Methodology: The Scorching Divide: How Extreme Heat Inflames Gender Inequalities in Health and Income

Prepared for the Adrienne Arsht-Rockefeller Foundation Resilience Center at the Atlantic Council
Created by Vivid Economics
May 2023

This note accompanies the reports Extreme Heat: The economic and social consequences for the United States and Hot cities, chilled economies: Impacts of extreme heat on global cities, which were prepared for the Adrienne Arsht-Rockefeller Foundation Resilience Center at the Atlantic Council. It provides an overview of the approach taken to quantify the gendered differences in heat-related labor productivity losses and mortality impacts, including a description of data sources and key assumptions.

Introduction

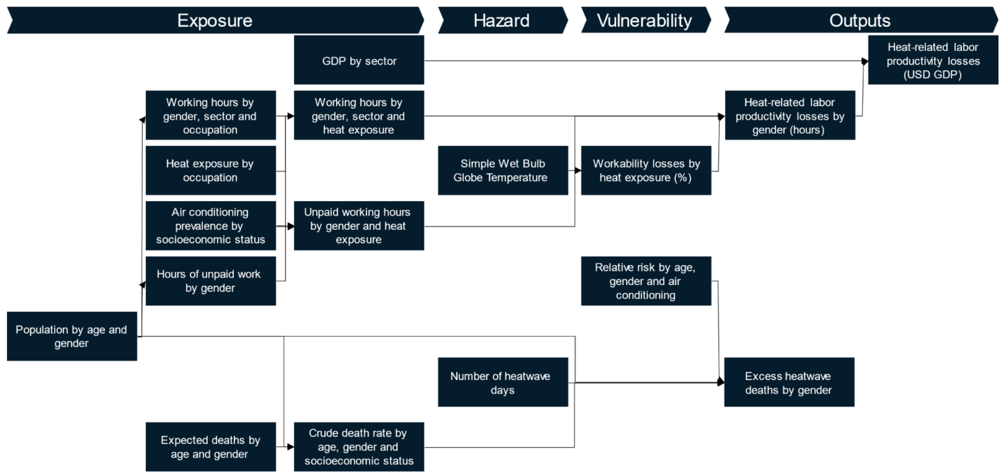
In brief, our approach can be summarized in the following steps:

We use best-in-class climate models to analyze heat conditions under current climate conditions and those expected in 2030 and 2050.

1. We compile data on socioeconomic variables – including work hours, economic output, and population demographics – and project these forward to 2030 and 2050.
2. We estimate the impact of heat on labor productivity losses in paid and unpaid work, under current and future climate conditions.
3. We analyze the impacts of heat-related labor productivity loss on sectoral economic output.
4. We estimate excess heat wave deaths under current and future climate conditions.

Figure 1 below summarizes the key variables in the analysis.

Figure 1: High level overview of approach for analysis in India, Nigeria, and the United States



Climate modeling

We analyze heat conditions under current and future climatic conditions using downscaled projections from the CMIP ensemble of climate models. This work uses output from the latest generation of Global Climate and Earth System models of the Climate Model Intercomparison Project 6 (CMIP6), which were used in the most recent IPCC AR6 report. Specifically, we use the output from four of the models that contain all the necessary variables for our heat calculations: CanESM5, EC-Earth3, MPI-ESM1-2-LR and MRI-ESM2-0 (Yukimoto et al., 2019; Swart et al, 2019; Mauritsen et al., 2019; Döscher et al., 2019). Since these models are employed at horizontal grid sizes of 100-250 km, they do not provide the granularity required in this work. To remedy this, we use a statistical *downscaling* technique (Abatzoglou and Brown, 2012) that generates climate output at a 9 km resolution across the globe, including the three countries of focus (The United States, India, and Nigeria). Along with providing enhanced granularity, this method also uses historical observations to correct any biases that are intrinsic to the climate models. We use two modelled outcomes of interest for this analysis:

1. Simple Wet Bulb Globe Temperature (sWBGT) – which we use to analyze the impact of heat on labor productivity.
2. Number of heat wave days (where a heat wave day is defined based on the local temperature profile) – which we use to analyze the impact of heat wave exposure on mortality.

These output variables are upscaled to the relevant geographic unit of analysis for use in the socioeconomic models.

Wet Bulb Globe Temperature (WBGT) is a measure of temperature which closely relates to human heat stress. WBGT accounts for an array of co-occurring factors that mediate the impact of temperatures on the human body including humidity, wind speed, and visible and infrared radiation. We use a simplified version of WBGT (Stull et al, 2011), referred to as sWBGT, which ignores the effect of wind on heat stress, and uses daily mean temperature, daily mean relative humidity and daily maximum temperature. The use of sWBGT as a measure of heat stress among workers is well accepted and widespread in the literature (e.g., ILO, 2019, Arsht-Rock, 2022, Parsons et al., 2021). In this analysis, the functional relationship between sWBGT and effective labor hours is used to determine losses in effective labor from higher temperatures (explained in Section 3).

