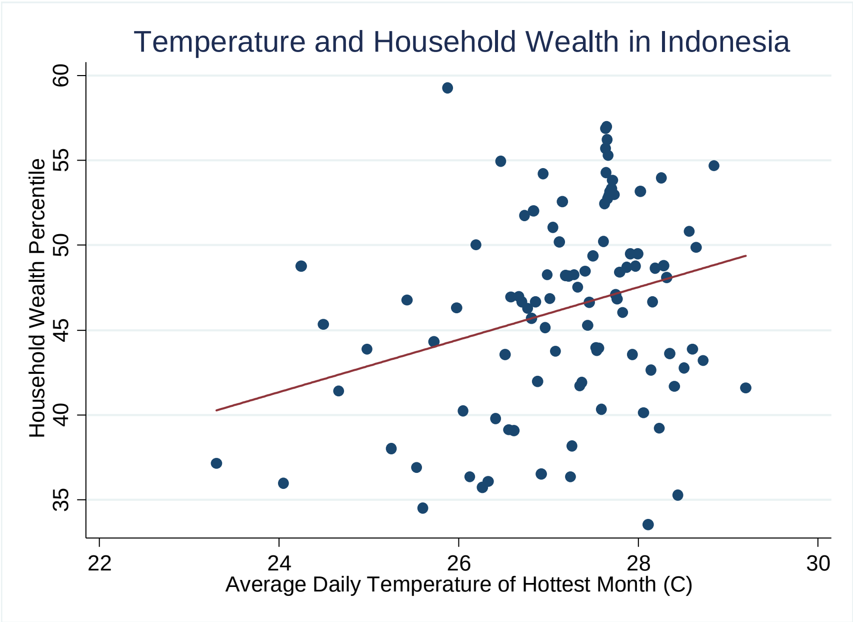


Controls: household size, urban/rural status, and precipitation.

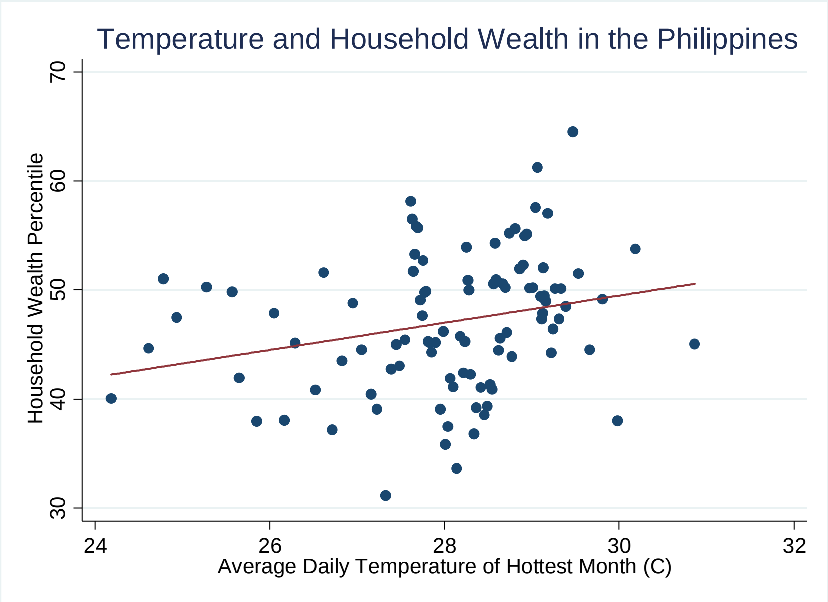


Controls: household size, urban/rural status, and precipitation.

