Hot and Bothered: Distributional Impacts of Climate Change in Developing Countries

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Abstract

Will global climate change affect labor productivity? If so, what will be the distributional consequences of this effect? The recent literature documents significant labor productivity impacts from extreme temperature stress on the order of 2 to 3 percentage points decline per degree C above an optimal temperature zone, though it is as yet unclear whether adaptation will reduce these impacts substantially. Ex ante, there are reasons to believe that the distributional consequences of this climate damage channel will be regressive, especially given the higher likelihood that poorer households face greater exposure (e.g. tend to be located in more marginal climates) and have scarcer means of taking defensive action (e.g. less likely to be electrified or able to afford air conditioning). Analysis of survey-based wealth and occupational data from over 690,000 households in 52 countries suggests that, while the aggregate impacts will likely be regressive, local context may matter considerably: in particular, whether or not climate change will lead to localized increases in extreme temperature events on net (including both heat and cold).

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Introduction

A wave of recent studies suggest that there may be significant productivity impacts from temperature stress which may be exacerbated by global climate change (Dell, Jones, Olken, 2014). In particular, there is mounting evidence for direct physiological effects of thermal stress of the human body, especially in the context of labor supply and labor productivity[1] (Heal and Park, 2015). These effects seem to be more pronounced in developing economies, and may interact adversely with important livelihood channels such as agriculture, education, and health.

Despite this emerging literature, potential labor productivity impacts from climate change remain omitted from most integrated assessment models. This suggests that the damages from climate change may be understated, to the extent that they exclude this important channel.

Furthermore, to the extent that developing economies are (1) more likely to experience greater extreme heat exposure in the future and (2) less likely to have the resources available to adapt rapidly to increased heat stress, it is possible that the labor productivity impacts from climate change will induce largely regressive welfare burdens on society – both globally across countries and locally within countries. While intuition and anecdotal evidence certainly suggest this to be likely, quantitative evidence documenting regressive impacts from climate-change induced labor productivity impacts, and climate-change induced damages generally, remains relatively thin.

Whether or not climate change will have disproportionately negative impacts on the livelihoods of the world's poor – due to the exposure bias of labor productivity or other mechanisms – is of non-trivial policy significance. It informs at least three policy decisions. First, distributional consequences will, for most reasonable social welfare functions[2], determine the overall welfare consequences of climate mitigation, thus informing the question of how much mitigation is optimal. Second, for any given level of total global emissions reduction targeted, they inform how these budgets should be fairly allocated. Third, irrespective of future mitigation decisions, understanding whether, and more importantly, how climate change may affect the world's most vulnerable populations will be crucial in enabling policymakers to target adaptation investments toward the right places (e.g. coastlines versus already heat-stressed regions?) and technologies (e.g. storm-surge protection versus air conditioning?).

Generally speaking, hotter countries tend to be poorer ones, though the mechanisms underlying this correlation have been debated for a very long time (Huntington 1915, Dell, Jones et al. 2012). Even within countries, there is evidence to believe that poorer households tend to be located in more marginal environments (Acemoglu and Dell 2009; Hsiang and Deryugina, 2014)[3]. And yet, whether or not these cross-sectional relationships are due to the direct impact of temperature on

[1] This literature is related to but separate from more traditional mechanisms such as agricultural yield or infrastructure loss which affect social welfare indirectly.

[2] Any (standard) combination of a utility function that features declining marginal utility of consumption and additive social preferences will produce this result.

[3] Based on these facts alone, some have suggested that the labor productivity impacts from climate change could be largely regressive. Whether and to what extent this is indeed the case may have implications for our understanding of theories of economic convergence (Solow 1956) and analysis of global trends in income inequality (Piketty 2014).

productivity or other confounding factors (e.g. institutions) remains an issue of considerable debate.

Previous research emphasizing the connection between temperature stress and productivity has been limited by the inability to claim direct causal attribution. The experimental literature on temperature and task productivity often does not replicate economically relevant contexts (e.g. Seppanen, Fisk, et al, 2006), while modeling studies often relied on extrapolations from cross-sectional associations (e.g. Horowitz, 2011).

Luckily, a wave of recent studies use panel data to estimate the causal impact of extreme temperature – for instance, hotter-than-average years or extremely hot days – 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, precipitation) over time, these studies allow researchers to estimate the historical causal impact of extreme temperature on economic productivity[4], which may or may not be useful in estimating the expected social costs of carbon.

In light of these recent developments, this paper has three related objectives.

The first is to provide a stylized synthesis of the new literature on temperature and productivity, with a focus on those studies that estimate causal impacts of temperature stress on outcomes related to labor productivity.

The second is to help guide thinking about the potential distributional consequences of this relatively new climate damage mechanism. To this end, the paper presents a simple conceptual framework for assessing social welfare consequences of the temperature-labor productivity relationship.

The third is to provide a preliminary quantitative assessment of the distributional implications of the labor productivity impacts of climate change, by evaluating the relationship between household wealth and exposure to temperature stress in the cross-section within countries.

The synthesis is organized according to two levels of analysis: (1) micro (individual) level studies which assess the causal impact of temperature shocks on firms and individuals in-situ; and (2) macro level studies which estimate temperature-driven output and productivity shocks at the level of regions and countries. There is remarkable consistency in point estimates across these levels of analysis, with treatment effects of a 1°C increase in temperature on the order of minus 2-3 percentage points of output. While translating such point estimates into future climate damage estimates is fraught with potential biases, due in large part to the prospect of adaptation (Mendelsohn, Nordhaus et al. 1994, Burke and Emerick 2013; Park, 2015), there seem to be ex ante reasons to believe that, regardless of the exact magnitude, the distributional implications for global social welfare may be significantly regressive.

[4] 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).

Relatively little research has been conducted on the possible intersection between temperature-driven labor productivity impacts and projections for global poverty alleviation. The simple conceptual framework presented here, which builds on Hallegatte et al (2014), identifies two key factors – exposure and adaptive capacity – that may determine the expected distributional impacts of climate change as it operates through the channel of diminished labor productivity.

By using household wealth and occupation data from the Demographic and Health Surveys (DHS) for 52 countries across Asia, Africa, South America, and Europe combined with weather data from the Climatic Research Unit (CRU), this paper provides a rough estimate of the exposure bias of poorer households to extreme heat stress. While the aggregate relationship between temperature and household wealth is strong, and is suggestive of regressive impacts, there is substantial heterogeneity in this relationship by local climate, suggesting that 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 are sorely needed.

The New Temperature-Labor Productivity Literature

A longstanding medical and task productivity literature documents a systematic relationship between temperature stress of the human body and reduced performance (Seppanen, Fisk et al. 2006). Lab experiments have quantified this relationship by randomly assigning subjects to rooms of varying temperatures and asking them to perform cognitive and physical tasks. These studies find that extreme temperature reduces human performance on a wide range of tasks, including estimation of time, vigilance, and higher cognitive functions, such as mental arithmetic and simulated flight (Grether 1973, Froom, Caine et al. 1993). In a meta-review of the experimental literature, Seppanen, Fisk et al. (2006) find that the average productivity loss from temperatures above 25°C is on the order of 2% per degree C for the various tasks surveyed.

At the same time, researchers have noted a strong cross-sectional relationship between temperature and economic variables – namely income and growth – for quite some time. As far back as Montesquieu (de Montesquieu 1758) and Huntington (1915), there has been a suggestion that climate is a central determinant of culture, and that extreme climate may reduce productivity and the potential for economic growth. Using data from agricultural and manufacturing occupations in North Carolina, Huntington (1915) for instance showed that productivity was highest in moderate temperatures (fall and spring), and lower in more extreme temperatures (summer, winter).

Cross-country analyses suggest that hotter countries have tended to grow more slowly on average. Gallup, Sachs et al. (1999) show that countries located in the tropics (i.e. between the Tropic of Cancer and the Tropic of Capricorn) were 50% poorer per-capita in 1950 and grew 0.9 percentage points slower per year between 1965 and 1990. Looking within the United States, counties with greater exposure to extreme heat stress have grown on average more slowly over the past four decades (Park, 2015).

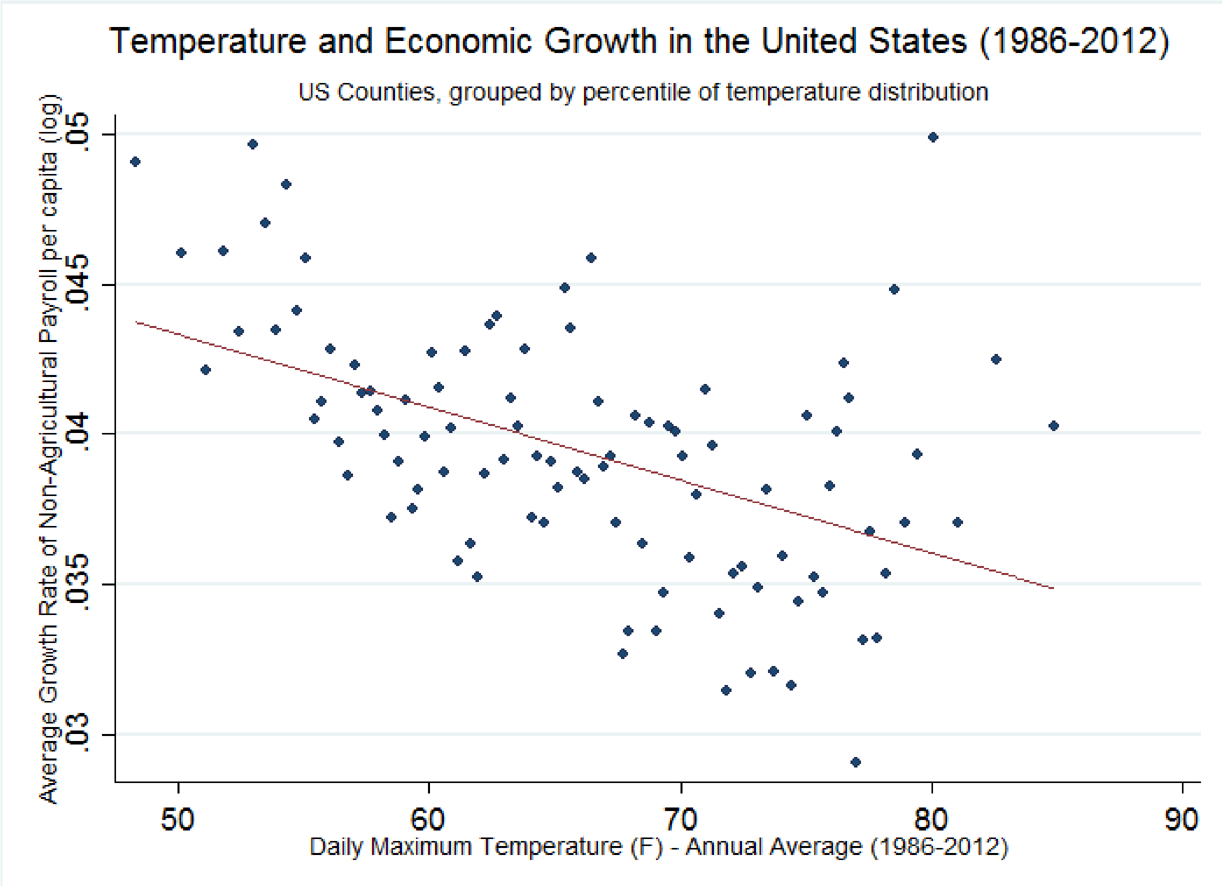


Figure 1: Hotter counties in the United States have tended to grow more slowly on average. Average growth rate of non-non-agricultural payroll and daily maximum temperature (by percentile) Source: Park (2015)