Heat wave days are projected and used as a key input to determine mortality impacts of extreme heat and are defined in relative terms for a particular geography. We advance previous work (Arsht-Rock, 2022) by using Guo et al.'s (2018) definition of heat waves. For each year and climate model in the three periods (2023, 2030, and 2050), we calculate total heat wave days as *the yearly sum of at least two consecutive days with daily mean temperature exceeding the 95th percentile.* Across all three time periods, the 95th percentile is defined according to current climate conditions.

We adopt a *warming level* framework rather than selecting specific time horizons and scenarios. This approach involves selecting periods corresponding to different levels of global temperature increase relative to the pre-industrial era (1850-1900). Utilizing this framework allows us to aggregate output of several climate models and ensures that our analysis remains independent of the choice of future scenario. We apply three warming levels in our analysis using the SSP3 scenario: a baseline period (indicative of the present-day climate, 1.1 °C warming), a 1.5°C warming level (indicative of climate conditions in 2030), and a 2°C warming level (2050).

In addition to human-induced global warming, climate is also governed by natural year-to-year variability in temperature and precipitation. These variations can explain stark differences in heat waves and heat stress between individual years, but they have not been taken into account in previous studies.
For each warming level, each of the four climate models produces twenty simulated years of data– meaning that there are eighty model-years for each climate period. In this work, we use the statistical distribution provided by the climate model data to calculate the heat wave and heat stress conditions in an 'average' year (mean) and an 'extreme' year (a 1-in-40 probability of occurrence).

Baseline and projected socioeconomic data

Another set of critical model inputs is underlying data on population, employment, health, and economic activity, both today and projected into the future. In all projections, we looked for consistency with the Shared Socioeconomic Pathways Scenario 3: "Regional Rivalry" (which is also consistent with the climate analysis described above). We estimated socioeconomic variables at the most disaggregated geographical unit for which we could collect data – in India this was at the district level (where there are 766 districts), in Nigeria at the state level (36 states) and in the US the county level (3,143 counties).[1] The critical variables in our analysis include:

- **Population by age and gender.** We categorize the population into three age groups: child (0-14), working age (15-64) and elderly (65+). We use World Population Prospects data for current population data, projecting it forward using Briggs (2021) under the United Nation's (UN) medium-to-high fertility scenario.

- **Crude death rates by age, gender and socioeconomic status.** This is a national-level variable, taking the number of deaths from the UN World Population Prospects and dividing it by the expected population. The crude death rates are adjusted for different socioeconomic groups using academic literature on inequalities in mortality rates.

- **Working hours by sector, gender and occupation.** In the United States, this information is extracted from the Census Bureau. In India and Nigeria, national-level working hours by sector, gender and occupation is estimated using data from the International Labor Organization (ILO). This information is downscaled to the local level using a combination of national statistics on local employment and Gross Domestic Product (GDP), and spatial data on the working age population. Working hours in all sectors are expected to increase in line with the working age population.

- **Working hours in unpaid work, by gender.** This data is taken from national time use surveys. We assume that all working age men and women conduct the national gender-specific average of unpaid work. Hours in unpaid work is expected to increase in line with the working age population.

- **Gross domestic product by sector.** This data is taken from national data sources (the Reserve Bank of India, the National Bureau of Statistics in Nigeria, and the Bureau of Economic Accounts in the US). In instances where state-level GDP data in Nigeria was incomplete, missing values were imputed, assuming that the GDP/capita for missing states was in line with the regional average. To project the GDP for all sectors we utilized Wang & Sun (2022), employing the SSP3 scenario.

- **Domestic rates of air conditioning prevalence, by socioeconomic status.** This data is estimated using national household level surveys. The prevalence of air conditioning is assumed to remain constant over time – i.e., the forward-looking results are with "no adaptation", assuming that people do not respond to increased heat stress by investing in air conditioning.

Box 1: Economic structure is assumed constant through time

In this analysis, the structure and spatial distribution of economic activity in 2030 and 2050 do not change from 2020. Key features of the economy remain fixed within each country at baseline levels:

- Sectoral composition of economic activity
- Share of capital and labor in each sector
- Sectoral and overall employment rates
- Exposure to heat within occupations

These are inherently unrealistic assumptions, in particular concerning the response to heat:

- Heavily exposed areas of economic activity should reduce their economic activity in outdoor or heat exposed work (sectoral shift)
- Heavily exposed sectors should increase their capital intensity (capital/labor shift)
- Employment rates may change due to transition effects (exposed occupations shrinking and requiring a smaller workforce)

However, these are useful assumptions to illustrate the effect of climate change without adaptation.