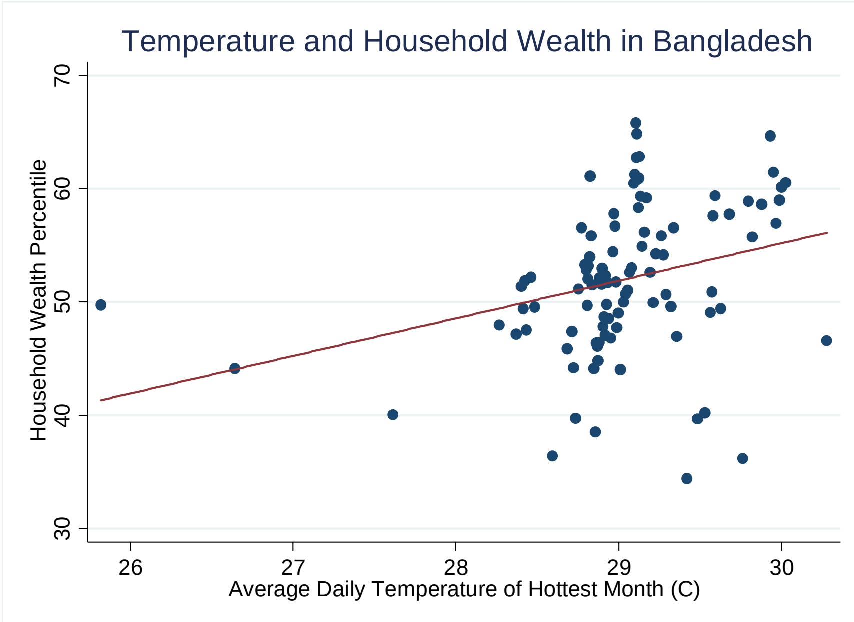
Temperature and Household Wealth: Notable Exceptions



Controls: household size, urban/rural status, altitude, and precipitation.



Controls: household size, urban/rural status, altitude, and precipitation.



Controls: household size, urban/rural status, altitude, and precipitation.

Table B: Temperature and Household Wealth: OLS Regression Coefficients by Country

Rows are sorted by coefficient and shaded by significance level (green for p<0.05, yellow for p<0.1, and red for p>0.1).

Out of the 938 strata in our data set, we encountered 4 with singleton PSUs. Variances for those strata are centered at the grand mean using Stata's singleunit(centered) command. While this procedure is imperfect, it seems to be the best available way of dealing with singleton PSUs in this case. The affected strata have very few observations, so it is unlikely that the "true" standard errors would differ substantially from our estimations.

OLS linear regression of household wealth percentile on hottest monthly temperature, controlling for household size, urban/rural status, altitude, and precipitation.

Country	Average Temperature (˚C)	$\beta_{\text{Hottest month temp}}$ (percentiles per degree C)	Standard Error	T-statistic	P-value
Comoros	25.33	-14.770104	2.61593	-5.6462152	4.69E-08
Timor-Leste	25.06	-8.5372101	2.0562427	-4.1518493	0.0000399
Ghana	27.48	-6.5128295	0.67608657	-9.6331295	8.16E-20
Benin	27.88	-6.5054552	0.57889932	-11.237628	4.06E-27
Nigeria	27.29	-6.2331911	0.59049823	-10.555817	1.33E-24
Sierra Leone	26.49	-5.871334	1.2680002	-4.630389	4.91E-06
Cambodia	27.99	-4.8617459	1.636353	-2.9710862	0.0030928
Central African Republic	25.45	-4.3704593	0.87091193	-5.0182564	1.08E-06
Senegal	27.3	-4.1714673	0.36340022	-11.478989	3.58E-26
Guinea	26.06	-3.542454	0.69010222	-5.1332308	5.22E-07
Togo	27.34	-3.5405888	0.58073089	-6.0967805	3.64E-09
Zimbabwe	20.56	-3.2243243	0.42443163	-7.596805	2.45E-13
Madagascar	21.65	-2.7611615	0.34269114	-8.0572889	5.00E-15
Uganda	22.99	-2.6570787	0.44017472	-6.0364183	3.74E-09
Egypt	22.39	-2.5078512	0.31992168	-7.8389536	9.73E-15
Congo (Kinshasa)	23.91	-2.052182	0.54903613	-3.7377906	0.00020845
Burkina Faso	28.79	-2.0106396	0.69863937	-2.8779362	0.0041691
Kenya	21.01	-1.8865034	0.52049087	-3.6244696	0.00032874
Moldova	10.92	-1.3669285	1.500654	-0.91088854	0.36291531
Zambia	21.73	-1.2433808	0.64204155	-1.9366048	0.05372943
Colombia	20.89	-1.2073289	0.0625475	-19.302593	4.80E-80
Swaziland	20.45	-1.0508171	0.6122296	-1.7163774	0.08727495
Ethiopia	19.46	-1.0409564	0.24797496	-4.1978287	0.00003142
Cameroon	25.2	-0.90331903	0.16047154	-5.629154	2.88E-08
Tajikistan	11.77	-0.83329432	0.32930191	-2.5304874	0.01184926
Morocco	17.79	-0.7556784	0.4048611	-1.8665127	0.0626184
Niger	29.25	-0.58062775	1.1198932	-0.51846707	0.60457852
Tanzania	23.02	-0.21843565	0.49381811	-0.4423403	0.65846282
Bolivia	14.07	0.10595015	0.07628625	1.3888499	0.16519393