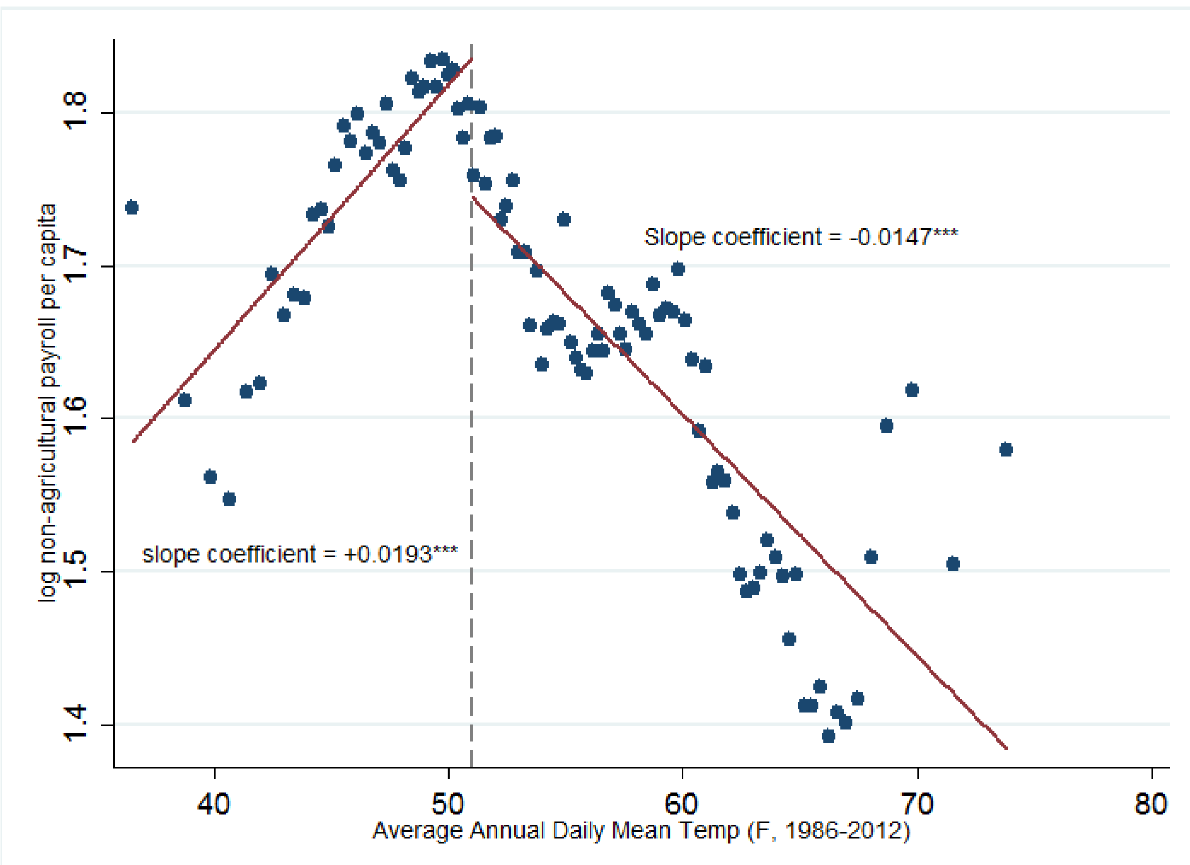
Similarly, many have noted that hotter countries tend to have lower income levels generally, with a gradient of roughly minus 8.5% per capita income per degree C hotter average temperatures (Dell, Jones et al. 2009, Horowitz 2009). But, as many have suggested, it is likely that these cross-country regressions suffer from substantial omitted variable bias in the form of country-specific factors that affect income but are unrelated to temperatures, including institutions, levels of human capital, and agricultural productivity.

There is some suggestion that this negative relationship between temperature and income holds within countries as well, albeit to a milder extent. Acemoglu and Dell (2009) assess incomes at the municipality level for 12 American countries, and find that a 1°C rise in temperature is associated with 1.2% to 1.9% lower per capita income. While the relationship is substantially weaker within countries than across countries, the fact that it remains statistically significant and economically meaningful suggests that institutional factors are not wholly responsible for the temperature-productivity relationship.

More recently, Hsiang and Deryugina (2014) and Park (2015), find similar results at the county level, using US income and payroll data from 1986-2012. In the case of Park, a county with 1°C warmer annual average mean temperatures has roughly 1.64% lower payroll per capita, controlling for average precipitation and snow. Using daytime maximum temperatures as the explanatory variable sharpens the gradient considerably; a place with 1°C hotter daytime high temperatures has approximately 8.22% lower payroll per capita, controlling for average precipitation and snow. Similarly, places with more extreme heat days (90°F or 32.2°C and above) per year have significantly lower payroll per capita, with a slope of roughly -0.307% per additional extreme heat day[5].

An Optimal Temperature Zone for Economic Activity?

While the stylized fact has been that hotter places tend to be poorer on average in the cross-section, recent work suggests that extreme temperature stress in either direction – hot and cold – seems to be suboptimal for economic activity. Indeed, a casual scatterplot of county-level US payroll shows that, at least in the US context, there is a single-peaked relationship between temperature and economic activity, with the optimum occurring somewhere between 50°F and 55°F average daytime temperatures. Places with more extreme cold days (defined as days with mean temperature below 15F) are roughly 0.81% poorer per additional day, when controlling for precipitation and snow. Nordhaus (2009) finds a similar single-peaked pattern using grid cell product, although it is worth noting that the dependent variable in this case is output density.



[5] The average US county experiences 12 such days, with considerable heterogeneity across regions. Boston experiences on average less than 3 extreme heat days per year by this definition. Houston experiences over 35.

Figure 2: An Optimal Temperature Zone for Economic Activity? Non-Agricultural Payroll and Average Annual Temperature in US Counties (by percentile) Source: Park (2015)

Methodological Issues in Estimating Climate-Related Damages

To the extent that one believes future climate change will increase the incidence of extreme heat stress, one might be tempted to extrapolate these point estimates to impute labor productivity losses expected from global warming. Some have applied the findings from laboratory studies to the global context, simulating what the impact of future climate change might be, given biological limits to heat stress (Kjellstrom, Holmer et al. 2009, Sherwood and Huber 2010, Tawatsupa, Lim et al. 2010, Bi, Williams et al. 2011). Others have attempted to use cross-sectional gradients to estimate damages from future climate change (e.g. Horowitz, 2009).

While such extrapolations may provide useful heuristic benchmarks, estimating the impacts of temperature stress on labor productivity due to climate change in this way is complicated by three sets of methodological issues: context, causal attribution, and adaptation.

First, it is unclear whether lab experiments provide economically relevant contexts, especially if one is interested in drawing welfare implications for a global public good problem such as climate change, which is expected to have sizable macroeconomic impacts. Many labor activities do not require exertion levels that near physical limits, as assumed by studies such as Kjellstrom, Holmer et al. (2009) or Sherwood and Huber (2010), and most labor in manufacturing or services can be expected to occur indoors, where individuals are likely to be shielded from outdoor temperatures to some degree. In general, the final economic impacts of reduced temperature stress may be different from the physiological impacts.

Second, while cross-sectional studies may provide the right context, they suffer from potential omitted variable bias that confounds the interpretation of the implied temperature-GDP relationship. For instance, areas in warmer climates may be associated with lower endowments of other productive assets, such as arable farmland or mineral resources. Perhaps most notably, hotter countries tend to be those with weaker institutions, in part by way of historical accident (Acemoglu, Johnson et al. 2000). Even within countries, it is possible that warmer regions have omitted characteristics that influence labor productivity but are wholly unrelated to temperature stress. In the US, Southeastern states (e.g. Mississippi, Georgia) have lower per capita incomes and labor productivity than Northeastern states, but it is possible that some of this has to do with the legacy of the Civil War.

Finally, neither experimental nor cross-sectional approaches convincingly address the issue of adaptation. Human beings are an adaptive species, and one would expect long-run adaptations to offset some of the adverse impacts of heat stress on economic welfare. The prospect of adaptation is addressed in greater detail by others including Mendelsohn et al (1994), Hallegatte (2009), and Burke and Emerick (2014).

While the issue of adaptation remains a significant methodological challenge, a wave of recent studies managed to address the first two issues successfully, by exploiting high-frequency weather variation and panel estimation methods. Pioneered by Deschênes and Greenstone (2007), the panel approach estimates the following: $y_{it}=\alpha+\beta_1 PANELT+\beta_2 X_i+\gamma_i+\epsilon_{it}$

Where $\ddot{y}it$ is income per capita, and T,X,ϵ denote temperature, a vector of other weather controls (e.g. average annual precipitation, snow days), and a location-specific error term respectively. The $\ddot{}$ superscript denotes de-meaned differences, and γi captures time-invariant, region-specific effects. In this case, $\beta 1PANEL$ represents the causal impact of deviations from the region-specific average temperature on output deviations from trend. The $\beta 1PANEL$ coefficients are, in some sense, estimates of the short-run impact of temperature fluctuations on economic activity.

The rest of this section surveys the recent literature on temperature and productivity, focusing on studies that use this panel-based estimation strategy.

Panel Estimates at the Micro (individual) Level

As Zivin and Neidell (2014) and Heal and Park (2013) note, responses by workers to temperature shocks may take many forms. Notably, there may be declines in task productivity, labor supply (hours worked), labor effort, or all three. The emerging micro-econometric literature finds evidence for at least the first two in particular, and likely reflect a combination of all three, the specific breakdown of which will depend on labor market institutions and specific incentives faced by workers.