Heat-related labor productivity losses

Exposure to heat results in labor productivity losses, where workers are obliged to spend more time to achieve the same output. The effect of heat stress on productivity comes through two channels: the need to take breaks, rest, hydrate, or seek cooling in a less exposed environment, and a natural self-limiting response of an overheated body reducing effort to maintain function (see Dunne et al. 2013). In our analysis:

- Workability functions are defined for different work types – based on exposure to heat and exhaustion – relating sWBGT to the effective reduction in labor.
- In paid/market sectors, time in different work types is calculated at the occupational and sectoral level.
- In unpaid/non-market work, time spent in different forms of unpaid work are calculated based on time use surveys and mapped to work types (exposure to heat and exhaustion).

Workability functions

Workability functions capture how labor productivity declines as workers are subjected to greater human heat stress. There is a well-established literature and experimental body of evidence relating productivity loss to the WBGT. The analysis for this report was based on previous work for the Adrienne Arsht-Rockefeller Foundation Resilience Center at the Atlantic Council and on work developed with the Woodwell Climate Research Center (WCRC) and external advisors to adapt existing models to reflect the current understanding of human heat stress and workability.

We use existing functions referenced in the literature that relate labor productivity loss to sWBGT. The model applied in this analysis adapts the formula of Dunne et al (2013) to allow for increased work at higher WBGT, following the guidance of expert advisors. Therefore, it provides a more conservative estimate of productivity losses from heat stress. This adjustment is conceptually consistent with Foster (2021).

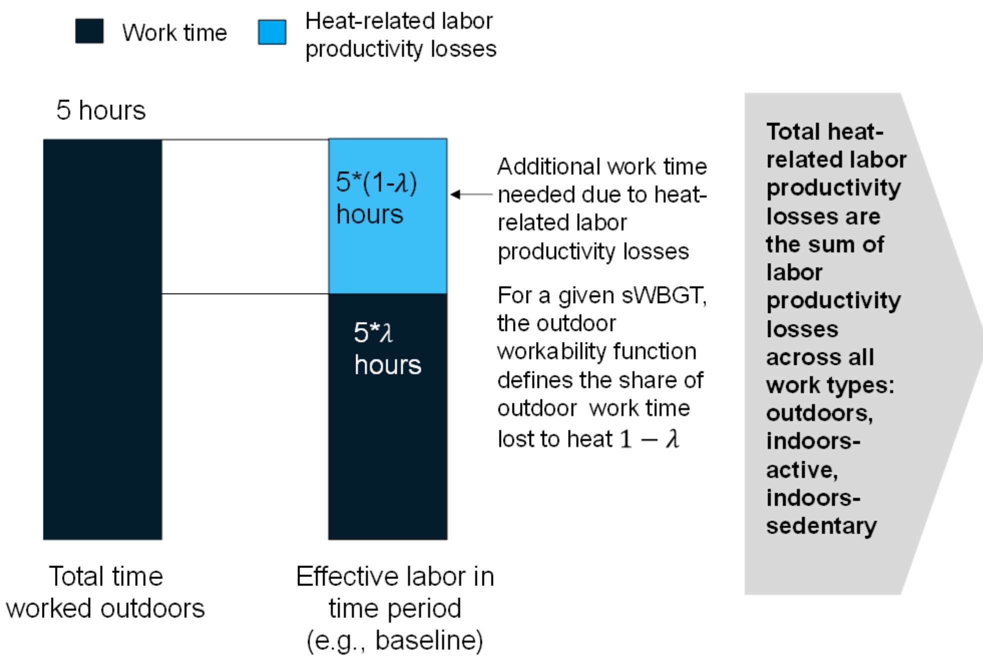
Three sets of workability functions are defined for different types of work environments or exposures to heat. The workability function gives the achievement of a unit of labor time at an exposed temperature relative to peak efficiency, $0<\lambda\leq1$. Based on prior literature, we differentiate the relationship between WBGT and productivity losses by four work 'types':

1. **Outdoor:** work done outdoors involving exposure to heat, in which estimated labor productivity losses from heat are based on Dunne et al (2013).
2. **Indoor, active:** work done indoors involving active or active work, in which labor productivity losses from heat are based on McKinsey Global Institute (MGI).
3. **Indoor sedentary:** work done indoors involving sedentary work, in which labor productivity losses from heat are based on Pilcher et al (2002).
4. **Air conditioned environment**: in which no productivity losses are assumed.

Heat-related labor productivity losses are defined as the additional time needed to complete a task due to heat exposure outdoors or indoors in a non-air conditioned environment (see Figure 2). The extent of this additional required time is determined by the workability function (where the labor productivity losses are calculated by $1-\lambda$, the workability of a unit of labor time). For example, the assumed workability modeling estimates a 20% loss in labor productivity for outdoor work, 10% for indoor active work, and 5% loss for indoor sedentary work in a given region. If 50% of female working hours in construction are outside, 10% are indoors and environmentally controlled, 20% are indoors with no air conditioning doing active work, and 20% are indoors with no air conditioning doing sedentary work, then the effective reduction in labor supply for females is 13% (20%*50%+10%*20%+5%*20%= 13%), i.e., it would take an additional 13% working hours to achieve the same output.