Malawi	22.29	0.16359438	0.47660903	0.3432465	0.73150623
Mali	28.42	0.21126458	0.96721856	0.21842487	0.82720893
Mozambique	24.24	0.29501742	0.47521627	0.62080666	0.5349674
Peru	16.04	0.38618239	0.08156083	4.7349002	2.47E-06
Honduras	23.04	0.69436635	0.2814719	2.4669118	0.01378504
Albania	14.55	0.86707462	0.47103403	1.8407898	0.06632094
Nepal	19.98	0.95396568	0.24575053	3.8818459	0.00012906
Dominican Republic	24.91	1.0241545	0.56838777	1.8018588	0.0721627
Namibia	21.18	1.0346204	0.45712779	2.2633068	0.024077
Kyrgyzstan	7.112	1.1468391	0.25611554	4.4778194	0.00001078
Burundi	20.78	1.3502724	0.6113885	2.2085342	0.02782456
Angola	22.38	1.812745	0.67091265	2.7019091	0.00742679
Philippines	26.59	2.0976112	0.37809252	5.5478781	4.03E-08
Indonesia	26.54	2.2627246	0.58108183	3.8939862	0.00010381
Cote d'Ivoire	26.63	2.4138272	0.67177564	3.5932045	0.00037803
Rwanda	19.33	2.8716341	0.75597578	3.7985795	0.00016561
Lesotho	14.39	4.27286	0.62661087	6.8190007	3.68E-11
Bangladesh	24.85	4.8173452	0.98622937	4.8846094	1.34E-06
Haiti	24.8	5.5383516	0.83052343	6.6685073	8.27E-11
Jordan	18.52	6.3264029	1.1963511	5.2880823	1.60E-07
Gabon	26.12	8.947171	0.90808164	9.8528266	3.99E-20
Guyana	25.88	9.3444326	1.8301401	5.1058564	5.88E-07
Liberia	25.96	19.29442	2.2276259	8.6614272	2.55E-16

Table C: Occupational Exposure and Household Wealth: Logistical regression results by country

Survey logit regression of an exposure dummy on household wealth percentile, with no controls.

Country	Coefficient	Standard Error	T-statistic	P-value
Burundi	-0.1455	0.011874	-12.2541	3.85E-29
Rwanda	-0.11149	0.007991	-13.9517	5.41E-37
Madagascar	-0.09444	0.004581	-20.617	3.7E-70
Ethiopia	-0.08694	0.003878	-22.4221	9.09E-79
Bolivia	-0.08392	0.002424	-34.6156	1E-171
Tanzania	-0.08137	0.005277	-15.4218	3.3E-43
Morocco	-0.07929	0.004267	-18.5813	3.75E-54
Central African Republic	-0.07864	0.004728	-16.633	9.04E-41
Egypt	-0.07651	0.00337	-22.7066	7.29E-91
Mozambique	-0.07448	0.002564	-29.0524	5.9E-115
Guinea	-0.07196	0.003079	-23.3705	9.73E-69
Peru	-0.07107	0.001601	-44.3889	2.4E-249
Nepal	-0.07051	0.003538	-19.9284	8.06E-56
Zambia	-0.07027	0.003494	-20.1135	1.68E-57
Niger	-0.06962	0.00263	-26.4667	2.32E-75
Ghana	-0.06842	0.002509	-27.274	1.1E-91
Sierra Leone	-0.06707	0.004745	-14.1362	3.3E-37
Moldova	-0.06549	0.002554	-25.6426	8.96E-86
Burkina Faso	-0.06512	0.002812	-23.1599	1.56E-81
Albania	-0.0629	0.002728	-23.0559	3.25E-77
Indonesia	-0.06225	0.001371	-45.3902	3.2E-267
Cote d'Ivoire	-0.06178	0.00247	-25.0172	3.33E-77
Liberia	-0.06036	0.003011	-20.0444	1.01E-57
Benin	-0.0594	0.001745	-34.0339	2.7E-152
Tajikistan	-0.05785	0.003383	-17.1012	1.6E-46
Cameroon	-0.05779	0.001871	-30.8904	1.2E-122
Timor-Leste	-0.057	0.003077	-18.5271	1.79E-56
Togo	-0.05699	0.002395	-23.7943	8.07E-69
Congo (Kinshasa)	-0.05453	0.002623	-20.7918	1.45E-68
Senegal	-0.04877	0.002392	-20.3864	2.11E-61
Philippines	-0.04798	0.001495	-32.0856	6.5E-142
Honduras	-0.04504	0.00138	-32.6475	1.9E-163
Colombia	-0.04342	0.000833	-52.1063	0
Haiti	-0.04106	0.001478	-27.7718	1.09E-96
Jordan	-0.04102	0.004548	-9.01935	2.11E-18
Guyana	-0.041	0.00273	-15.0154	5.23E-38
Nigeria	-0.03868	0.001229	-31.4665	4.6E-146

