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Caste inequality in occupational exposure to heat waves in India

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Arpit Shah
Indian Institute of Management Bangalore
arpit.shah@iimb.ac.in

Sneha Thapliyal
National Law School of India University
snehathapliyal@nls.ac.in

Anish Sugathan
Indian Institute of Management Ahmedabad
anishs@iima.ac.in

Vimal Mishra
Indian Institute of Technology Gandhinagar
vmishra@iitgn.ac.in

Deepak Malghan
Indian Institute of Management Bangalore & Stockholm Environment Institute
dmalghan@iimb.ac.in

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Arpit Shah[a], Sneha Thapliyal[b], Anish Sugathan[c], Vimal Mishra[d], Deepak Malghan[a]

[a] *Indian Institute of Management Bangalore*
[b] *National Law School of India University*
[c] *Indian Institute of Management Ahmedabad*
[d] *Indian Institute of Technology Gandhinagar*

Abstract

India is a leading global hotspot for extreme heat waves induced by climate change. The social demography of India is centered on its caste hierarchy rooted in endogamous occupational groups. We investigate the association between caste and climate inequality by studying occupational exposure during the 2019 and 2022 heat waves. We combine high spatio-temporal resolution heat stress information from satellite imagery with a large nationally and regionally representative labor force survey with rich socio-economic and demographic information ($n > 100{,}000$ individuals). The slope of the heat stress dose – workhours curve corresponding to the marginalized caste groups is between 25–150% steeper than that for dominant caste groups for UTCI (Universal Thermal Climate Index) thresholds between 26°C and 35°C. Our models control for other economic-demographic confounders, including age, gender, education, and economic status, besides political-geographic controls and fixed effects. Our robust evidence for the association between caste identity and exposure to heat stress shows why adaptation and mitigation plans in India must account for the hierarchical social order characterized by the division of laborers along caste lines rather than the mere division of labor. Methodologically, our analysis demonstrates the utility of pairing satellite imagery and detailed demographic data.

Keywords: Climate change and Demography · Caste · Extreme Heat · Paired Data

Email addresses: `arpit.shah@iimb.ac.in` (Arpit Shah), `snehathapliyal@nls.ac.in` (Sneha Thapliyal), `anishs@iima.ac.in` (Anish Sugathan), `vmishra@iitgn.ac.in` (Vimal Mishra), `dmalghan@iimb.ac.in` (Deepak Malghan)

Introduction

Climate change is causing an increase in the severity, duration, and frequency of heat waves worldwide, which has significant implications for human health (Perkins-Kirkpatrick and Lewis, 2020; Khosla et al., 2021). According to the 2022 report of the Lancet Countdown, which tracks health and climate change, heat exposure led to the potential loss of 470 billion labor hours globally in 2021, resulting in a global income loss of USD 669 billion (Romanello et al., 2022). Labor loss, especially among lower-income populations, can undermine livelihood security and impact the socioeconomic determinants of health (Day et al., 2019). Furthermore, extreme heat has severe health impacts, with estimates suggesting that 37% of heat-related deaths can be attributed to human-caused climate change (Vicedo-Cabrera et al., 2021).

The demographic, health, and economic impacts of climate change are further worsened by inequality and inter-group differences (Wilkinson, 2002; Kawachi et al., 2002). Heat wave trends over the last four decades have been more pronounced in lower-income countries, leading to ≈40% higher exposure compared to higher-income nations (Alizadeh et al., 2022; Mishra et al., 2017). Vulnerable populations, including children and older adults, have experienced an additional 3.7 billion person-days of heat waves between 2012 and 2021 compared to the two decades leading up to 2005 (Chambers, 2020). However, most analyses of inequality in exposure to heat tend to be restricted to variables such as age, gender, country, or place of residence (urban vs. rural, low-income vs. high-income). There has been limited attention given to studying how historical injustices, exclusion, and oppression mediate exposure to excess heat (Kotsila and Anguelovski, 2023).

This study investigates group inequalities based on caste in relation to occupational heat stress exposure in India. Empirically, we focus on the summer heat waves (April to June) of 2019 and 2022 in India. Both heat waves set temperature records in their respective years, and were considered remarkable because of their early onset in the summer and prolonged duration. Researchers predict that such extreme events will occur more frequently in the future (Aadhar and Mishra, 2023). We specifically focus on the excess heat that workers are exposed to in outdoor settings, which represents the most significant source of occupational heat stress exposure dose (Tustin et al., 2018; Jacklitsch et al., 2016). Workers engaged in outdoor activities often lack access to air-conditioning, electric fans, or other conventional cooling methods (Sylla et al., 2018). Occupations such as mining, construction, agriculture, and municipal work involve prolonged periods of moderate to heavy workloads, which can expose individuals to heat stress (Schulte et al., 2016). Existing literature suggests that engaging in strenuous activities in hot and humid conditions can lead to elevated physiological heat strain, resulting in reduced cognitive and physical performance (Piil et al., 2017). Furthermore, occupational heat stress increases the risk of various health conditions, including dehydration, heat-related accidents, and heat stroke (Piil et al., 2017).

We examine whether India's hierarchical caste structure rooted in endogamous occupation groups is associated with inequalities in exposure to harmful heat stress. Caste could potentially influence outdoor occupational heat exposure through occupational segregation and labor market discrimination. Despite limited but important progress in addressing caste discrimination (Hnatkovska et al., 2013), evidence clearly indicates the continuing persistence of caste-based occupational segregation in India's modern economy (Deshpande, 2011; Asher et al., 2018; Munshi, 2019). In addition, caste-based discrimination continues to persist both in determining wages and candidate selection for jobs (Das and Dutta, 2007; Banerjee et al., 2009). Caste, as India's central social demography variable, is also more directly implicated in public health processes, including, for example, during the COVID-19 pandemic (Islam et al., 2021).