Workability functions are assumed to be the same for males and females. This is due to a lack of detailed information on how workability may differ by gender. In our model, gendered differences in labor productivity losses due to heat are therefore attributable to: i) their time allocation between the four types of work environments; and ii) their total time spent in work. **The next step of the analysis is to allocate time worked by males and females into each of these four work-types and estimate the productivity losses based on sWBGT exposure.**

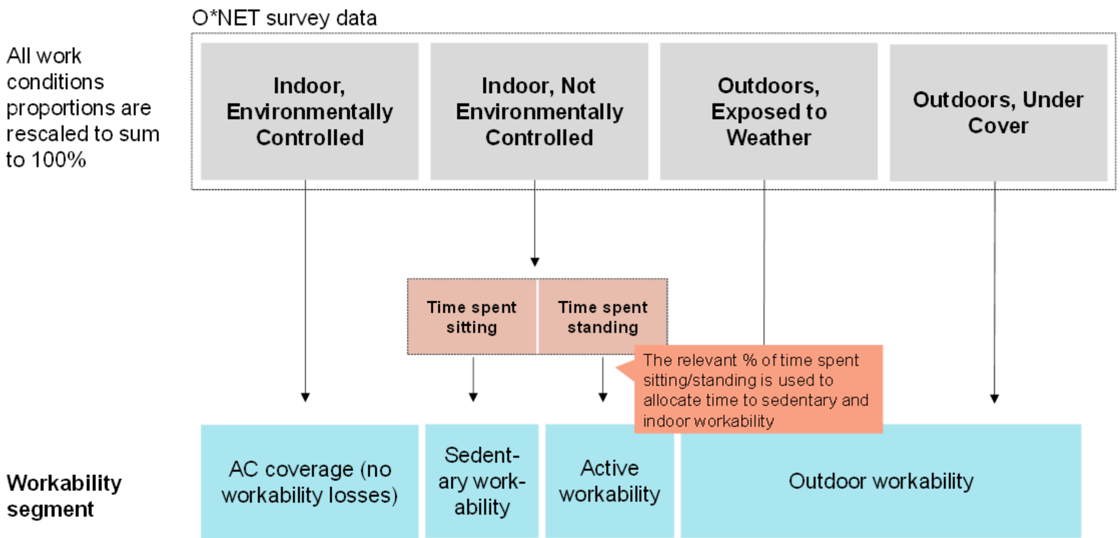
Figure 2: Example of approach for estimating labor productivity losses from heat for outdoor work, total losses are the sum of all labor productivity losses across all work types



Labor productivity losses in paid work

Heat-related labor productivity losses in paid work depend on the following factors: i) the share of hours spent in different work conditions, ii) working hours categorized by sector, occupation and gender, and iii) exposure to heat.
In the United States, the distribution of working hours spent across different working conditions is calculated at the occupational level using survey data from O*NET. This is a survey dataset, which reports occupation-specific information regarding the proportion of work done outdoors, inside non-climate-controlled buildings, and inside climate-controlled buildings, as well as the amount of time spent sitting and standing. Figure 3 illustrates how we allocate work conditions as reported in O*NET to workability segments. Greater detail is provided in the Annex.

Figure 3: Workability is determined by exposure to heat and physical intensity of work and is categorized using O*NET data on work conditions at the occupational level



Due to data limitations in India and Nigeria, US O*Net data scores are used as main input to determine working environment exposure across all three countries. In this approach, we assume that for a given occupation the proportion of time spent inside or outside, and the proportion of time spent sedentary or active, is the same around the world. However, we adjust the amount of time spent indoors in environmentally controlled conditions. For example, if:

- 90% of the working hours of US managers are spent indoors in environmentally controlled conditions, while the remaining 10% are spent indoors without air conditioning, doing sedentary work.
- National household air conditioning prevalence in the US is 88%, and in the Nigerian state under analysis it is 8.8%, i.e., household air conditioning prevalence is 10% of what it is in the US.
- Based on these findings, we would assume that managers in that state in Nigeria spend 9% of their working hours indoors in environmentally controlled conditions, and 91% of their working hours indoors without air conditioning doing sedentary work.

Furthermore, the occupational composition of sectoral employment varies significantly by country. For example, 42% of men and 25% of women employed in the agriculture sector in the US work as managers, while in Nigeria only 9% for men and 3% for women work as manager, with a much greater share (86% of men and 94% of women) working as skilled agricultural workers.