Niemelä et al. (2002) examine the productivity of call center workers in different ambient temperatures and find that, above 22 degrees C, each additional degree C is associated with a reduction of 1.8 percent in labor productivity. Federspiel et al. (2004) find similar results for call center workers, noting that high temperatures above 24-25 degrees C are associated with poorer performance. 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. Sudarshan et al (2014) find similar plant-level productivity declines among Indian manufacturers, even when controlling for region, firm, and individual-specific factors. Hot days above 25 degrees C cause lower productivity in manufacturing plants, with a magnitude of roughly minus 2.8% per degree C. Sudarshan et al (2014) are able to show that the effect is driven mostly through reduced worker productivity while working, as opposed to increased worker absenteeism due, for instance, to disrupted sleep during warm nights.

These studies occur in developing countries where air conditioning is, for the most part, a scarce commodity. There seems to be evidence, however, that labor productivity impacts of temperature stress occur even in developed economies such as the US, which one might suppose to have high levels of air conditioning penetration.

Cachon, Gallino et al. (2012) take plant-level output data from 1994-2004 for one particular sector – automobiles – and test whether hot days reduce output, controlling once again for fixed effects, as well as for other weather shocks (e.g. wind storms, snow, rain). They 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%. While their study design is unable to fully disentangle the contributions of task productivity decline and worker absenteeism, 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.

There is also evidence of reduction in labor supply in response to heat stress. Using data from the American Time-Use Survey, Zivin and Neidell (2014) find evidence for significant changes in time-use decisions resulting from temperature shocks. 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[6]. At temperatures over 100 degrees F, labor supply in outdoor industries drops by as much as one hour per day compared to temperatures in the 76-80°F range.

While there is as yet limited research regarding the differential in such 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[7]) suggests that there may be important differences in impact magnitudes by occupation.

Panel Estimates at the Macro (economy) Level

Recent studies also document evidence suggestive of labor productivity impacts at the level of local and national economies. Such macroeconomic impacts of temperature shocks are of particular relevance to economic policy in that they may inform our understanding of the potential impacts of future climate change as well as longstanding debates over the deep determinants of economic growth and convergence (Sala-i-Martin, 1997) and the comparative wealth of nations (Smith, 1776).

Hsiang (2010) measures the impact of hot summers on output in 28 Caribbean countries from 1970 to 2006, while controlling for precipitation and cyclones. Unusually hot summers lead to nonagricultural output declines of 2.4% per 1°C. Two of the three affected sectors are service-oriented and provide the majority of output in these Caribbean economies, while the other affected sector is industrial (mining and utilities).

Dell, Jones et al. (2012) measure the effect of hotter-than-average years on industrial value-added output within a global sample of 124 countries over the period 1950 to 2003. They find that hotter years are associated with lower industrial output, to the tune of minus 2% per degree Celsius, but only in poor countries (countries with below median world income in 1990. Jones and Olken (2010) use trade data and find similar results: a 2.4% decline in exports per degree C hotter-than-average year in poor countries.

Park and Heal (2013) use similar cross-country weather data to Dell, Jones et al. (2012) but different income data and test the hypothesis that, due to the heterogeneity in initial climate zones, labor productivity impacts of a given temperature shock will have heterogeneous effects by average climates. They find that hotter-than-average years lead to lower-than-average output and implied total factor productivity in already hot countries, and the reverse effect in colder countries.

Evidence from the United States strengthens the case for macroeconomic impacts driven by temperature stress and its effect on labor productivity. Using county-level income data from the United States, Hsiang and Deryugina (2014) find a negative relationship between extreme temperature stress and lower economic activity. Average productivity of individual days declines roughly linearly by 1.5% for each 1C (1.8F) increase in daily average temperature beyond 15C

[6] 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.
[7] Graff Zivin and Neidell (2013, 2014)

(59F). Relative to a day with an average temperature of 15C (59F), a day at 29C (84F) lowers annual income by roughly 0.065%. This amounts to -23.6% lower productivity on a hot day versus an optimal day. Similarly, Park (2015) uses county-level payroll data from 1986 to 2012 and find that hot days (above 80°F, 26°C) have a significant negative impact on output per capita. A county with one additional day above 90°F (32°C) experiences 0.048% lower per capita payroll, an effect that is magnified in regions that are not accustomed to heat stress at such extremes.

Both Hsiang and Deryugina (2014) and Park (2015) find impacts on non-agricultural sectors, suggesting that the impact is not due to contemporaneous decline in agricultural yield. Furthermore, Park (2015) finds that the sectors that the National Institute of Occupational Safety and Health designate as 'highly exposed' experience significantly larger impacts[8].

In summary, there seems to be a significant negative impact of temperature stress on variables that affect labor productivity. There is remarkable consistency in the sizes of the effects across levels of analysis, with per degree C point estimates clustered around minus 2 to 3%, although there is some evidence that the impacts are smaller in developed economies such as the United States.

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.

While further research is needed to incorporate adaptive responses, the recent literature provides valuable clues to researchers and policymakers regarding the potential welfare consequences of climate change.

What does this mean for thinking about Global Climate Change and Poverty?

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 multiple generations. Debates concerning the correct discount rate focus primarily on the issue of inter-generational equity[9]: the realized distribution of costs and benefits between current and future generations[10]. A related issue has to do with intra-generational equity, which involves the ways in which costs and benefits are distributed across individuals in any given generation, for instance, between developed and

[8] These sectors include construction, mining, utilities, transportation, and wholesale.
[9] 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.
[10] For a review of recent research on the issue of intertemporal discounting in the context of climate change, see Arrow et al (2014).

developing economies. "Costs" in this context usually refers to the costs of mitigating climate change; "benefits", the damages avoided from doing so.

From the perspective of development economics, an emphasis on poverty alleviation implies a particular stance on the optimal extent of intra-generational equity[11]. This often assumes a social welfare function that puts additional emphasis on the consumption (e.g. log utility) and/or realized individual-specific welfare (e.g. progressive welfare weighting on part of a global social planner) of the world's poor. To the extent that a warmer world may be one in which adverse productivity impacts due to heat stress become more frequent, and insofar as decision-makers today (through various policy decisions regarding climate mitigation, adaptation, and economic development) will affect the rate and intensity of future warming, assessing the distributional consequences of these effects is of timely importance.

Studies of the heterogeneity of impacts from climate change within countries are scarce (Tol 2009). Still, economists have noted that there are a priori reasons to believe that the effects of climate change would not be homogenous within countries, and that the impacts may be regressive. Some have suggested that particular economic sectors (like agriculture), regions (like already heat-stressed areas, marginal climates), and age groups (like the elderly) are more likely to be heavily affected than others (O'Brien, Sygna et al. 2004).

While the labor productivity channel – and mechanisms of welfare loss arising from thermal stress of the human body more generally – represent only one of many climate damage channels, its ubiquity may make it an important area for future research assessing the distributional heterogeneity of impacts across various income or demographic groups.

A Conceptual Framework

In this section, we develop a simple extension of the standard asset-based framework presented in Hallegatte et al, 2014, Attanasio and Székely (1999), and Carter and Barrett (2006), focusing on the ways in which temperature shocks may affect labor productivity, and ultimately, social welfare. The framework suggests several key factors which may make the distributional impacts from climate change highly regressive both across and within countries, at least as it operates through the labor productivity channel.

Let household utility be written as: $Max\ (c)\ s.t.\ p*c \leq y$

Where c is a vector of household consumption of goods and services, p is a price vector, and y denotes total household income.

Households generate income through a number of channels, the aggregation of which comprises total income (y) for household i: $yi = \Sigma \alpha j,, iJj = 1$

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

[11] For instance, the official mission of the World Bank is the eradication of global poverty.

physical capital (equipment, land, livestock). The term βj 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 shocks. Specifically, labor productivity depends on T, the ambient temperature (specifically, the wet-bulb globe temperature, which is inclusive of humidity), and $\kappa \in J$ the level of adaptive capital (e.g. air conditioning, clothing, and electric infrastructure): $(T,)$

Temperature stress is expressed as absolute degree deviations of the ambient temperature from the optimal temperature zone noted in medical studies (i.e. room temperature). Adaptive capital investments enter as a modifier on the experienced temperature of the worker.

The central insight arising from the task productivity literature is that $d\beta ldT<0$; that is, task productivity associated with labor-intensive production activities will decline as temperatures deviate from the thermoregulatory optimum, which is typically thought of as being between 18 and 22 degrees Celsius (64 and 72 degrees Fahrenheit).

Total labor income depends on two additional factors: labor effort $E \in J$, and labor supply (hours) $H \in J$, both of which can be thought of as comprising parts of the total bundle of livelihood-generating assets α. Heal and Park (2013) formalize the impact of temperature stress on labor supply, effort, and productivity, and show that, with minimal assumptions on the functional form of utility[12], temperature shocks away from the thermoregulatory optimum will lead, in addition to the raw task productivity effect documented in the medical literature, to reduction in effort (E), labor supply (H), or both[13]. Thus, one might reasonably assume that, in most contexts:

$d\beta ldT<0$; $dEdT<0$;$T<0$

That is, temperature stress results in diminished task productivity, reduced labor effort, and reduced labor supply, net of optimizing decisions by workers. For a given temperature shock above (or below) the thermoregulatory optimum, and holding adaptive investments fixed, we expect the individual to optimize in response to reduced task productivity (and increased direct disutility) by reducing labor effort, labor supply, or both. Note that, despite the varying determinants of labor supply, labor effort, and task productivity in the context of temperature stress, all three factors have the same comparative static.

As such, one would expect extreme temperature to adversely affect income, unless adaptive investments are sufficient to offset the adverse productivity impacts:

$dydT \leq 0$

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[12] Namely, log utility and the absence of strong income effects.

[13] The institutional context in which the worker is situated may matter in this instance. The way in which hotter temperatures affects the marginal utility of leisure may be an important factor here. If it reduces the marginal utility of leisure disproportionately more than it affects the disutility of labor, and there are sufficiently rigid contracts such that the link between effort and wages is not direct, then you might have the perverse outcome of hotter days leading to more time spent engaged in work.

This may be true at the individual (Sudarshan et al, 2014; Cachone et al 2013), household, or even macroeconomic (Dell, Jones, Olken, 2011; Hsiang, 2010; Park and Heal, 2014) levels of aggregation.

Investment in adaptive technologies may offset some or all of these negative impacts. However, note that, if the cost of these adaptations is non-zero, the overall welfare impacts of a given temperature shock will be non-zero as well. This is true even if the realized, post-adaptive-investment productivity shock is reduced to close to zero[14].

The magnitude of this temperature-productivity impact may depend on the type of occupation. One would expect manual, outdoor occupations, which are typically subject to greater heat stress which cannot be easily offset using adaptive technologies, to suffer larger productivity declines for a given temperature shock ($d\beta ldT$), and thus greater total income shocks ($dydT$), inclusive of subsequent adjustments in labor supply and effort.