Our results show that India's marginalized caste groups are more likely to be exposed to outdoor heat while working, after controlling for a variety of socio-economic and demographic factors. In doing so, our work also speaks to the literature on occupational risks. In the context of heat as an occupational risk, recent work in India shows that heat can impact both labor productivity and supply (Heyes and Saberian, 2022; Somanathan et al., 2021). The economics literature on compensating wage differentials has argued that workers demand extra payment for jobs that are riskier, to compensate for the additional risk undertaken (Rosen, 1986; Lavetti, 2023). Heat stress exposure driven by outdoor work represents a serious occupational risk. However, our analysis here suggests that occupational segregation rooted in India's caste hierarchy are more likely to take up jobs that require outdoor work. While workers in a free market would be free to choose combinations of wages-occupational risks that optimize their preferences, our findings imply that the positions of these combinations are shifted by caste, to the detriment of marginalized groups in India.

Data and Methods

Our analytical strategy relies on pairing India's Periodic Labor Force Survey (PLFS) data with remote-sensing information on heat. We build on prior work in demography that has shown the value of pairing survey and remote sensing data to provide novel insights into the connections between human health and environmental change (Brown et al., 2014; Kugler et al., 2019). For instance, researchers have combined diverse datasets to show that lower-class individuals and poorer households are disproportionately impacted by climate-linked diseases (Dickinson et al., 2012), climate-related threats to food security (Randell et al., 2022), and heat-related mortality (Ellena et al., 2020). In addition to pairing PLFS data with thermal information, we also use night-time temperature data to show how occupational segregation, rather than temperature differences in the place of residence is the primary driver of occupational heat stress exposure.

Spatial Demography of Outdoor Work

To examine outdoor work, we utilize socio-economic-demographic and occupation data from the 2018-19 and 2021-22 rounds of the PLFS. The PLFS is a nationally and state-representative survey that has been collecting annual data on various aspects of employment and unemployment in India since 2017 (NSO, 2023). The survey covers nearly all districts in India and captures information on individuals' occupations, including the number of hours spent at the workplace. We use individual-level information on gender, caste, religion, and education. In addition, we use the average monthly per-capita expenditure (MPCE) variable as the indicator of the individual worker's economic status.

The PLFS sampling strategy differs for rural and urban areas. For rural areas, a cross-sectional approach is used, constructing a new and independent sample each year. Each household is visited once during the year. Similar to the long-standing National Sample Survey (used to primarily to determine consumption expenditure), the PLFS allocates 25% of the rural sample size to each quarter of the year, such that independent labor force estimates can be constructed for each quarter. While the final data is published annually, the data released for the PLFS indicates the quarter in which the rural household was surveyed. We use the 2019 and 2022 April–June quarters to achieve perfect temporal matching with the heat wave period.

In urban areas, the PLFS employs a rotational panel sampling design, collecting data quarterly. This rotational panel design lies between a cross-sectional design (independent random samples in each period) and a panel design (surveying the same set of households in each period). In the case of the PLFS, 25% of the urban sample is replaced each quarter, while 75% of the sample is retained for the next quarter. Each household is surveyed four times before being dropped from the sample. This approach allows estimates to reflect both panel designs and dynamic changes in the labor market[1].

[1] A rigorous analysis of rotational designs can be found in Nijman and Verbeek (1990)

Outdoor exposure to harmful heat stress is a concern in both rural and urban settings. To ensure consistency between rural and urban areas, we use the urban PLFS data from the April to June months for 2019 and 2022. Specifically, we use the first visit made to a household in the April to June quarter for 2019 and 2022. To ensure representativeness of the data and consistency between rural and urban samples, we do not include urban revisits in the analysis. For each year, we combine the rural and urban first-visit data for the same quarter and use it as a cross section dataset for our analysis. Our sample allows for robust inter-group comparisons with sufficient statistical power — the primary focus of our empirical analysis (Jajoria and Jatav, 2020; Guha and Chandra, 2022).

The PLFS survey asks respondents about the number of hours they have spent working every day in the week prior to the date of the survey. We use simple averaging to determine the average hours/day spent working by the individual. Given that employment patterns tend to be fairly consistent over a single season, we assume that the workhours recorded by the PLFS are valid for the entire quarter in which the survey is conducted. This assumption that allows for the data to be comparable across individuals who may have been surveyed in different weeks in the quarter is also supported by the fact that almost all circular migration in India is seasonal.

As a conservative measure of direct occupational exposure dose to thermal stress during the heat wave, we only consider exposure for individuals when they are working outdoors. Our analysis does not encompass exposure for individuals who may be exposed to outdoor heat during their daily commutes or for other reasons. The PLFS 2021-22 data allows us to compute the total number of outdoor hours an individual spends at her workplace. Specifically, if the workplace was in an "open area," "adjacent to a dwelling," "on the street," or on a "construction site,", we coded the individual as an outdoor worker. Additionally, for rural areas, we classify employment in agriculture (both self-employed and casual labor) as outdoor work.

The PLFS data includes information on administrative social group categories that align well with the hierarchical ranking of occupational groups within India's caste structure. The aggregate administrative social group identities captured in the PLFS data consist of Scheduled Tribes (STs), which represent India's indigenous tribes that historically have lived within tribal communities in relative geographical isolation (e.g., forested/hilly districts), Scheduled Castes (SCs), which comprise the formerly "untouchable" caste groups at the bottom of the caste hierarchy, Other Backward Classes (OBCs), representing the peasant and working castes in India's traditional agrarian economy, and a residual category labeled as OTHERS, which encompasses all other caste groups, primarily consisting of "upper" caste group. The three broad administrative categories of SC, ST, and OBC are used for affirmative action (reservation) quotas in public universities and public sector employment and are sociologically salient. The four-fold division of Indian society (SC, ST, OBC, OTHERS) also represents the central demographic determinants of health, educational, and economic outcomes in contemporary India (Coffey et al., 2019; Munshi, 2019). Above all, this four-fold division is congruent with the broad contours of closed occupation groups at the heart of our focus on the association between caste and heat exposure.