Lesotho	-0.03829	0.00216	-17.73	6.75E-51
Namibia	-0.03733	0.002309	-16.1658	3.01E-46
Comoros	-0.03693	0.002809	-13.1482	1.72E-29
Kenya	-0.03683	0.002081	-17.7004	2.5E-51
Gabon	-0.03647	0.002405	-15.1668	2.99E-39
Malawi	-0.03517	0.001229	-28.6202	1.9E-123
Zimbabwe	-0.034	0.002134	-15.9285	1.47E-43
Swaziland	-0.03181	0.002894	-10.9889	3.19E-23
Dominican Republic	-0.03046	0.001514	-20.1205	1.83E-66
Kyrgyzstan	-0.02859	0.002616	-10.9287	1.73E-23

Table D: Occupational Exposure and Temperature: Logistical regression results by country

Survey logit regression of an exposure dummy on average temperature, controlling for urban/rural status.

Country	Coefficient	Standard Error	T-statistic	P-value
Liberia	-1.70353	0.229483	-7.42336	1.13E-12
Gabon	-0.39196	0.099083	-3.95587	9.46E-05
Haiti	-0.29799	0.066306	-4.49425	9.07E-06
Cote d'Ivoire	-0.24805	0.151657	-1.63561	0.102908
Egypt	-0.21737	0.090527	-2.40116	0.016542
Lesotho	-0.21241	0.039398	-5.39145	1.27E-07
Philippines	-0.20912	0.039714	-5.2657	1.85E-07
Burkina Faso	-0.17491	0.142998	-1.22316	0.221837
Burundi	-0.1734	0.112192	-1.54556	0.123079
Jordan	-0.16503	0.243091	-0.67888	0.497457
Indonesia	-0.1526	0.071513	-2.13391	0.033046
Zambia	-0.13616	0.088017	-1.54692	0.12294
Namibia	-0.10119	0.051115	-1.97971	0.048375
Dominican Republic	-0.06793	0.039961	-1.6999	0.08977
Malawi	-0.06064	0.044944	-1.34927	0.177644
Tanzania	-0.04988	0.045241	-1.10259	0.270818
Albania	-0.04951	0.034361	-1.44094	0.150328
Nepal	-0.0373	0.01753	-2.12771	0.034225
Morocco	-0.03319	0.061865	-0.53654	0.591923
Nigeria	-0.03292	0.040358	-0.81574	0.41487
Zimbabwe	-0.02879	0.059815	-0.48135	0.630565
Honduras	-0.0278	0.01962	-1.41707	0.156757
Kenya	-0.02598	0.021481	-1.20946	0.227252
Congo (Kinshasa)	-0.00918	0.05882	-0.15606	0.876051
Cameroon	0.001544	0.027556	0.056049	0.955323
Central African Republic	0.00237	0.119959	0.019755	0.984256
Bolivia	0.005957	0.008991	0.662531	0.507788
Peru	0.007278	0.009533	0.763484	0.445335
Ethiopia	0.009565	0.028822	0.331877	0.740114
Colombia	0.028399	0.005593	5.077404	3.97E-07
Tajikistan	0.05974	0.024838	2.405179	0.016756
Kyrgyzstan	0.060814	0.028043	2.168589	0.030932
Togo	0.080907	0.099747	0.81112	0.417996
Rwanda	0.082242	0.075475	1.089648	0.276454
Guyana	0.097817	0.184466	0.53027	0.596335
Madagascar	0.104082	0.029947	3.47555	0.000551
Moldova	0.138084	0.190361	0.72538	0.468653

Guinea	0.146896	0.142633	1.029887	0.303918
Senegal	0.26666	0.061857	4.310891	2.12E-05
Swaziland	0.283432	0.06453	4.392255	1.65E-05
Ghana	0.283708	0.113134	2.507708	0.012566
Niger	0.319605	0.107741	2.966429	0.003297
Mozambique	0.33727	0.070032	4.815953	1.88E-06
Timor-Leste	0.415684	0.168723	2.46371	0.014154
Benin	0.444863	0.196749	2.261063	0.024052
Sierra Leone	0.465954	0.265776	1.75318	0.080322
Comoros	0.539392	0.13266	4.065967	6.67E-05

Table E: Occupational Exposure and Household Wealth: Logistical Regression results by country and development group

Rows are sorted by ascending coefficient, within the three World Bank development groups.