Welfare Analysis and Distributional Equity

The central challenge from a welfare perspective is to measure the true social cost associated with future climatic change, and the additional temperature-related productivity shocks that may arise. To the extent that anthropogenic climate change may result in the exacerbation of existing temperature-related labor productivity impacts, one might think of inaction on climate mitigation at the global level as analogous to a policy action which saves mitigation costs today but imposes a cost or tax on labor in the future.

As noted above, in addition to aggregating the discounted stream of benefits (damages) that arise from (not) engaging in mitigation today over the course of the ensuing decades and centuries, assessing these social costs also involves aggregating over billions of individuals. This requires assumptions about the underlying social welfare function, which may or may not take society's preferences toward progressivity or equality of opportunity (Mankiw and Weinzierl 2009) into account. One might also want to quantify the 'hidden', non-market costs of temperature stress, for instance, in the form of direct disutility from heat stress or adverse health consequences[15].

To assess the distributional impacts of such a policy, define an aggregate social welfare function, W, as: $W=\Sigma\theta(c;y(T,E,\kappa,H))Ni=1$

Where θi denotes welfare weights for individuals i…N in the population. Depending on the social planner's preferences for equity (e.g. Rawlsian, utilitarian, etc), these weights 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 $ui(c)$ will also affect the progressivity or

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[14] In other words, even if a worker, due to real (or perceived) productivity impacts of heat, invests κ dollars in air conditioning equipment and thus is able to completely offset the adverse labor productivity impacts of temperature stress, the welfare impact of temperature stress would be at least κ dollars.

[15] Similarly to the way in which Chetty (2009) finds the welfare costs of reducing unemployment insurance coverage (duration) to be understated by the observed aggregate response (in terms of search effort), it may well be the case that the measured macroeconomic responses to heat shocks under (or over) estimate the true social cost. This could be due, for example, to underlying labor market rigidities, consumption commitments, human capital and health shocks that are not recognized or counted in national accounts.

regressivity of any climate-policy decision, to the extent that it may or may not put a higher emphasis on consumption by poorer individuals.

The distributional impacts of an increase in global average surface temperatures ($\bar{\bar{T}}$) will then depend on several factors.

First, it will depend on household i's realized exposure to temperature stress due to global warming; that is, (1) the mapping from global climate change ($\bar{\bar{T}}$) to local weather shocks (Ti).

In addition, it will depend on the covariance between this realized incidence of additional extreme heat events in the locality of household i, (Ti), and household i's total income, or (2) temperature-income covariance, $cov(Ti,yi)$; household i's endowment of adaptive capital, or (3) temperature-adaptation covariance, $cov(Ti,,\kappa i)$; as well as (4) the covariance between occupation-specific temperature sensitivities and the total income or assets of those households with individuals engaged in temperature-sensitive occupations, $cov(d\beta ldT,yi|Hl>0)$.

Other possible determinants may include the average age or physiological vulnerability of poorer households; the correlation between expected temperature stress and changes in prices of particular necessity goods; the correlation between expected temperature stress and other climate stressors that may affect non-labor outcomes, including agricultural productivity; the correlation 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).

More generally, one may think of the key determinants of distributional equity in the context of a basic hazard model: namely, (1) exposure to the hazard, in this case extreme temperature stress, and (2) adaptive capacity, which may take the form of financial or other resources.

The Distributional Impacts of Temperature Related Labor Productivity Shocks

What do we know about the expected distributional impacts of labor productivity shocks arising from future climate change? Based on the above analysis, the following dimensions may provide suggestive evidence as well as a guide to further research.

(1) Exposure

The relationship between average global warming and realized extreme heat events is far from certain, especially given the myriad factors that influence local weather patterns (e.g. urban heat island effects, interactions with precipitation and atmospheric moisture content). Moreover, projections regarding increases in extreme heat events are complicated by the fact that some locales will experience concomitant reductions in extreme cold events, which may or may not have an offsetting welfare impact on net.

Will areas with poorer households experience more extreme heat events? 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 temperature increases at higher latitudes, which tend to be more sparsely populated, and often involve richer economies. 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, which tend to be more densely populated. Even if researchers take current climate models as accurate representations of heterogeneous local weather changes, it is as yet unclear whether, on net, global warming will lead to greater exposure to heat stress in higher or lower latitudes.

If, however, it turns out that the bulk of labor productivity impacts from climate change arise from a relatively small number of extreme heat events, one would expect the impacts to be regressive to the extent that already hot and poor places will experience a larger increase in the number of extremely hot days. The extant literature suggests that there may be significant non-linearity in temperature impacts, and that the most noticeable labor productivity impacts occur beyond some heat threshold (between 25° and 32°C).

Even if climate change is simply a spread-preserving mean-shift of average temperatures, this would likely manifest as a greater additional number of extreme heat days for places that are already warmer on the whole, such as Central America or Sub-Saharan Africa, than for places that are currently relatively cool, such as France or Germany. This is an area in urgent need of more accurate climate modeling.

Demographic factors also suggest that realized exposure to labor productivity impacts may be more heavily concentrated on poorer individuals. 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.

Given life-cycle income trajectories, there are reasons to believe that the very young and very old may be those who, regardless of their permanent income, are at a stage of life where their current income is relatively low. It is unclear whether extreme heat has different effects on relatively young and old segments of the working age population: for instance, between a 25 year-old versus a 55 year-old. And, of course, low levels of income often mask higher levels of wealth for retired individuals. But to the extent that many developing countries may not have adequate social safety nets for young orphans or retired elderly, the labor supply and labor productivity impacts of extreme heat stress may fall along regressive lines.

Poorer individuals are also more likely to live in areas with higher levels of ambient air pollution, which has been shown to interact with temperature in harmful and even deadly ways. For instance, in the United States, individuals with low incomes below ($15,000) live in MSAs with an air quality index (AQI) that is six times lower than those with higher incomes (above $75,000) (Graff Zivin and Neidell, 2014).

Poorer households are more likely to comprise individuals who work in sectors that are more sensitive to temperature stress: namely, manual labor intensive industries, and outdoor work intensive sectors such as agriculture or construction. It is also likely the case 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.

(2) Adaptive Capacity

Perhaps most importantly, 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); for example, living 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.

Temperature and Household Wealth within Countries

In this section, we present data from the Demographic and Health Surveys (DHS) and the Climatic Research Unit (CRU) to provide a first pass at quantifying the distributional consequences of added extreme heat stress due to climate change, and the labor productivity impacts that this may entail. The objective is to utilize household wealth and occupation data to assess the bias in the exposure variable noted above.

For instance, if poorer households tend to be located in hotter places within countries, one might expect the labor productivity impacts from a warmer world to be distributionally regressive. Alternatively, if for whatever reason poorer households are located in environments that are less prone to extreme heat stress currently, and less likely to experience added heat stress in the future, one would expect the opposite to be true. Occupational data can provide additional insight, on the basis that some jobs are more sensitive to extreme temperature stress than others (e.g. agriculture and construction versus white-collar work).

Household wealth data are taken from the Demographic and Health Surveys (DHS) for 52 countries across Asia, Africa, South America, and Europe. The DHS Program constructs a relative wealth index for each country using detailed asset surveys, which acts as a composite measure of household cumulative living standards. The universe of households surveyed includes over 690,000 households.

Wealth scores are computed based on household ownership of a standard set of assets, housing construction materials, and quality of water access and sanitation facilities. The contrived scores are more difficult to interpret than simple income data, but they are useful for our purposes precisely because reliable government-collected income data are unavailable in many of the poorest countries. In order to make interpretation more intuitive, we have converted the scores into percentiles for all our analysis.

To assess local climatic characteristics, weather data are taken from the Climatic Research Unit (CRU) at the University of East Anglia. Specifically, CRU provides time-series 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.

We perform ordinary linear regression of household wealth percentile on the average temperature of the hottest month experienced by households in the DHS survey year. The baseline regression takes the following form: $y_{i,}=\beta_0+\beta_1 T_{i,c}+\beta_2 W_{i,c}+\beta_3 Z_{i,c}+\epsilon_{i,c}$

$y_{i,c}$ denotes wealth index percentile of household i, country c. $T_{i,c}$ denotes the average temperature of the hottest month in the centroid of the nearest grid cell to household i. $W_{i,c}$ represents a vector of controls for other weather variables, including humidity, average precipitation, and elevation. Z_i, represents a vector of economic controls, including household size and a rural/urban dummy[16].

To the extent that poorer households tend to be located in hotter environments – that is, β_1 is negative – this would suggest that the labor productivity impacts from future climate change would likely fall along regressive lines.

The recent literature on temperature and human physiology (documented above) provides an additional informative prior for this analysis. If it is the case that extreme temperatures – be it hot or cold – reduce task and labor productivity, one would expect heterogeneity in this relationship by average climate. That is, in countries with relatively warm average climates, warmer places would correspond to areas that are subject to greater extreme heat stress and its attendant negative impacts on labor productivity and labor supply. 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[17].

The Relationship between Temperature and Household Wealth

Running the baseline regression for each of the 52 country sub-samples yields the following results (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

[16] The hottest month is chosen as opposed to the average month because extreme temperatures are the proposed driving force behind wealth-temperature sensitivity, and average temperature would wash out both extreme heat and extreme cold. Due to the design of the DHS survey apparatus, we weight households in the dataset by their probability of being sampled in order to obtain coefficients that are representative of the entire population of a country. We also cluster and stratify standard errors based on primary sampling units (PSUs) provided by DHS, and strata built by grouping region and urban/rural category. (See the appendix for greater detail on standard errors.)

[17] 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.

relationship, and 18 show a significant positive relationship. Most of the countries with statistically insignificant relationships feature relatively little cross-sectional variation in average temperature (for instance, the standard deviation of average hottest month temperature across households in Moldova is only 0.51 degrees C). The vast majority of those countries exhibiting negative relationships are tropical countries such as Ghana, Zimbabwe, or Egypt.

On the other hand, most though not all of the 18 countries featuring a positive relationship are cold or temperate ones, including Peru, Lesotho, and Kyrgyzstan. While many other omitted variables may be contributing to this relationship, these findings are consistent with a model of temperature stress affecting labor productivity and supply through physiological channels[18].

For countries with average temperatures below 20 degrees C, the average significant regression coefficient is 1.8 percentiles per degree C. For countries with average temperatures above 20 degrees C, the average significant regression coefficient is -0.9 percentiles per degree C. For extremely hot countries – say, those with average temperatures above 27 degrees C – the average significant regression coefficient drops to -2 percentiles per degree C.