Universal Thermal Climate Index (UTCI)

The effective heat stress experienced by individuals is not only a function of air temperature but is modulated by other factors, including humidity, solar radiation, and wind speed. Meteorologists use the "wet bulb globe temperature," or WBGT, to capture the combined effect of air temperature, humidity, wind speed, and solar radiation. Direct ground measurements of WBGT are employed by organizations like the US Army and the World Health Organization (WHO) to establish heat safety standards (Moran et al., 2001; Flouris et al., 2018). However, such direct measurements are not possible at high spatial and temporal resolutions due to complexities associated with measuring the black globe temperature component (Moran and Pandolf, 1999).

In this research, we use one of the most reliable proxies for WBGT, the Universal Thermal Climate Index (UTCI), to measure the quantum of heat stress (Jendritzky et al., 2012; Bröde et al., 2012). The International Society of Biometeorology developed the UTCI as a comprehensive index that captures the thermal environment experienced by humans, considering both atmospheric heat exchanges with the body (heat stress) and the body's physiological response (heat strain) (Jendritzky et al., 2012). The UTCI was devised through collaboration between meteorologists, climatologists, and human thermophysiological modelers, with the goal of incorporating various factors that influence physiological reactions to temperature stress (Błażejczyk et al., 2013). It has been demonstrated that the UTCI outperforms other thermal indices, such as the heat index, effective temperature, and physiological equivalent temperature, across diverse climatic conditions and locations (Broede et al., 2013). The UTCI is what weather stations refer to as the "feels like" temperature in addition to the local air temperature. In contrast to the WBGT, UTCI values at high spatio-temporal resolutions are easily computed using imagery from remote sensing satellites.

The UTCI provides an equivalent temperature value that produces the same level of physiological strain in humans under reference conditions for other climatic variables — 50% relative humidity, calm air conditions, and radiant temperature equal to air temperature (Blazejczyk et al., 2012). It assumes that individuals are employing standard practices for thermal insulation when exposed to outdoor environments. Hence, the UTCI takes into account air temperature, humidity, radiation, and wind speed to determine the physiological impact of heat stress on the human body (Blazejczyk et al., 2012). In addition to using the UTCI for our main analysis, we conduct robustness checks using an alternate metric — the Environmental Stress Index (ESI). The ESI is also commonly used to evaluate moist heat stress (Moran et al., 2004).

Hourly UTCI

For our analysis, we estimate hourly UTCI values for all districts in India between April 1 and June 30, for 2019 and 2022, encompassing the summer period in the country. We obtained hourly values of the UTCI from the ERA5 reanalysis dataset (Hersbach et al., 2020). The ERA5 data set is available at a 31 km resolution, which was re-gridded to 0.25°.[2] Figure 1 shows the maximum UTCI recorded in different parts of India during the summer heat waves of 2019 and 2022.

To ensure compatibility between the UTCI data and the district-level spatial frames of PLFS 2019 and PLFS 2022, we utilized the official district boundary definitions from the 2011 national census. These definitions allow us to extract UTCI values at the district level, aligning with the spatial resolution of the PLFS data. It's worth noting that the PLFS 2018-19 and 2021-22 data utilizes district boundaries that were updated after the census was conducted in 2011. To account for any districts that may have been split since the 2011 census, we adapt the concordance table developed by Rajan and Malghan (2022).[3] We used an extraction routine that accounts for the partial overlaps between raster pixels in the UTCI data available from the ERA5 Reanalysis dataset and the district polygons to provide weighted average estimates of hourly UTCI for all districts (Baston et al., 2022).[4]

[2]Other thermal indices that we considered included the CHIRTS (Verdin et al., 2020) and HiTiSea datasets (Yan et al., 2021) While CHIRTS provides thermal information at a higher resolution than UTCI (6 km vs 31 km), its temporal coverage (1983-2016) does not extend to the 2019 and 2022 heatwaves, and CHIRTS provides 1 reading/day as opposed to the hourly information we use from the UTCI. The HiTiSea data (11 km resolution) also does not extend to the 2022 heat wave. We select the UTCI data as it is a good proxy for WBGT, has a high temporal resolution (hourly data), and has a spatial resolution of 31 km that is appropriate for our district-level analysis.

[3]We also benchmarked our concordance against the India Sate and District Evolution Project — the most comprehensive dataset yet tracing the evolution of sub-national boundaries in India (`https://datawrapper.dwcdn.net/LvLBl/4/`) The full district concordance table that we developed for our analysis including references to publicly available local government data is available on request.

[4]Refer Figure A1 in the Online Appendix for further details.

UTCI Dose

In order to assess the heat stress exposure dose experienced by individuals in each district during the 2019 and 2022 Indian summer heat waves, we combined the district-level UTCI estimates with the occupation data from the PLFS 2018-19 and 2021-22 surveys (April–June Quarter data) to obtain heat stress exposure dose (EXP_{ij}) for individual i in district j. Using the UTCI estimates at the district level for each year, we first calculated the number of hours during April to June for which the UTCI values in a district exceeded a specified threshold ($UTCI^*$). We represent $\overline{UTCI_j^*}$ as the average number of hours during normal daytime working hours when $UTCI_j$, the measured UTCI values in the district j, exceeded the threshold value, $UTCI^*$. In our study, we set the threshold at 32°C, as previous research has indicated that physical exertion at UTCI levels beyond this threshold can lead to significant heat stress and related health issues (Błażejczyk et al., 2013).