We estimate the distribution of working hours spent across different working types by sector and gender, relying on the national-level occupational composition of sectors. For example, suppose:

- Skilled laborers in India spend 100% of their work hours outside, while managerial workers are estimated to spent 100% of their time inside – doing sedentary work without access to air conditioning.
- Sector A is made up of 80% skilled laborers and 20% managerial workers.
- Then we would assume that 80% of working hours in sector A are spent outside (80%*100%+20%*0%), and 20% of working hours in sector A are spent indoors doing sedentary work without access to air conditioning (80%*0%+20%*100%).
- Outdoor workers experience heat-related losses in labor productivity of 50%, and indoor sedentary workers experience heat-related losses in labor productivity of 10%.
- Sector A experiences total losses in labor productivity of 42% (80%*50%+20%*10%).

Labor productivity losses in unpaid work

A key extension of this work from previous literature is the incorporation of unpaid work in estimates of labor productivity losses from heat. Unpaid work is generally measured as total time spent on[2]:

- **Household work:** Time spent doing household activities, consumer purchases, professional and personal care services, household services and travel related to household activities.
- **Primary care work:** Time spent performing a given activity with or for the person for whom they are caring, encompassing both children and older adults. This category includes caring for and helping household members, caring for and helping non-household members, travel relating to caring for and helping non-household members, and telephone calls to/from paid child or adult care providers.
- **Secondary child-care:** Time spent with child under 13 years old "in his or her care" while doing something else as a primary activity.

Time use data is utilized to classify male and female unpaid activities into time spent in the four work 'types' (outdoor, indoor active, indoor sedentary, and air conditioned). This is done through the following steps:

1. Map or assign a proportion of unpaid work activity to categories such as indoors active, indoors sedentary and outdoors time (see Table 1). For example, unpaid care work is assumed to consist of 100% indoors, active work.
2. Adjust the indoors portion of time based on the data for region-specific access to domestic air conditioning. For example, if 15% of the relevant population has access to domestic air conditioning then 15% of indoors active unpaid work time is calculated as 'air conditioned.' The new exposed indoors unpaid time shares are calculated using the remaining fraction (85%). Of note, in the US, an adjustment is made to account for lower air conditioning use among poorer households (see Box 1 below).

Table 1: Key labor productivity variables, sources and assumptions[3]

Country	Unpaid work	Assumptions around categorization to "work type"
India	Production of goods for own final use	50% outdoors; 50% indoors and active
	Unpaid domestic services for household members	00% indoors and active
	Unpaid caregiving services for household members	00% indoors and active
Nigeria	Collection of fuel or water	00% outdoors
	Unpaid care and domestic work	00% indoors and active
USA	Caring for household members	00% indoors and active
	Caring for non-household members	00% indoors and active
	Domestic housework and related activities	90% time spent inside; 10% time spent outside

Box 1: Adjusting for air conditioning use in the United States

To account for income constraints on the use of air conditioning in the US, county level air conditioning access is adjusted to account for differences in ability to pay for air conditioning. While air conditioning use is high in the US, there is large divergence in the ability to pay due to energy poverty and insecurity among poorer households (Cong et al., 2022). Data on air conditioning use and consumption from the 2015 RECS[4] by household income is used to derive multipliers for poor and rich households based on the following calculation[5]

$$M(poor),\ \ M(not\ poor)$$

[Equation]
[Equation]

Where consumption is defined as annual Btu of energy used of air conditioning and prop_ac_use is the proportion of households who state they used air conditioning at least once in the previous year. Multipliers for both poor and non-poor are defined in relation to the average (or total) values. The following gender-specific multiplier is calculated for each county (C) and gender (g) to account for shares of men and women in each household income category at the county level:

$$\hat{M}_c(g) = M(poor) * proportion\ of\ gender\ g\ poor\_c + M(not\ poor) * proportion\ of\ gender\ g\ rich\ \_c$$

Air conditioned indoor unpaid work is calculated by further multiplying the estimated proportion of unpaid work time inside with air conditioner access by this adjustment multiplier $\hat{M_c}(g)$, and recalculating the proportion of time inside without air conditioning access as the remaining proportion of time.[6]

Labor productivity losses in unpaid work is calculated by applying the workability analysis to hours across the four work 'types.' This depends on regional climate projections of sWBGT and time spent in exposed work types during unpaid work.

Heat-related output losses

We use a simple economic model to estimate the impact of worker heat stress on economic production. Production within each sector follows a Cobb-Douglas production function with constant returns to scale, where Y represents output, A is total factor productivity, L is labor input, K is capital input, and β is the labor share in production. Exposure to extreme heat reduces the productivity of labor, reducing the effective size of the labor force.

$$Y = A L^{\beta} K^{1-\beta}$$

$$\textit{Marginal product of labor } (MPL): \frac{\partial Y}{\partial L} = \beta \frac{Y}{L}$$

The marginal product of labor differs for males and females, based on the relative share of labor input in each sector.
Labor share in production β is approximated by the relative earnings for labor in each sector. We assume β is sector and country specific but does not vary across subnational regions or over time. The sectoral share of labor in the production function is estimated from relative earnings in the Global Trade Analysis Project (GTAP). Relative earnings to labor at the sectoral level is calculated as:

$$\beta = \textit{rent paid to labor} / (\textit{rent paid to capital} + \textit{rent paid to labor})$$

Output losses from heat are the result of the effective reduction of labor input for men and women due to heat. Effective reduction in labor supply is the result of reductions in labor inputs from heat based on workability analysis outlined above.