While it is difficult to compare the magnitudes of these gradients with previous findings (e.g. Horowitz, 2009), which are based on real per capita income, the per degree Celsius decline for hot countries is broadly consistent with the cross-country gradient of -8% income per capita per degree C. Urban households are richer on average, as are those with larger families. Precipitation is positively correlated with household wealth, consistent with the notion that in primarily agricultural environments, more rainfall is associated with higher yields.

Taking Nigeria, the largest country in Africa by population and GDP, 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).

[18] There are a few notable exceptions. Indonesia, the Philippines, Rwanda, Jordan, and the Ivory Coast all exhibit significant positive correlations between temperature and household wealth.

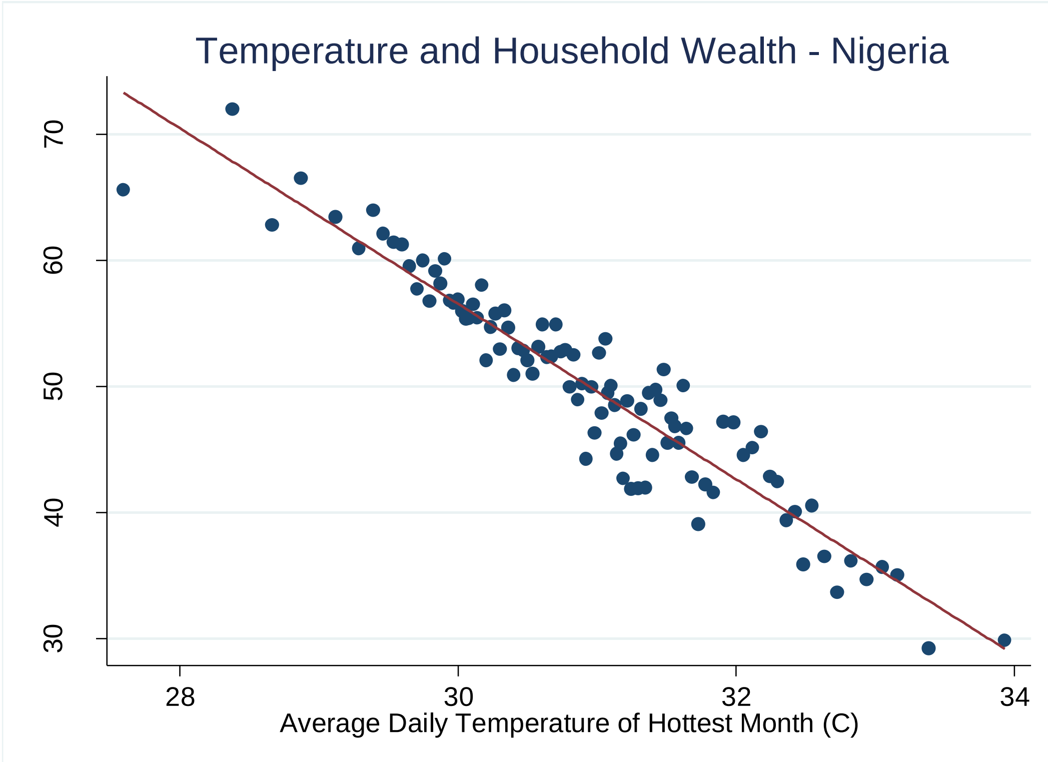

Figure 3: Average hottest month temperature and Nigerian household wealth by temperature bin. Controls for precipitation, elevation, household size, and urban/rural included.

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[19]. 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.

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, 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.

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

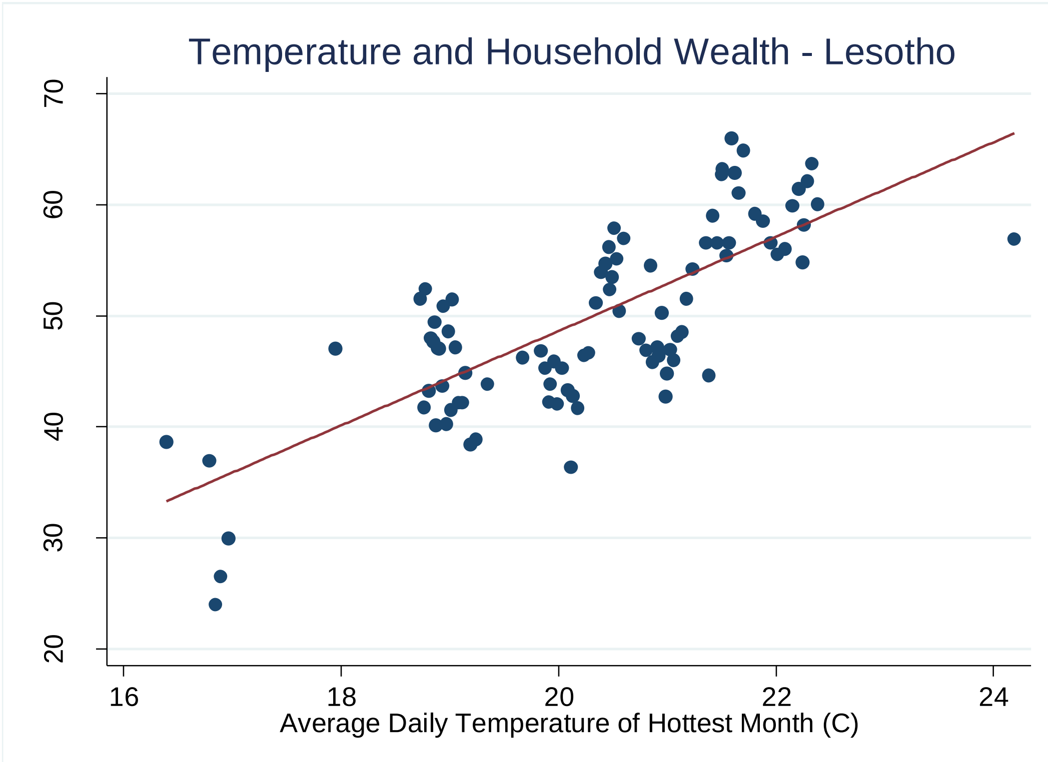

Figure 4: Average hottest month temperature and household wealth by temperature bin for Lesotho. Controls for precipitation, elevation, household size, and urban/rural included.

Both of these relationships could be due to the cumulative effect of lower productivity in these heat stressed areas. They could, of course, also be a product of any number of omitted characteristics, including systematically less effective institutions and cultural norms, correlation with soil quality or other climatological factors correlated with extreme heat, or country-specific historical factors which have caused the hotter parts of the country to be less economically developed. They could also, in principle, be due to individual sorting based on amenity value of climate[20]. However, while one cannot for these and many other reasons claim that it is the high heat exposure that has caused lower levels of household wealth in these areas, the relationship is striking in its significance and consistency across the vast majority of the countries surveyed.

To focus on the impact of very extreme heat, 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. For a conservative estimate, we take the 7 hottest countries with significant regression results. These countries have hottest monthly temperatures greater than 29°C. 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. Out of those 7 countries, all show the expected

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[20] To the extent that milder or more temperate climates can be thought of as a housing amenity, one would expect richer households to systematically select into areas that have this amenity in greater abundance, a dynamic that would manifest as a negative correlation between temperature and household wealth in the cross section.

negative coefficient. Thus, for the majority of "hot" countries in the dataset, we confirm the hypothesized negative relationship between temperature and household wealth.

For the majority of "cold" countries in the dataset – countries with coldest monthly average temperatures below 10 degrees C – we confirm the hypothesized opposite relationship. 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.

The Significance of Occupations

We will now examine household occupations to determine whether the poor, in addition to living in more weather-extreme (hot or cold) regions, also work jobs which make them more exposed to the effects of temperature stress, such as worse health outcomes and diminished labor productivity.

The DHS Program provides occupational data alongside the wealth data we've used above. Specificity varies a great deal between countries, with some having hundreds of distinct occupational categories. But in general, DHS provides 9 aggregated categories: professional/technical/managerial, clerical, sales, agricultural, household and domestic, services, skilled manual, unskilled manual, and army. Occupational data were not collected for all surveyed households. Out of the nearly 700,000 observations in our dataset, about 74% provide some occupational information, so we still have a sufficient sample size for robust analysis.

We have defined a binary variable for occupational exposure to temperature stress. Workers are considered exposed if they are employed in agriculture, unskilled manual labor, or the army.

We will address the following questions:

- What is the relationship between occupational exposure and household wealth?
- What is the relationship between occupational exposure and temperature?
- How significant is agriculture in driving these relationships?

We will then take a detailed look at Nigeria as a case study.

We were unable to obtain complete occupational data for Cambodia, Angola, Uganda, Mali, or Bangladesh, so they will be excluded from this portion of the analysis, leaving us with 47 countries.

Occupational Exposure and Household Wealth

We find a clear negative relationship between exposure likelihood and household wealth in all 47 countries. 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.

Occupational Exposure and Temperature

The relationship here is somewhat less clear-cut. In a logit regression of an exposure dummy on average temperature, controlling for urban/rural status, we find 21 results (45% of the total 47) significant at $p<0.05$, or 23 (49%) significant at $p<0.1$. Taking only the results which are significant at $p<0.05$, 9 have negative coefficients and 12 have positive. In other words, 57% of countries with significant regression results exhibit a positive relationship between exposure likelihood and temperature. There is no evident heterogeneity of the regression results between hot and cold countries. Detailed regression results are presented in the Appendix, Table C.

The Role of Agriculture

In the context of developing countries, it almost goes without saying that agriculture plays an outsized role in many economic phenomena. For partners' occupations, agriculture makes up 37.9% of workers, unskilled manual labor makes up 7.77%, and the army makes up 0.22%. For respondents' occupations, agriculture makes up 38.2%, unskilled manual labor makes up 4.25%, and the army makes up 0.11%. As a result, it is worth looking under the hood to determine whether the overall coefficients found above also apply to the smaller unskilled manual labor and army subcategories.

In a simple logit regression of a non-agricultural exposure dummy on household wealth percentile, we find 39 results (83% of the total 47) significant at $p<0.05$, or 40 (85%) significant at $p<0.1$. Taking only the 39 countries significant at the 95% confidence level, 16 show negative coefficients and 23 show positive coefficients, essentially indicating that in just over half of the sampled countries, there is a positive relationship between wealth and likelihood of working in unskilled manual labor[21]. 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 grouped countries by their World Bank income level classifications: low, lower-middle, and upper-middle. The World Bank also provides a high-income category, but no such countries are present in our dataset. Out of the 39 countries with significant regression results, 17 are low-income, 17 are lower-middle-income, and 5 are upper-middle-income. 82% of low-income countries have positive coefficients, then 41% of lower-middle-income countries, then 40% of upper-middle-income countries. This confirms the intuition that a country's development level affects the relationship between wealth and occupations therein.