However, it's important to note that physiological heat strain is influenced by individual-specific factors such as metabolic rate, insulation, and clothing worn, in addition to environmental conditions (Moran et al., 2003; Błażejczyk et al., 2013). Since we lack individual-specific data on these additional factors, we rely on the assumption of standard clothing with a certain level of thermal insulation, as assumed by the UTCI index. While this simplification may not capture the full complexity of heat strain, our primary objective is to assess inequality in exposure to environmental conditions that can potentially cause heat strain among different population groups.

To conduct robustness checks, we perform our analyses with varying UTCI threshold values ($UTCI^*$) ranging from 26°C to 35°C. The lower bound of 26°C is chosen as strenuous work at UTCI values beyond this threshold can result in moderate heat strain (Błażejczyk et al., 2013). By considering this range of thresholds, we ensure that our analysis captures a broad spectrum of environmental conditions that could potentially lead to heat strain during outdoor work.

To calculate the heat stress exposure dose (EXP_{ij}) for each individual i in district j, we combine the information on the number of hours for which the UTCI threshold was breached with the occupation data from the PLFS 2018-19 and 2021-22 summer quarter surveys. We assume that a typical individual's working hours to be between 8 AM and 6 PM, as these are considered normal daytime working hours. Before 8 AM and after 6 PM, we assume that individuals are either not working or are indoors, thus not exposed to outdoor heat stress. The details are provided in Equation 1.

$$EXP_{ij} = \begin{cases} hrs_i, \text{when } hrs_i \leqslant \overline{UTCI_j^*} \\ \overline{UTCI_j^*}, \text{when } hrs_i > \overline{UTCI_j^*} \end{cases} \tag{1}$$

where EXP_{ij} is the average daily stressful UTCI exposure of individual i in district j. hrs_i is average daily number of hours that the individual i works outdoors as recorded by PLFS data. $\overline{UTCI_j^*}$ is the average daily number of hours in district j during the summer months when the UTCI value exceeded a specified threshold, $UTCI^*$ between 8 AM and 6 PM.

Regression model

We use an OLS model described in Eq. 2 to characterize the association between caste ($group$) and exposure to stressful UTCI levels (EXP).

$$EXP_i = \beta_0 + \beta_1 \cdot (workhours_i) + \beta_{2k} \cdot group_{ik} + \beta_{3k} \cdot group_{ik} \times (workhours_i) + \ldots + \epsilon_{ij} \tag{2}$$

The model evaluates the slope of the heat stress dose (EXP_i) – workhours ($workhours_i$) curve for each of the four broad social groups (SC, ST, OBC, and OTHERS). As discussed in the description of the PLFS data, the residual OTHERS group is the reference category in Eq. 2 (OTHERS largely represents the dominant "upper" caste groups in India). Thus, β_1 is the slope of the heat-stress – works hours curve for this reference group, and $(\beta_1 + \beta_{3k})$ is the slope for $group_k$ ($k \in \{\text{SC, ST, OBC}\}$; $group_{ik} = 1 \,\forall\, i \in k$, and $group_{ik} = 0 \,\forall\, i \notin k$). Thus, an increase in the hours of work by an individual belonging to marginalized $group_k$ will lead to a larger increase (or smaller decrease depending on the sign of β_1) in exposure to stressful UTCI levels compared to the reference group OTHERS (after controlling for other confounding factors such as age, expenditure levels, location, and gender described below). Given the occupational segregation by caste in India, our expectation is that the coefficient β_{3k} will be positive.

Our regression model in Eq. 2 includes controls for age, gender, education, and economic status (measured as household consumption, MPCE, discussed above). 0.02% of individuals report themselves as belonging to a third gender, and we exclude these individuals from the analysis because of this low sub-sample size.[5] We divide education levels into three categories - individuals with no education, individuals educated upto primary school, and individuals educated beyond primary school. Our analysis incorporates state-fixed effects to account for unobservable factors at the state-government level in India. The state is the second administrative level in the Indian federal system. The labor laws are placed in the "Concurrent List," under India's federal structure — both the federal and state-level governments have the authority to enact labor legislation. Using state-level fixed effects enables us to account for differences between states regarding labor laws and occupational safety regulations. We cluster standard errors in all models at the district level.

[5]While individuals outside the male–female binary are among the most marginalized in India, there are currently no regionally representative datasets that permit such sub-group analysis. Our results remain unaltered if we coded gender as "male" and "non-male."

Results

UTCI at the district level

Figure A2 depicts the 2019 and 2022 heat waves across India's districts. As one might expect, UTCI values were highest in India's northern plains, western regions and parts of the Deccan Plateau. UTCI values cross the threshold of 32°C more than 7 hours/day on average across most of the country during the summer months, implying substantial risks of heat-related illnesses because of strenous activity for outdoor workers (Błażejczyk et al., 2013). The average daily exposure for a district was 8.90 hours/day in 2019 (range: 0 – 9.97 hours/day), and 7.57 hours/day in 2022 (range: 0 – 9.93 hours/day).

Inequality in outdoor work

Table 1 provides descriptive statistics for the variables used in the regression model by social group. Total work hours are comparable for the different groups across 2019 and 2022, varying from 2.13 hours/day for STs in 2019 to 2.36 hours/day for the OTHERS category in 2022. However, significant variations arise when examining the percentage of time spent working outdoors and the exposure to stressful heat as a result (*cf.* Figure A3). The OTHERS category spends 27%-28% of their working time outdoors, whereas ST individuals allocate 43-49% of their working hours to outdoor work. Figure 2 provides a visual representation of this variation at the district level, illustrating a higher proportion of outdoor work for marginalized social groups throughout the country. Notably, SC and ST individuals spend more than 75% of their working hours outdoors in atleast 65 districts across both time periods. The corresponding number for OTHERS is 32 districts in 2022. The statistics for MPCE and education are also indicative of caste-based inequality, with the OTHERS category having the highest average education and expenditure levels. Outdoor work is the primary driver of outdoor exposure to stressful UTCI conditions, and the numbers for exposure provide a preliminary sense of inequality in heat stress exposure dose. Across the range of UTCI thresholds from 26°C to 35°C, OTHERS are less exposed to stressful UTCI conditions than the remaining caste groups.