Heat-related mortality

We estimate the number of excess heat wave deaths by gender, age group, poverty status, and other relevant demographic characteristics across the three countries of focus: India, Nigeria and the US. Figure 4 outlines the key steps in the analysis.

Figure 4: Approach to estimating excess heat wave deaths

1 Estimate population distribution

For each district estimate the number of people by:
- age group
- gender
- domestic air conditioning
- wealth

For 2020, 2030 and 2050

e.g. in 2020 in district A, there are X many elderly men with domestic air conditioning living in households in the richest wealth quintile

2 Estimate daily non-heatwave mortality probability

Estimate crude daily mortality probability by:
- age group
- gender
- wealth

For 2020, 2030 and 2050

e.g. in 2020, elderly men living in households in the richest wealth quintile have a X% probability of dying on a given day

3 Determine daily heatwave mortality relative risk

From the literature (Sera et al., 2020; Benmarnhia, 2017), extract relative risk factors for people by:
- domestic air conditioning
- age group – elderly or non-elderly
- gender

e.g. elderly women without access to air conditioning are 1.18 times more likely to die on a heatwave day than a non-heatwave day

4 Estimate number of heatwave days

For each district, estimate the number of heatwave days expected in climate conditions consistent with 2020, 2030 and 2050.

e.g. in district A, under a 1.1°C warming level scenario, there are expected to be 16 heatwave days a year

5 Estimate heatwave deaths

$$Excess\ heatwave\ deaths^{Y,A,G,C,W,D} = Population^{Y,A,G,C,W,D} \times Daily\ crude\ death\ probability^{Y,A,G,W} \times (Relative\ risk\ from\ heatwaves^{A,G,C} - 1) \times No.of\ heatwave\ days^{Y,D}$$

$Y = year; A = age\ group, G = gender, C = domestic\ air\ conditioning\ ownership, W = wealth, D = district$

1. **We estimate the current and projected distribution of the population.** This is described in the section "Baseline and projected socioeconomic data".

2. **We estimate the crude daily non-heat wave deaths.** As described above, we estimate crude mortality rates at the country-level by gender, age, and socioeconomic status. The daily mortality rate is assumed to be constant across the year (annual mortality is divided by 365 days).

3. **We determine the relative risk of mortality from heat waves based on the findings in the existing literature.** The relative risk of mortality from heat waves is calculated by determining the ratio of deaths of people exposed to heat waves to the deaths of people not exposed to heat waves, representing the additional likelihood of death for a group that occurs as a result of heat wave exposure (Tenny & Hoffman, 2022). Relative risk factors for heat wave mortality are calculated based on reported relative risk factors from heat waves in Sera. et al. (2020) and Benmarnhia (2017).[7] Note that when estimating the relative risk of mortality from heat waves in India and Nigeria we use the average relative risk factors for the 4 developed countries reported in Sera et al. (2020). Despite the additional vulnerability of healthcare systems in these countries, there is no compelling evidence in the literature to suggest we should adjust the relative risk upwards for India and Nigeria.[8] We assume people experience different relative risk factors depending on whether or not they have air conditioning, and the relative risk factors are also age- and gender- specific. However, we assume that holding air conditioning constant, people in different socioeconomic groups experience the same relative risk.

4. **Heat wave days are estimated at the local level based on climate modeling.** Following Guo et al. (2018), heat wave days are defined as 2 consecutive days with daily mean temperature exceeding the 95th percentile of daily mean temperature across all models and years in the baseline (1.1^{o}C).[9]

5. **Excess heat wave deaths are calculated, differentiated by age, gender, air conditioning ownership, socioeconomic status, and geography.** This is determined by i) crude mortality rates, ii) relative risk of mortality from heat waves, iii) climate modeling projections of heat wave days as defined above.