Case Study: Nigeria

Nigeria illustrates the negative relationship between household wealth and occupational extreme temperature exposure well, with a logistical regression coefficient of -0.04, significant at the 99% confidence level. This yields the following regression equation:

[21] 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.

$$E = \frac{1}{e^{0.0413874\,W - 1.59726} + 1}$$

Where E represents probability of occupational exposure from 0 to 1, and W represents household wealth in percentile units. So, for example, 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.

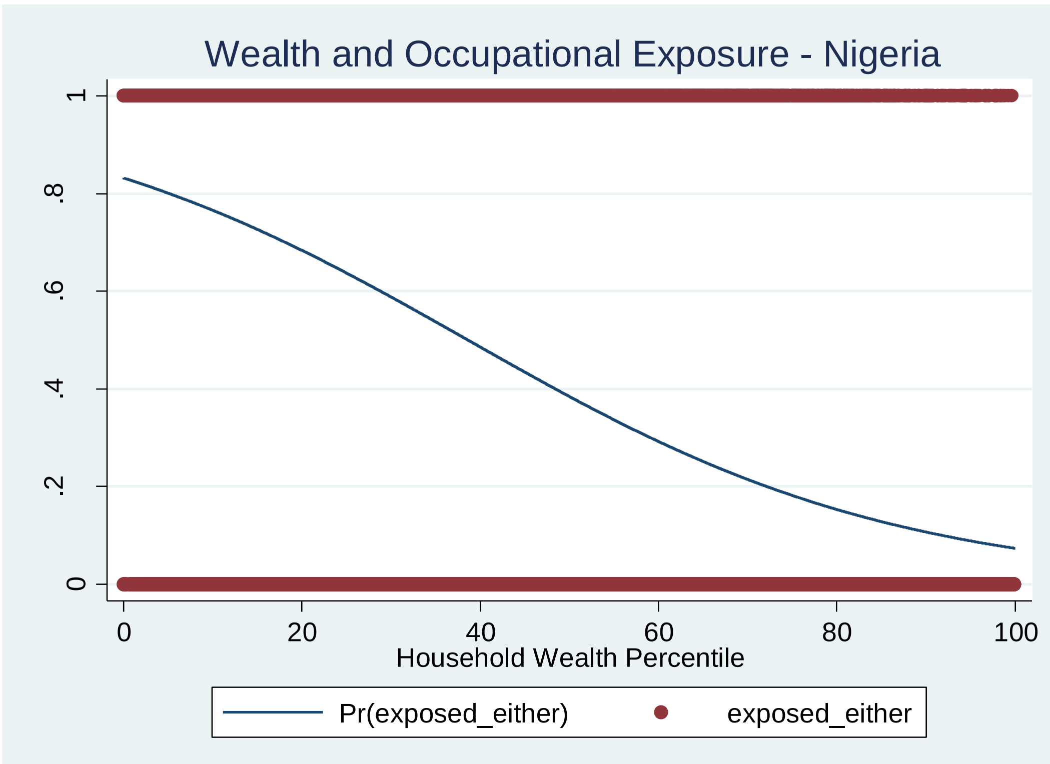

Figure 5: Occupational extreme temperature exposure and household wealth in Nigeria, values fitted by logistical regression. Dummy is 1 if either parent is exposed, 0 if neither.

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.

Policy Implications

Three main policy implications emerge from this analysis.

Social Cost of Carbon (SCC) estimates biased downward?

The existence of labor productivity impacts from temperature stress may imply that social costs of carbon are systematically understated. Most integrated assessments of climate damages do not include labor productivity impacts as part of the suite of damage channels that may affect human welfare. As Tol (2009) notes in a review of social cost of carbon estimates, "the direct impact of climate change on labor productivity has never featured on any list of missing effects." If it is indeed the case that losses due to labor productivity decline are on the order of two percentage points of output per degree Celsius, then this new channel alone would imply social costs of carbon that are much higher than current estimates, which, irrespective of discount rates, take damages to be on the order of several percentage points of world GDP.

Of course, as stated previously, the exact magnitude of these effects will depend greatly on assumptions regarding adaptation. But this is a caveat that applies to all damage mechanisms currently present in integrated assessment models. In this sense, new evidence regarding the potential labor productivity impacts of climate change suggest ex ante that current mitigation targets are more likely to be less stringent than socially optimal – all other factors (e.g. discount rates, adaptation) remaining equal.

Distributional impacts likely regressive, but more research is needed

Moreover, there are reasons to expect the distributional consequences of this "new" damage channel to be largely regressive. Both across countries as well as within countries, poorer households tend on average to be those who are likely to experience increased incidence of heat stress. In many African countries, the strength of the heat-poverty correlation is striking, with within-country gradients of minus 10 percentiles of household wealth per degree Celsius or more in some cases. To the extent that this kind of relationship hold generally and given the fact that most of the world's poorest countries are in tropical climates, one would expect the labor productivity impacts of climate change to cause disproportionate welfare burdens on the world's poor, due simply to the relationship between poverty and geographic exposure to heat stress. This would be true even if climate change simply manifests as a spread-preserving mean-shift in the average weather distribution; likely more severe if climate change entails an increase in the spread (i.e. more extreme events).

However, the preliminary analysis presented above suggests that country-specific context may matter considerably. While poorer households tend to be located in more heat prone areas overall, in colder climates such as the former Soviet Union or the Tibetan Plateau the relationship between temperature and wealth seems to be reversed. In countries such as Lesotho, poorer households tend to live in colder environments, perhaps because these places are more 'marginal' relative the local average (which suggests sorting based on climate amenities), perhaps because extreme cold reduces productivity as well. Whatever the cause, this positive relationship between temperature and wealth suggests that, at least in these contexts, climate change may actually help reduce the welfare burden imposed by extreme temperature stress on the poorest households.

Effective Adaptation Policies will be critical

While research quantifying the extent of adaptive capacity (e.g. air conditioning penetration) in developing countries remains thin, it seems almost tautologically true that poorer households will in general have fewer disposable resources to adapt to increased heat stress due to climate change. In this sense, it seems that identifying cost-effective measures to protect the most exposed populations against extreme heat stress may be an important policy priority. This will be true almost regardless of the amount of mitigation that is achieved in coming decades, due largely to the climate change that is already 'baked into' the earth's atmosphere as a product of past emissions.

More generally, the causal impacts of temperature stress on labor productivity highlight the important intersections between environment and development policy. This is especially true in the context of climate change, which has been called the mother of all externality problems (Weitzman 2012), and highlights important gaps in our understanding of the welfare implications of environmental stress across varying levels of development (Greenstone and Jack 2013). It remains to be seen whether policymakers who are accustomed to performing cost-benefit analyses in the context of isolated externality and public good problems (for example, separately for air quality regulation and electric infrastructure projects) can effectively incorporate these important environment-development interactions in the policymaking process.

Conclusion

This paper attempts three primary undertakings. First, it surveys the recent empirical literature on the economic consequences of temperature stress, with an emphasis on panel estimates that successfully identify causal impacts of short-run weather variation. There is remarkable consistency in point estimates across micro- and macro-contexts, suggesting that the magnitude of historical labor productivity shocks due to temperature stress has been around 2 percentage points per degree Celsius above room temperature.

Second, it provides an analytical framework for assessing the possible distributional impacts of this hitherto unincorporated climate damage channel, which highlights the factors that are relevant in determining the ways in which climate change may affect the world's poor.

Third, it uses household wealth data from the DHS to uncover within-country temperature-wealth gradients in 52 different developing economies. The results suggest that there is a strong correlation between extreme heat and lower household wealth, and a weaker but still statistically significant relationship between extreme cold and lower wealth, both of which are consistent with accumulated disadvantages operating through the negative productivity impacts of temperature stress, but may suggest slightly different distributional implications.

Two main lessons arise from this analysis. First, the labor productivity impacts from climate change may be non-trivial, although the exact magnitude of additional labor productivity losses that may arise in the future remains uncertain, due in large part to the fact that the extent and costs of adaptation in this context remain unknown. Social cost of carbon estimates may be systematically biased to the extent that they do not include these effects.

Second, there seem to be ex ante reasons to believe that, irrespective of the exact magnitude, the distributional consequences of this effect will likely be regressive, particularly in the absence of targeted adaptation funding for more vulnerable populations.

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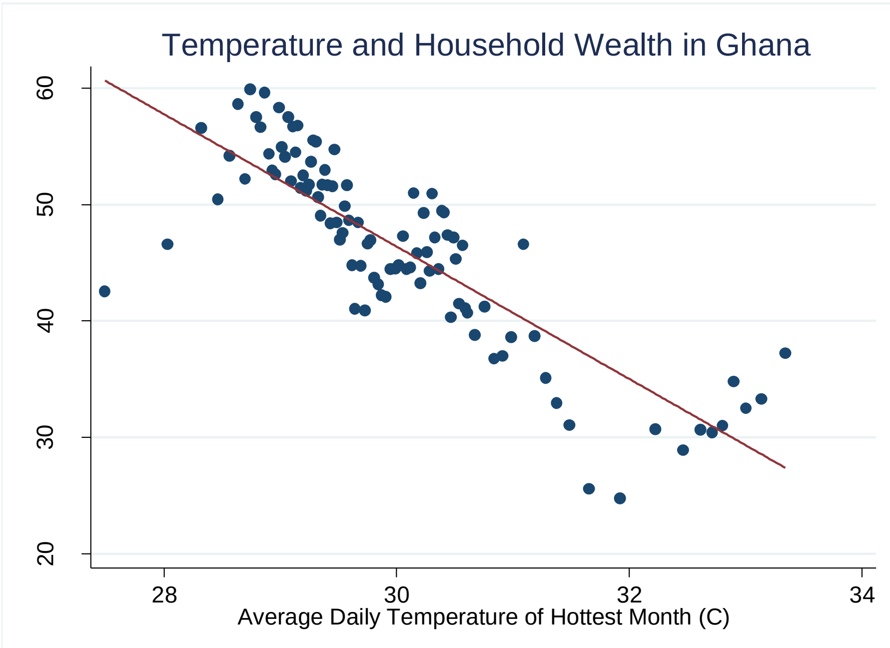
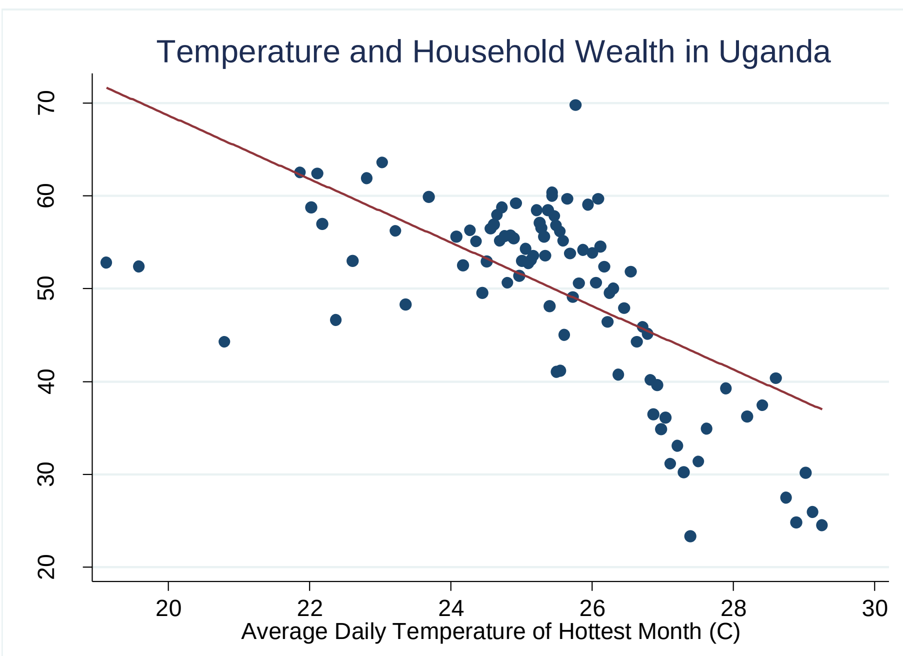
Appendix