Table A1 provides the result of an OLS model that formally tests the association between caste identity and outdoor work. Models 1 and 3 test the interaction between caste and workhours on outdoor work for 2019 and 2022, respectively, while accounting for state fixed effects, while Models 2 and 4 adds controls for age, gender, MPCE, and education level. The reference caste group is OTHERS, and the positive interaction terms for workhours and caste for the other caste groups shows that outdoor workhours rise faster for other groups relative to OTHERS. Figure A4 uses Models 2 and 4 from Table A1 to present predicted values of outdoor workhours for different levels of work for individuals from the four caste groups.

Inequality in exposure to heat stress

Table 2 provides the results of the main regression model (Eq 2) for an UTCI threshold of 32°C. The distribution of the dependent variable is provided in Figures A5 and A6. Models 1 and 5 provide the basic OLS estimates for caste, workhours, and their interaction on exposure to stressful UTCI levels for 2019 and 2022, respectively. Our main interest is in the coefficients of the interaction terms, which indicate the extra exposure per hour of work for a member of that particular caste group relative to the reference category of OTHERS. The estimates for OBC, SC, and ST are all positive, indicating that exposure increases faster for marginalized groups as compared to OTHERS. Models 2 and 6 add state-fixed effects — the results are robust to this change. Models 3 and 7 include additional controls for gender, age, MPCE and education levels, while Models 4 and 8 further add interaction terms for caste with gender and education levels. Across all models, the interaction between social group and workhours is positive for all social groups.

The values of the coefficients for workhours and the group-workhour interaction terms in Models 4 and 8 also indicate the relative importance of the interaction term. For the OTHERS category in the year 2022, exposure increases by 0.080 hours per extra hour of work (β_1). In contrast, exposure for OBCs, SCs, and STs increases by 0.153 hours/workhour, 0.194 hours/workhour, and 0.125 hours/workhour, ($\beta_1 + \beta_3$), respectively. These values are 91%, 143%, and 56% higher than the increase for OTHERS. The numbers are comparable for Model 4 for 2019 (with the exception that the interaction term for ST is larger, corresponding to a 153% increase over OTHERS).

Figure 3 uses Models 4 and 8 from Table 2 to present predicted values of exposure for different levels of work for individuals from the major caste groups. Exposure rises with increasing workhours, with ST individuals the most affected. Figure A7 uses Models 4 and 8 to further disaggregate differences between caste groups at the state level. While SC and ST individuals are exposed for more than 1 hour/day at a UTCI threshold of 32°C in 20 and 21 states, respectively, OTHERS face similar UTCI exposure in just 11 states in the summer of 2022. The numbers for 2019 are similar.

In addition, the interaction coefficients for gender and education are along expected lines. Models 4 and 8 indicate that exposure to stressful UTCI increases faster with increasing workhours for males, and for less educated individuals. In India, males are more likely to be working outdoors as compared to women.[6] In addition, less educated workers are more likely to be engaged in occupations that involve outdoor work, and not surprisingly, less educated workers are more exposed to heat stress as work increases.

Robustness Checks

Pooled model

As a robustness check, we test a model that combines the 2019 and 2022 summer heat wave data (including an additional year fixed effect). Results are provided in Table A2.

[6] Recount that our analysis is limited to occupational exposure. Women, however, are likely more exposed to outdoor heat stress while performing unpaid work that is not enumerated by labor force datasets such as PLFS or CPHS.

All interaction terms retain their signs and significance levels.

Varying the UTCI threshold

To ensure that the results are not an artifact of the specific UTCI threshold (32°C), we check the model for different combinations of UTCI. The results are provided in Tables A3, A4, and A5. For a UTCI threshold of 35°C for 2022, the interaction term for ST individuals retain their signs, but not their significance levels (Table A5). Other than this, the results are qualitatively unchanged across all models, with the coefficients retaining their signs and significance levels. It is important to note that the rate of increase of exposure for OBC, SC and ST groups is at least 25% higher than the increase for OTHERS when workhours rise even at an UTCI threshold of 35°C, which represents highly stressful conditions for outdoor work.

Flexibility to avoid stressful heat

In the analysis presented in Table 2, we implicitly assume that individuals working outdoors will be exposed to stressful heat if the UTCI crosses specific threshold values between 8 AM and 6 PM. However, it is possible that individuals could reduce their exposure by shifting their work timings (LoPalo, 2023).[7] Specifically, individuals could begin work before 8 AM or finish later than 6 PM. As a robustness check, we test five separate models that provide all individuals the flexibility to shift between 1 hour and 5 hours of their daily work to times when UTCI values do not cross the specified thresholds for heat stress. It is important to note that the estimates produced by these models are a potential lower-bound for outdoor thermal inequality because marginalized-caste workers are likely to have lesser flexibility to shift their working time as compared to individuals with more privilege. Multiple reports have pointed out discrimination in the labor market in India, with marginalized caste workers having the least flexibility because they are

[7] We are grateful to an anonymous reviewer for suggesting this robustness check.

disproportionately likely to be engaged in daily wage labor as compared to other castes (Thorat, 2018). The results of our analysis are presented in Table A6. Across all values of flexibility, the results are qualitatively unchanged.