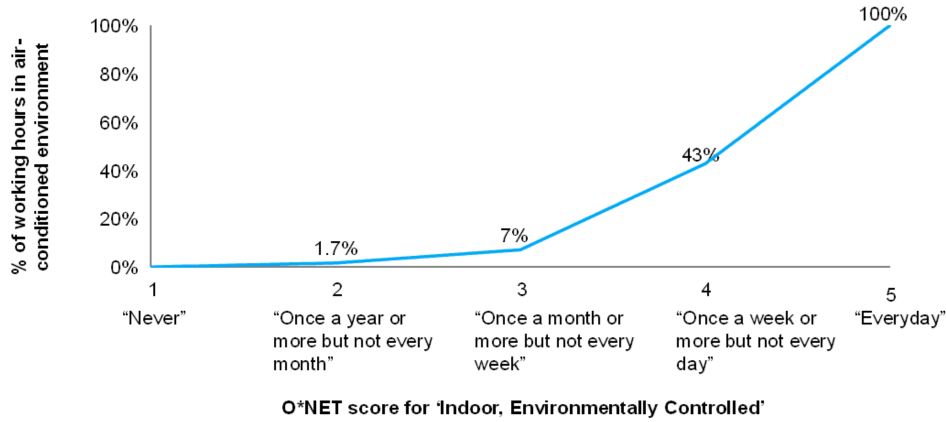
Annex

Interpreting the O*NET data

O*NET is the data source used to determine the work types of different occupations. O*NET OnLine is a resource developed by the US Department of Labor to catalog the working conditions and skill requirements of detailed occupation.[10] It reports how frequently work is done outdoors, inside in non-climate-controlled buildings, and inside in climate-controlled buildings, as well as the amount of time spent sitting and standing.

O*NET scores report frequency of exposure to different types of work conditions and is converted into percentages of time exposed. The relevant O*NET variables are shown in table 5 and are used to estimate the share of total work time in each of the four work-types that correspond to a workability function.[11] O*NET scores are based on a qualitative frequency of how often work takes place in each 'condition'. Variables which indicate the frequency that work takes place outdoors or indoors, exposed or air conditioned, or indoors and not exposed to air conditioning are related to percentage exposure based on the following formula: a score of 1 corresponds to zero percent ("Never"), 2 corresponds to once every 2 months ("Once a year or more but not every month"), 3 corresponds to once every second week ("Once a month or more but not every week"), 4 corresponds to 3 day a week ("Once a week or more but not every day"), 5 corresponds to all the time – 100% ("everyday"). Figure 5 illustrates the function relating the O*NET score from 1-5 to a percentage from 0-100 and Table 4a and 4b further outline the assumptions made. Time in each category is adjusted to ensure all work type exposures sum to 100%.

Figure 5: Assumptions made on proportion of time spent in indoors and outdoors work conditions example for 'Indoor, Environmentally Controlled'



Note: Identical O*NET score and assumption for indoor and outdoor O*NET variables: 'Indoor, Environmentally Controlled'; 'Indoor, Not Environmentally Controlled'; 'Outdoors, Exposed to Weather'; 'Outdoors, Under Cover'

Table 2: Quantitative assumptions made on the amount of time spent in each category

ualitative O*net response[12]	**uantitative assumption on time spent in work**
Never”	)% (never)
Once a year or more but not every month”	.64% (once every 2 months)
Once a month or more but not every week”	'.12% (once every second week)
Once a week or more but not every day”	-2.74% (3 days a week)
Everyday”	00% (always)

Table 3: Quantitative assumptions made on the amount of time spent in each category for time spent standing, time spent sitting

ualitative O*net response [13]	**uantitative assumption on time spent in work**
Never”	)%
Less than half the time”	!5%

About half the time”	50%
More than half the time”	75%
Continually or almost continually”	100%

We use O*NET data to derive relative share of time in paid work exposed to different work conditions. Namely we construct paid work shares in the following work types:

$$s_{outside},\ s_{ac},\ s_{inside\ active},\ s_{inside\ sedentary}$$

where the share of time inside is equal to the sum of share of time indoors in an air conditioned environment (s_{ac}), share of time indoors doing active work ($s_{indoors\ active}$) and share of time indoors doing sedentary work ($s_{indoors\ sedentary}$).

Table 4: Summary of assumptions and calculations for work types

Work types	**O*Net variables**	**Calculations**
Outdoors	Time spent Outdoors, Exposed to Weather (% total time) Time spent Outdoors, Under Cover (% total time)	Sum two outdoor work variables.
Indoors – doing active work without AC access	Time spent indoors, not environmentally controlled (% total time) Time spent sitting (% total time)	Assume that sitting/standing is independent of working environment. Multiply share of time spent sitting by share of time spent indoors, not environmentally controlled.
Indoors – doing sedentary work without AC access	Time spent indoors, not environmentally controlled (% total time) Time spent sitting (% total time)	Assume that sitting/standing is independent of working environment. Multiply share of time spent standing by share of time spent indoors, not environmentally controlled.
Indoors with access to AC	Time spent indoors, environmentally controlled (% total time)	N/A – except in Nigeria and India which requires adjustment by relative AC factor.

References

Abatzoglou, John T., and Timothy J. Brown. “A Comparison of Statistical Downscaling Methods Suited for Wildfire Applications.” *International Journal of Climatology* 32, no. 5 (April 2012): 772–80. https://doi.org/10.1002/joc.2312.