Temperature and Household Wealth in Representative Hot Countries

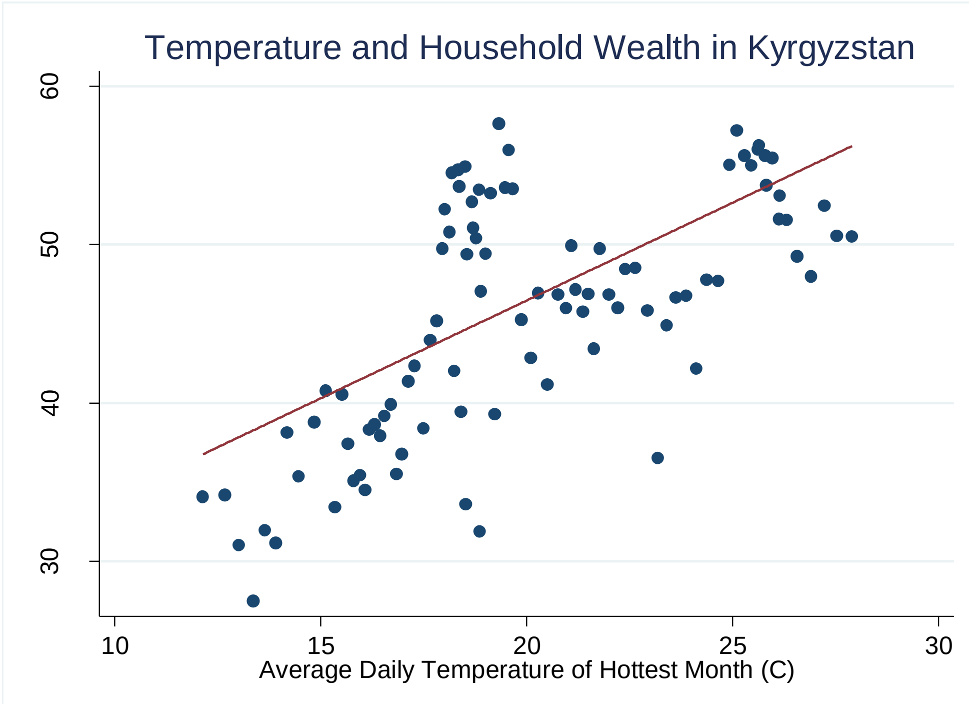


Controls: household size, urban/rural status, altitude, and precipitation.

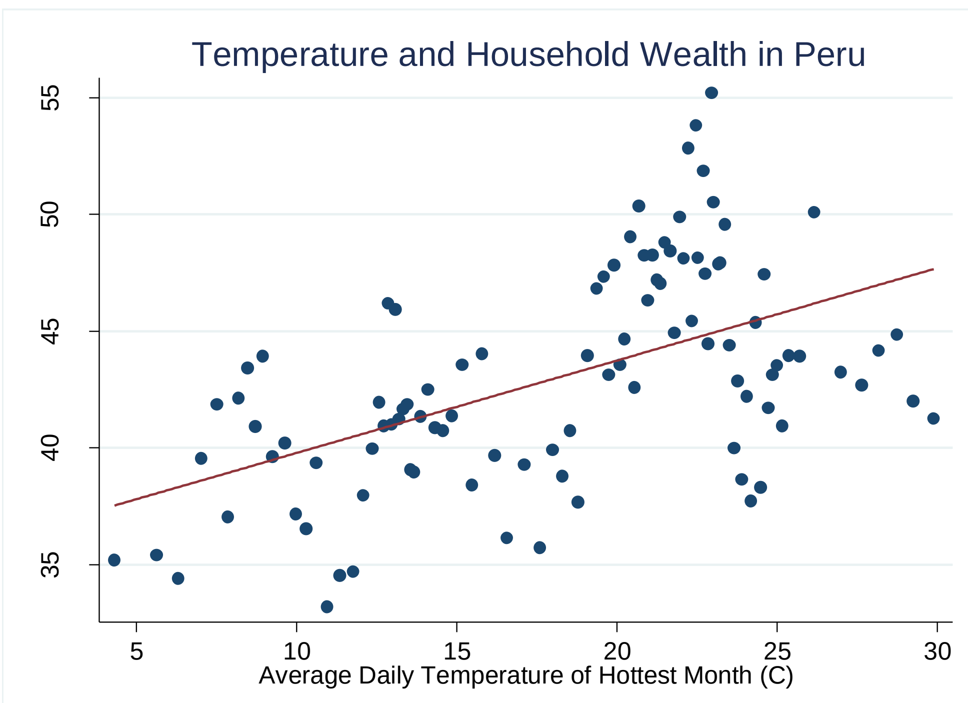


Controls: household size, urban/rural status, and precipitation.

Temperature and Household Wealth in Representative Cold Countries

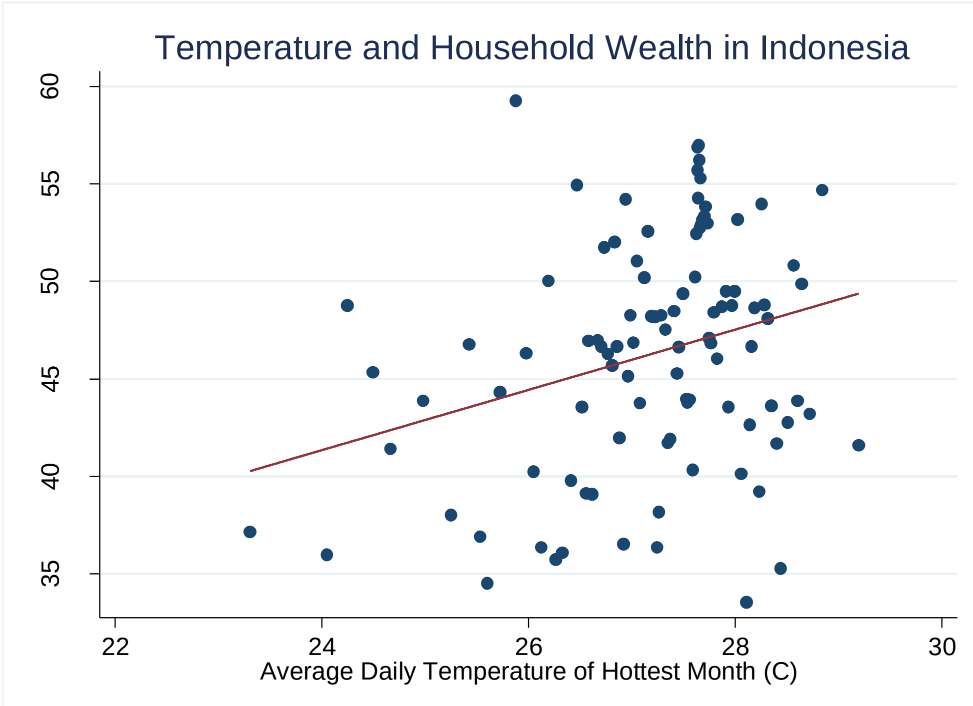


Controls: household size, urban/rural status, and precipitation.

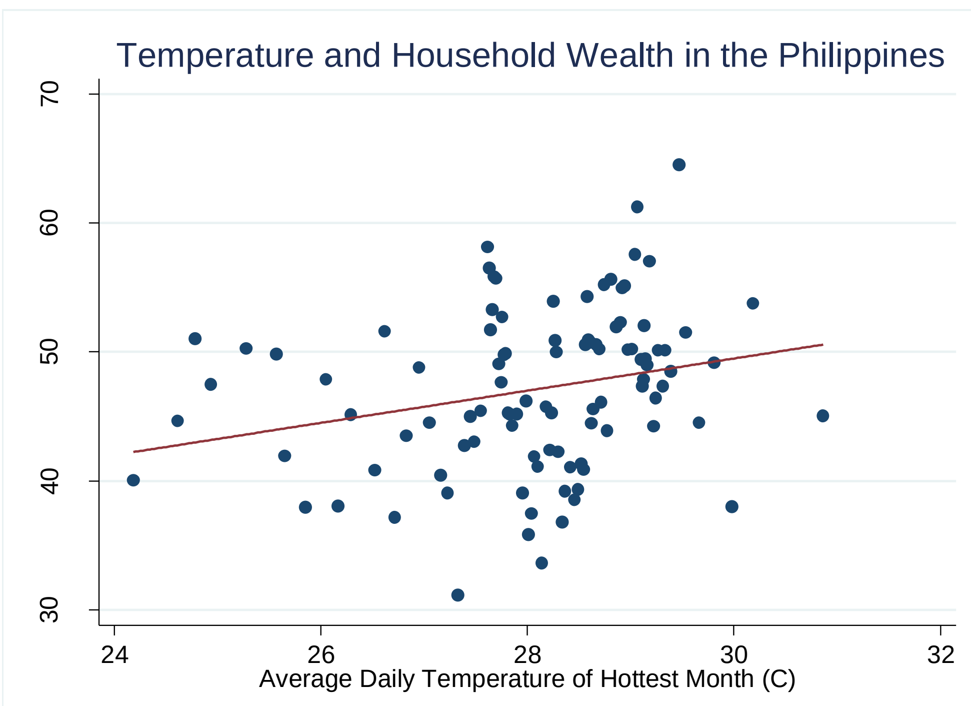


Controls: household size, urban/rural status, and precipitation.