Subsample analysis for the adult population

As an additional robustness check, we analyze the results of the main regression model for a subsample of the PLFS population that belongs to the adult age group (18 - 65 years old). 95% of individuals that have non-zero working hours belong to this age group. Table A7 shows the findings from the regression model. The results are qualitatively unchanged, with all group-workhour interaction terms retaining their signs and significance levels. significant. Figure 4 shows the change in exposure for varying workhours for adults.

Subsample analysis for working individuals

Since exposure to stressful UTCI is driven by outdoor work, we run a robustness check with a subsample that only includes individuals with non-zero workhours. The regression output is provided in Table A8. While all of the group-workhour interaction terms retain their signs, it is interesting to note that the coefficient of workhours (β_1) reverses in sign across most models. Figure 5 shows the change in exposure for varying workhours for working individuals. Our main results still hold — exposure values are higher for individuals from marginalized caste groups and lowest for OTHERS (except for the coefficient on the OBC-workhours interaction term which is not significant in Model 8).

We explore the reasons behind the change in sign/significance of the workhour term in Figure 6. For all social groups, the proportion of work done outdoors decreases with increasing workhours. This could be a function of the nature of occupation, with higher workhours implying that individuals are more likely to have stable jobs that are done indoors. However, this is an hypothesis at this point that needs more verification in future research.

Seasonality in workhours

Our main analysis demonstrates inequality in exposure to outdoor heat stress during the summer heat waves of 2019 and 2022. As an additional analysis, we check for seasonal variations in thermal stress inequality. Work patterns can change over seasons, especially for rural agricultural workers whose outdoor work patterns would depend on the agricultural requirements at the time (Jha and Basole, 2023). We use the PLFS data from 2021-2022 for this analysis. For each quarter, our sample includes the rural population surveyed in the quarter and the first visit to urban households for the quarter (this sample is nationally representative for the quarter). For each season, we use UTCI data from the ERA5 Reanalysis dataset for the corresponding quarter (Balsamo et al., 2015).

The results are provided in Tables A9, A10, and A11. Additionally, we also provide an analysis for the period July 2021 to June 2022 in Table A12 (covering the PLFS 2021-22 cycle). The results are qualitatively unchanged from our findings during the summer heat wave of 2022. All group-workhour interaction terms retain their signs and significance levels across quarters and for the 12-month analysis.

Alternate thermal metric - the Environmental Stress Index (ESI)

While the UTCI is widely used to understand heat stress, there are multiple metrics that can be used to quantify the human experience of thermal stress. One of the most commonly used metrics is the ESI that has been been widely used to understand heat stress and strain (Moran et al., 2003, 2004). We calculate the ESI using standard approaches available in the literature (Moran et al., 2001; Yan et al., 2021). We obtain the variables required to calculate the ESI values from the publicly available ERA5-Land dataset at a resolution of 0.1°(Balsamo et al., 2015). Our results are presented in Table A13. Following guidelines from health research, we use an ESI threshold of 30°C for the analysis (Armstrong et al., 2007). The results are qualitatively unchanged.

Alternate labor force data

Our main analysis relies on the nationally representative PLFS data for the summer of 2019 and 2022. Recently, a new dataset called the Consumer Pyramids Household Survey (CPHS) was launched by a private agency, CMIE. The CPHS has a larger sample size and a higher frequency, and potentially provides a panel dataset by following the same households and individuals over time. We did not use the CPHS for our main analysis because of limitations pointed out by other researchers. Specifically, the CPHS is known to underestimate poorer populations (particularly marginalized caste/class households in rural areas), and has non-random drop off among participants (Dreze and Somanchi, 2021; Somanchi, 2021). In addition, a significant proportion of households (around 30%) in the CPHS do not provide caste information, and it is not known whether the non availability of caste information is random across caste groups.

We use the CPHS data to conduct a robustness check for our analysis. We replicate the same analytical strategy used in the main analysis with UTCI data and labor force data from the CPHS. While the CPHS is conducted thrice a year (January-April, May-August, September-December), the data also provides information on the month in which the household was surveyed. We extract all information for individuals and households that were surveyed during April to June 2022. We restrict our sample to individuals for which complete information on the variables of interest is available in the CPHS data. We identify an individual as an outdoor worker if the place of work is one of the following: 'market place', 'own farm', 'farm owned by other', or 'leased farm'. The results of our analysis are presented in Tables A14 and A15. The results are qualitatively unchanged, with the group-workhour interaction terms retaining their signs and significance levels.

Inequality in exposure to night-time temperatures

Heat stress during the night is linked to a range of health problems (Obradovich et al., 2017). The occupational heat stress inequality that we observe during the daytime could potentially be exacerbated by heat stress inequality at night. To assess this, we use block-level population data from the Census of India 2011 (Registrar General of India, 2011), and night-time Land Surface Temperature data from the MODIS Aqua MOD21A2 product. We also conduct an additional analysis at the ward level for the city on Bengaluru in India. Details regarding the analysis are provided in the online appendix. The results are presented in Tables A16, A17 and A18. We do not find evidence for inequality in exposure to night-time LST.

The findings provide context to our analysis and show that the inequality in daytime exposure is not being driven by the fact that marginalized caste groups tend to live in hotter regions. Rather, the daytime occupational heat stress inequality that we observe is driven by occupational segregation, with marginalized caste groups facing higher heat stress because they are more likely to be engaged in outdoor work.

Inequality in access to adaptive mechanisms

The lack of inequality in exposure to night-time LST does not imply that different caste groups are equally able to adapt to night-time temperatures. Coping mechanisms for night-time heat in India typically imply air-conditioners, coolers and fans. We use data from the National Family and Health Survey (NFHS 5 - 2019-2021) to understand the variations in access to heat adaptive mechanisms by caste group at the household level. The results are presented in Table A19. Marginalized caste households have lower access to fans, air conditioners and coolers as compared to households from the OTHERS category.