Briggs, David. (2021). A global downscaled age structure data set for assessing human impacts of climate change, 1970-2100. 10.13140/RG.2.2.15429.17124.

Döscher, Ralf, Mario Acosta, Andrea Alessandri, Peter Anthoni, Thomas Arsouze, Tommi Bergman, Raffaele Bernardello, et al. 2022. “The EC-Earth3 Earth System Model for the Coupled Model Intercomparison Project 6.” *Geoscientific Model Development* 15 (7): 2973–3020. https://doi.org/10.5194/gmd-15-2973-2022.

Dunne, John P., Ronald J. Stouffer, and Jasmin G. John. 2013. “Reductions in Labour Capacity from Heat Stress under Climate Warming.” *Nature Climate Change* 3 (6): 563–66. https://doi.org/10.1038/nclimate1827.

Guo, Yuming, Antonio Gasparrini, Shanshan Li, Francesco Sera, Ana Maria Vicedo-Cabrera, Micheline de Sousa Zanotti Stagliorio Coelho, Paulo Hilario Nascimento Saldiva, et al. “Quantifying Excess Deaths Related to Heatwaves under Climate Change Scenarios: A Multicountry Time Series Modelling Study.” *PLOS Medicine* 15, no. 7 (July 31, 2018): e1002629. https://doi.org/10.1371/journal.pmed.1002629.

John P. Dunne et al., “Reductions in labour capacity from heat stress under climate warming,” Nature Climate Change, February 2013, Volume 3
McKinsey Global Institute (MGI). Climate risk and response: Physical hazards and socioeconomic impacts.
https://www.mckinsey.com/capabilities/sustainability/our-insights/climate-risk-and-response-physical-hazards-and-socioeconomic-impacts

US Bureau of Economic Analysis (BEA). CAGDP2 Gross domestic product (GDP) by county and metropolitan area 1/ (accessed Wednesday, March 29, 2023). Last updated: December 8, 2022 -- new statistics for 2021, revised statistics for 2017-2020

Mauritsen, Thorsten, Jürgen Bader, Tobias Becker, Jörg Behrens, Matthias Bittner, Renate Brokopf, Victor Brovkin, et al. 2019. “Developments in the MPI-M Earth System Model Version 1.2 (MPI-ESM1.2) and Its Response to Increasing CO2.” *Journal of Advances in Modeling Earth Systems* 11 (4): 998–1038. https://doi.org/10.1029/2018MS001400.

Parsons, L.A., Shindell, D., Tigchelaar, M. et al. Increased labor losses and decreased adaptation potential in a warmer world. Nat Commun 12, 7286 (2021).
https://doi.org/10.1038/s41467-021-27328-y
Pilcher, June J, Eric Nadler, Caroline Busch 2002. “Effects of hot and cold temperature exposure on performance: a meta-analytic review”. *Ergonomics* 45 (10): 682-98.
https://doi.org/10.1080/00140130210158419

Sera, Francesco; Hashizume, Masahiro; Honda, Yasushi; Lavigne, Eric; Schwartz, Joel; Zanobetti, Antonella; Tobias, Aurelio; Iñiguez, Carmen; Vicedo-Cabrera, Ana M; Blangiardo, Marta; Armstrong, Ben; Gasparrini, Antonio; (2020) Air Conditioning and Heat-related Mortality: A Multi-country Longitudinal Study. EPIDEMIOLOGY, 31 (6). pp. 779-787. ISSN 1044-3983 DOI: https://doi.org/10.1097/EDE.0000000000001241

Stull, Roland. “Wet-Bulb Temperature from Relative Humidity and Air Temperature.” *Journal of Applied Meteorology and Climatology* 50, no. 11 (November 2011): 2267–69. https://doi.org/10.1175/JAMC-D-11-0143.1.

Swart, Neil C., Jason N. S. Cole, Viatcheslav V. Kharin, Mike Lazare, John F. Scinocca, Nathan P. Gillett, James Anstey, et al. 2019. “The Canadian Earth System Model Version 5 (CanESM5.0.3).” *Geoscientific Model Development* 12 (11): 4823–73. https://doi.org/10.5194/gmd-12-4823-2019.

Tenny S, Hoffman MR. Relative Risk. [Updated 2022 Mar 26]. In: StatPearls [Internet]. Treasure Island (FL): StatPearls Publishing; 2023 Jan-. Available from: https://www.ncbi.nlm.nih.gov/books/NBK430824/

Yukimoto, Seiji, Hideaki Kawai, Tsuyoshi Koshiro, Naga Oshima, Kohei Yoshida, Shogo Urakawa, Hiroyuki Tsujino, et al. 2019. “The Meteorological Research Institute Earth System Model Version 2.0, MRI-ESM2.0: Description and Basic Evaluation of the Physical Component.” *Journal of the Meteorological Society of Japan. Ser. II* 97 (5): 931–65. https://doi.org/10.2151/jmsj.2019-051.