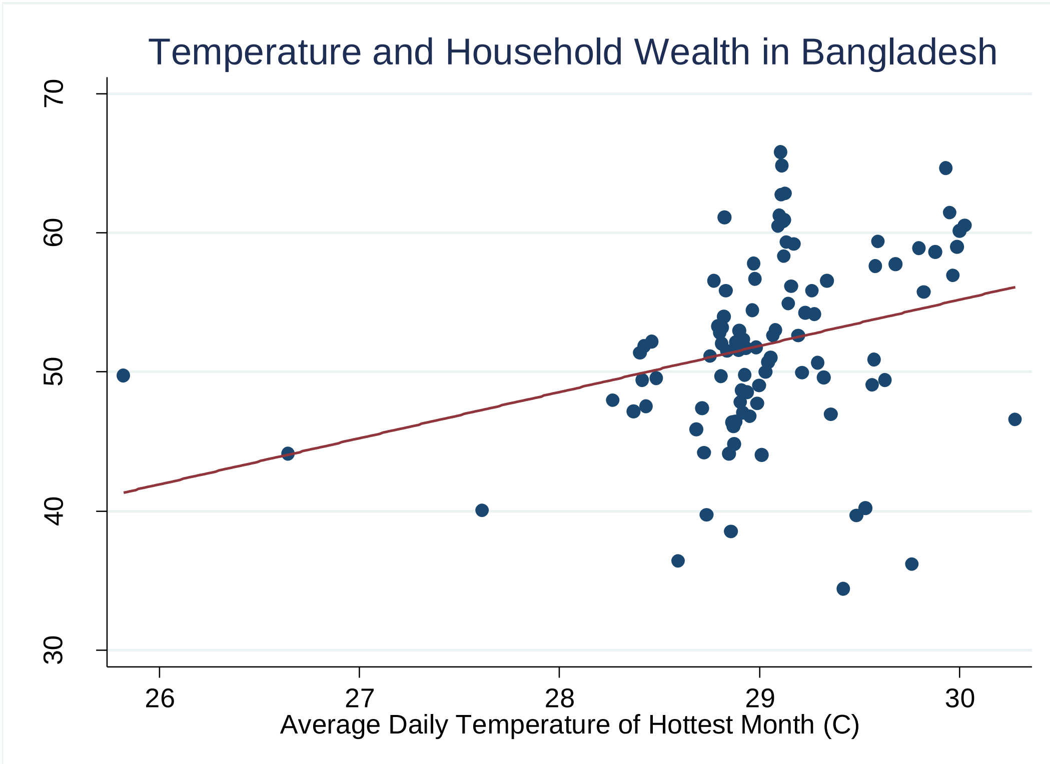
Temperature and Household Wealth: Notable Exceptions



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 A: Summary Statistics and 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 dataset, 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.

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	0.081556083	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 B: Summary Statistics and Logit Regression Coefficients by Country

Country	Standard Error	Coefficient	T-statistic	P-value
Burundi	0.011874	-0.1455	-12.2541	3.85E-29
Rwanda	0.007991	-0.11149	-13.9517	5.41E-37
Madagascar	0.004581	-0.09444	-20.617	3.7E-70
Ethiopia	0.003878	-0.08694	-22.4221	9.09E-79
Bolivia	0.002424	-0.08392	-34.6156	1E-171
Tanzania	0.005277	-0.08137	-15.4218	3.3E-43
Morocco	0.004267	-0.07929	-18.5813	3.75E-54
Central African Republic	0.004728	-0.07864	-16.633	9.04E-41
Egypt	0.00337	-0.07651	-22.7066	7.29E-91
Mozambique	0.002564	-0.07448	-29.0524	5.9E-115
Guinea	0.003079	-0.07196	-23.3705	9.73E-69
Peru	0.001601	-0.07107	-44.3889	2.4E-249
Nepal	0.003538	-0.07051	-19.9284	8.06E-56
Zambia	0.003494	-0.07027	-20.1135	1.68E-57
Niger	0.00263	-0.06962	-26.4667	2.32E-75
Ghana	0.002509	-0.06842	-27.274	1.1E-91
Sierra Leone	0.004745	-0.06707	-14.1362	3.3E-37
Moldova	0.002554	-0.06549	-25.6426	8.96E-86
Burkina Faso	0.002812	-0.06512	-23.1599	1.56E-81
Albania	0.002728	-0.0629	-23.0559	3.25E-77
Indonesia	0.001371	-0.06225	-45.3902	3.2E-267
Cote d'Ivoire	0.00247	-0.06178	-25.0172	3.33E-77
Liberia	0.003011	-0.06036	-20.0444	1.01E-57
Benin	0.001745	-0.0594	-34.0339	2.7E-152
Tajikistan	0.003383	-0.05785	-17.1012	1.6E-46
Cameroon	0.001871	-0.05779	-30.8904	1.2E-122
Timor-Leste	0.003077	-0.057	-18.5271	1.79E-56
Togo	0.002395	-0.05699	-23.7943	8.07E-69
Congo (Kinshasa)	0.002623	-0.05453	-20.7918	1.45E-68
Senegal	0.002392	-0.04877	-20.3864	2.11E-61
Philippines	0.001495	-0.04798	-32.0856	6.5E-142
Honduras	0.00138	-0.04504	-32.6475	1.9E-163
Colombia	0.000833	-0.04342	-52.1063	0
Haiti	0.001478	-0.04106	-27.7718	1.09E-96
Jordan	0.004548	-0.04102	-9.01935	2.11E-18
Guyana	0.00273	-0.041	-15.0154	5.23E-38
Nigeria	0.001229	-0.03868	-31.4665	4.6E-146
Lesotho	0.00216	-0.03829	-17.73	6.75E-51

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

Table C: Summary Statistics and Logit Regression Coefficients by Country

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

Tajikistan	0.024838	0.05974	2.405179	0.016756
Kyrgyzstan	0.028043	0.060814	2.168589	0.030932
Togo	0.099747	0.080907	0.81112	0.417996
Rwanda	0.075475	0.082242	1.089648	0.276454
Guyana	0.184466	0.097817	0.53027	0.596335
Madagascar	0.029947	0.104082	3.47555	0.000551
Moldova	0.190361	0.138084	0.72538	0.468653
Guinea	0.142633	0.146896	1.029887	0.303918
Senegal	0.061857	0.26666	4.310891	2.12E-05
Swaziland	0.06453	0.283432	4.392255	1.65E-05
Ghana	0.113134	0.283708	2.507708	0.012566
Niger	0.107741	0.319605	2.966429	0.003297
Mozambique	0.070032	0.33727	4.815953	1.88E-06
Timor-Leste	0.168723	0.415684	2.46371	0.014154
Benin	0.196749	0.444863	2.261063	0.024052
Sierra Leone	0.265776	0.465954	1.75318	0.080322
Comoros	0.13266	0.539392	4.065967	6.67E-05

Table D: Summary Statistics and Logit Regression Coefficients by Country

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

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

Section E: Occupational Breakdown for Nigeria

The DHS dataset includes separate variables for respondents' (typically female) occupations and husbands' or partners' occupations. The tables below detail the husbands' occupations because the husbands tend to be the primary workers in the household. 5% of husbands did not work in the year preceding the survey, whereas 34% of respondents did not work.

Overall occupational view for husbands in Nigeria:

Husband/partner's occupation (grouped)	Freq.	Percent	Cum.
[5] Agricultural - employee	7,437	30.48	30.48
[8] Skilled manual	5,034	20.63	51.11
[3] Sales	4,322	17.71	68.82
[1] Professional/technical/managerial	3,400	13.93	82.75
[7] Services	1,458	5.98	88.73
[4] Agricultural - self employed	1,054	4.32	93.05
[9] Unskilled manual	1,014	4.16	97.21
[0] Did not work	318	1.30	98.51
[2] Clerical	208	0.85	99.36
[99] Missing value	148	0.61	99.97
[96] Other	6	0.02	99.99
[6] Household and domestic	2	0.01	100.00
Total	24,401	100.00	

Unskilled manual labor breakdown for husbands in Nigeria:

Husband/partner's occupation	Freq.	Percent	Cum.
Achaba Rider (Okada Rider), Commercial	787	77.61	77.61
Butcher	191	18.84	96.45
Truck Pusher, Wheelbarrow Pusher	13	1.28	97.73
Transportation or Material Moving Worke	8	0.79	98.52
Transport Clerk	6	0.59	99.11
Oil Servicing Worker	4	0.39	99.51
Dock Worker	1	0.10	99.61
Safety Officer	1	0.10	99.70
Aircraft Cargo Handling Supervisor	1	0.10	99.80
Traffic Controller (Ship)	1	0.10	99.90
Traffic Controller (Train)	1	0.10	100.00
Total	1,014	100.00	

Agriculture breakdown for husbands in Nigeria:

Husband/partner's occupation	Freq.	Percent	Cum.
Farmer (General)	4,881	57.48	57.48
Farmer (Cocoa)	649	7.64	65.13
Farmer (Mixed)	582	6.85	71.98
Fisherman	512	6.03	78.01
Farmer-Cereal and Legume (Rice, Beans,	482	5.68	83.69
Farmer-Root Crop (Cassava, Yam, etc.)	438	5.16	88.85
Animal Keeping/ Rearing (Cattle, Goat,	415	4.89	93.73
Bee Rearing/Collection, Farming Honey	96	1.13	94.87
Palm Wine Tapper	69	0.81	95.68
Farmer (Cash Crop)	67	0.79	96.47
Farmer (Groundnut)	61	0.72	97.19
Farmer (Tomatoes)	30	0.35	97.54
Hunter or Related Worker	24	0.28	97.82
Agricultural/ Animal Husbandry/ Forest/	22	0.26	98.08
Farmer (Livestock)	21	0.25	98.33
Farmer (Fish)	20	0.24	98.56
Farmer (Poultry)	19	0.22	98.79
Gardener (Nursery inclusive)	17	0.20	98.99
Farmer (Vegetable)	15	0.18	99.16
Forest or Conservation Worker	12	0.14	99.31
Farmer (Cotton)	10	0.12	99.42
Tree Fellers and Logger	10	0.12	99.54
Farmer-Plantation (Tea, Rubber, Palm, e	9	0.11	99.65
Rubber Tapper	8	0.09	99.74
Agricultural, Animal Husbandry and Fore	7	0.08	99.82
Agricultural Extension Worker	4	0.05	99.87
Farmer (Sugar-cane)	4	0.05	99.92
Farmer (Fruits)	3	0.04	99.95
Farmer (Dairy)	2	0.02	99.98
Farmer (Onions)	1	0.01	99.99
Horticulturist	1	0.01	100.00
Total	8,491	100.00	