Discussion

Our analysis builds on the emerging literature that has combined in-situ survey data with remote sensing information to provide insights at the intersection of demography and the environment (Brown et al., 2014; Kugler et al., 2019; Randell et al., 2022). Our results show how the slope of the heat stress dose – workhours curve corresponding to the marginalized social groups in India is between 25–150% steeper than that for dominant caste groups for UTCI thresholds between 26°C and 35°C. The results are robust to different thresholds for harmful heat stress exposure (26°C to 35°C), alternate measures of thermal inequality (UTCI and ESI), alternate labor force data (PLFS and CPHS), different seasons of the year, and for different heat wave seasons (2019 and 2022). These results also hold for subsamples with only adults or individuals in the labor force.

By analyzing exposure to land surface temperature at night, we show that the results are not being driven by the fact that individuals from marginalized social groups reside in hotter regions. Rather, the findings are primarily driven by how an individual's caste identity is strongly associated with her occupation. Marginalized caste groups in India dominate occupations requiring outdoor physical labor. While modernization and urbanization was supposed to reduce the pernicious influence of occupational segregation based on caste in India, recent work has documented the persistent influence of caste in the labor market (Munshi, 2019; Asher et al., 2018). These strong associations between caste, occupation, and heat stress exposure are best described as "thermal injustice." Akin to how the environmental justice question in the United States is primarily a racial justice question, thermal injustice in India is rooted in caste injustice. Despite caste and the environment being inextricably interlinked, the environmental literature in India that puts caste at its center is limited (Sharma, 2017). By delineating how social demography modulates thermal injustice, this paper adds to this sparse but growing debate at the intersection of caste and environment.

While our analysis demonstrates caste-based inequality in exposure to occupational heat stress, further research is needed to understand the exact mechanisms at work. Evidence suggests that caste discrimination in the formal labor market can determine both candidate selection and wages (Das and Dutta, 2007; Banerjee et al., 2009). This could lead to marginalized caste workers being underrepresented in formal jobs which are less likely to involve outdoor work. Additionally, transaction costs are higher for marginalized-caste individuals looking for regular formal sector jobs (Ito, 2009). Persistent caste-related disparities in education levels and social networks could also drive occupational segregation, with marginalized castes disproportionately represented in lower-paying jobs (Desai and Dubey, 2012). While researchers have argued that the links between caste and occupational inheritance are weakening in India, members of specific castes could control social, economic, and political resources that provide advantages in the labor market (Vaid, 2014).

The stark heat stress exposure differences we uncover between different social groups in India likely understate the extent of thermal injustice in India. First, the UTCI assumes all individuals follow standard thermal insulation practices. The realities of India's caste system imply that workers from marginalized groups will likely have lower resources to adapt to stressful environmental conditions and could potentially experience higher levels of heat strain at the same UTCI. Second, emerging evidence suggests that occupations with an over-representation of workers from marginalized social groups experience greater heat strain symptoms with WBGT (Wet Bulb Globe Temperature) values between 27.5 °C and 31 °C (Venugopal et al., 2016). The threshold levels of heat that induce the most severe heat strain responses are lower for occupations involving heavy work (ISO, 2004), and these are the occupations where workers from marginalized social groups are over-represented in India. Third, our analysis focused only on daytime exposure to heat stress. However, there is robust evidence that climate change is also driving night-time temperatures — especially in regions such as South Asia (Mukherjee and Mishra, 2018). Adequate cooling of the human body during night-time is an essential physiological coping mechanism against daytime heat stress exposure. Rising night-time temperatures directly influence mortality and morbidity burdens (He et al., 2022). While we do not find evidence for inequality in exposure to night-time temperatures across groups (both nationally and within a metropolitan city), we do find evidence that marginalized social groups are less likely to have access to thermal adaptive mechanisms such as fans, coolers, and air conditioners. Fourth, while we focus on outdoor heat stress, it is possible that indoor heat stress can be a serious issue if residents lack access to ventilation. Marginalized groups and women are more likely to bear the brunt of indoor heat stress as they tend to disproportionately reside in informal dwelling units without adequate ventilation.

The PLFS data that we have used here cannot characterize neighborhood and street-level micro-processes that modulate exposure to heat stress. Neighborhood processes are also crucial determinants of vulnerability and adaptation capabilities. For instance, evidence suggests that green spaces help ameliorate local urban heat island effects in India (Shah et al., 2021). A plausible pathway underlying thermal injustice that we report here is the spatial segregation of marginalized social groups that can impact levels of effective heat stress, physiological strain response, and access to mitigating infrastructure such as green spaces (Acevedo-Garcia et al., 2003). Inequality at the local scale could imply that our analysis potentially underestimates occupational thermal inequality in India - future thermal injustice research should uncover inequality at a higher spatial resolutions. In addition, there could be intra-district factors that influence thermal stress and occupational choices of individuals, and could potentially impact the results. We constructed the UTCI data at a 31 km resolution (0.25°grid) — a spatial resolution appropriate for our nationally representative analysis at the district level. While it is now possible to uncover social processes at much higher spatial (and temporal) resolutions using satellite imagery, the binding constraint is the availability of high-resolution in situ survey data that provides occupational information (Burke et al., 2021). With the increasing availability of demographic "big microdata" (Ruggles, 2014), demographers can play a leading role in using such satellite imagery to address central questions surrounding climate inequality.