Survey logit regression of a non-agricultural exposure dummy on household wealth percentile, with no controls.

Country	Dev. Group	Coefficient	Standard Error	T-statistic	P-value
Nepal	Low	-0.01838	0.001943	-9.45812	1.30E-18
Malawi	Low	-0.00828	0.001116	-7.42316	3.00E-13
Zimbabwe	Low	-0.00388	0.001899	-2.0414	0.041944
Liberia	Low	-0.00314	0.002067	-1.52057	0.129398
Burundi	Low	0.003811	0.008691	0.438474	0.661303
Rwanda	Low	0.004397	0.002789	1.57666	0.11558
Comoros	Low	0.008123	0.003585	2.26576	0.024444
Benin	Low	0.012638	0.003664	3.44885	0.000596
Guinea	Low	0.012675	0.003798	3.33695	0.000957
Haiti	Low	0.015693	0.001363	11.5149	8.20E-27
Mozambique	Low	0.017451	0.002682	6.50715	1.70E-10
Central African Republic	Low	0.02238	0.003375	6.63078	2.50E-10
Ethiopia	Low	0.027421	0.005705	4.80637	2.00E-06
Burkina Faso	Low	0.027693	0.00353	7.84527	2.60E-14
Tanzania	Low	0.029462	0.001759	16.7527	0
Congo (Kinshasa)	Low	0.030696	0.002734	11.2294	4.40E-26
Sierra Leone	Low	0.032122	0.002066	15.5476	0
Togo	Low	0.03357	0.002727	12.3123	4.60E-28
Niger	Low	0.034874	0.0121	2.88222	0.004283
Madagascar	Low	0.043009	0.002108	20.4011	0
Tajikistan	Lower-Middle	-0.04289	0.003318	-12.924	8.30E-31
Egypt	Lower-Middle	-0.03723	0.002933	-12.6964	3.90E-34
Swaziland	Lower-Middle	-0.02177	0.003946	-5.51736	8.50E-08
Guyana	Lower-Middle	-0.01564	0.002905	-5.38288	1.50E-07
Moldova	Lower-Middle	-0.01534	0.002996	-5.11917	4.80E-07
Morocco	Lower-Middle	-0.01408	0.002403	-5.86016	1.10E-08
Philippines	Lower-Middle	-0.0138	0.001566	-8.81383	8.70E-18
Kyrgyzstan	Lower-Middle	-0.01258	0.003636	-3.46038	0.000621

Bolivia	Lower-Middle	-0.01016	0.002374	-4.28085	0.00002
Nigeria	Lower-Middle	-0.00548	0.001447	-3.78348	0.000165
Cote d'Ivoire	Lower-Middle	0.001184	0.003334	0.355081	0.722763
Kenya	Lower-Middle	0.001393	0.002016	0.69061	0.49024
Honduras	Lower-Middle	0.00546	0.00109	5.0098	6.40E-07
Lesotho	Lower-Middle	0.005633	0.001955	2.88089	0.004205
Senegal	Lower-Middle	0.009934	0.002957	3.35907	0.000868
Indonesia	Lower-Middle	0.010019	0.00109	9.19207	1.50E-19
Cameroon	Lower-Middle	0.014668	0.002685	5.46277	7.10E-08
Ghana	Lower-Middle	0.020291	0.010854	1.86949	0.06232
Timor-Leste	Lower-Middle	0.021997	0.002929	7.50952	3.60E-13
Zambia	Lower-Middle	0.026081	0.007878	3.31072	0.001045
Jordan	Upper-Middle	-0.03124	0.006787	-4.60305	5.00E-06
Dominican Republic	Upper-Middle	-0.02381	0.001489	-15.9903	0
Albania	Upper-Middle	-0.00902	0.002163	-4.17171	0.000037
Peru	Upper-Middle	-3.8E-05	0.001296	-0.0293	0.976634
Namibia	Upper-Middle	0.001412	0.002887	0.489095	0.625025
Colombia	Upper-Middle	0.00469	0.001016	4.61459	4.00E-06
Gabon	Upper-Middle	0.008161	0.002703	3.01967	0.002741