Climate change-induced global temperature rise will increase the frequency, severity, and duration of heat waves in South Asia (Aadhar and Mishra, 2023). However, even advanced economies such as the United States lack well-developed federal standards for occupational heat exposure (Gubernot et al., 2014). New evidence from India shows how heat strain impedes labor productivity and even the ability to work (Heyes and Saberian, 2022; Somanathan et al., 2021). However, the intimate connection between occupation and ascriptive caste identity has escaped both scholarly and policy attention. The Indian caste system is "not merely a division of labor. It is also a division of laborers" (Ambedkar, 1936). For example, despite a statutory prohibition on manual scavenging, Dalits, the formerly "untouchable" caste groups are forced to manually clean and maintain India's sewerage network. Heat wave conditions make this already dangerous job potentially fatal (Kuntamalla, 2022). Thus, public health focused heat plans in the Indian context must recognize how caste drives heat strain inequality. More generally, our results show why status inequality must be studied as an analytically independent distinct public health channel. Our results complement arguments for why income inequality and health outcomes are not always accounted for by status markers such as race (Subramanian and Kawachi, 2003).

References

Aadhar, S. and Mishra, V. (2023). The 2022 mega heatwave in south asia in the observed and projected future climate. *Environmental Research Letters*.

Acevedo-Garcia, D., Lochner, K. A., Osypuk, T. L., and Subramanian, S. V. (2003). Future directions in residential segregation and health research: a multilevel approach. *American journal of public health*, 93(2):215–221.

Alizadeh, M. R., Abatzoglou, J. T., Adamowski, J. F., Prestemon, J. P., Chittoori, B., Akbari Asanjan, A., and Sadegh, M. (2022). Increasing heat-stress inequality in a warming climate. *Earth's Future*, 10(2):e2021EF002488.

Ambedkar, B. R. (2014 [1936]). *Annihilation of caste.* Verso Books.

Armstrong, L. E., Casa, D. J., Millard-Stafford, M., Moran, D. S., Pyne, S. W., and Roberts, W. O. (2007). Exertional heat illness during training and competition. *Medicine and Science in Sports and Exercise*, 39(3):556–572.

Asher, S., Novosad, P., and Rafkin, C. (2018). Intergenerational mobility in india: Estimates from new methods and administrative data. *World Bank Working Paper.*

Balsamo, G., Albergel, C., Beljaars, A., Boussetta, S., Brun, E., Cloke, H., Dee, D., Dutra, E., Muñoz-Sabater, J., Pappenberger, F., et al. (2015). Era-interim/land: a global land surface reanalysis data set. *Hydrology and Earth System Sciences*, 19(1):389–407.

Banerjee, A., Bertrand, M., Datta, S., and Mullainathan, S. (2009). Labor market discrimination in delhi: Evidence from a field experiment. *Journal of comparative Economics*, 37(1):14–27.

Baston, D., ISciences, L., and Baston, M. D. (2022). Package 'exactextractr'. *terra*, 1:17.

Blazejczyk, K., Epstein, Y., Jendritzky, G., Staiger, H., and Tinz, B. (2012). Comparison of utci to selected thermal indices. *International journal of biometeorology*, 56:515–535.

Błażejczyk, K., Jendritzky, G., Bröde, P., Fiala, D., Havenith, G., Epstein, Y., Psikuta, A., and Kampmann, B. (2013). An introduction to the universal thermal climate index (utci). *Geographia Polonica*, 86(1):5–10.

Bröde, P., Fiala, D., Błażejczyk, K., Holmér, I., Jendritzky, G., Kampmann, B., Tinz, B., and Havenith, G. (2012). Deriving the operational procedure for the universal thermal climate index (utci). *International journal of biometeorology*, 56:481–494.

Broede, P., Blazejczyk, K., Fiala, D., Havenith, G., Holmer, I., Jendritzky, G., Kuklane, K., and Kampmann, B. (2013). The universal thermal climate index utci compared to ergonomics standards for assessing the thermal environment. *Industrial health*, 51(1):16–24.

Brown, M. E., Grace, K., Shively, G., Johnson, K. B., and Carroll, M. (2014). Using satellite remote sensing and household survey data to assess human health and nutrition response to environmental change. *Population and environment*, 36(1):48–72.

Burke, M., Driscoll, A., Lobell, D. B., and Ermon, S. (2021). Using satellite imagery to understand and promote sustainable development. *Science*, 371(6535):eabe8628.

Chambers, J. (2020). Global and cross-country analysis of exposure of vulnerable populations to heatwaves from 1980 to 2018. *Climatic Change*, 163(1):539–558.

Coffey, D., Deshpande, A., Hammer, J., and Spears, D. (2019). Local Social Inequality, Economic Inequality, and Disparities in Child Height in India. *Demography*, 56(4):1427–1452.

Das, M. B. and Dutta, P. V. (2007). Does caste matter for wages in the indian labor market. *Washington, DC, USA: The World Bank*.

Day, E., Fankhauser, S., Kingsmill, N., Costa, H., and Mavrogianni, A. (2019). Upholding labour productivity under climate change: an assessment of adaptation options. *Climate policy*, 19(3):367–385.

Desai, S. and Dubey, A. (2012). Caste in 21st century india: Competing narratives. *Economic and political weekly*, 46(11):40.

Deshpande, A. (2011). *The grammar of caste: Economic discrimination in contemporary India*. Oxford University Press.

Dickinson, K. L., Randell, H. F., Kramer, R. A., and Shayo, E. H. (2012). Socio-economic status and malaria-related outcomes in mvomero district, tanzania. *Global public health*, 7(4):384–399.

Dreze, J. and Somanchi, A. (2021). View: New barometer of india's economy fails to reflect deprivations of poor households. *The Economic Times*, 21.

Ellena, M., Ballester, J., Mercogliano, P., Ferracin, E., Barbato, G., Costa, G., and Ingole, V. (2020). Social inequalities in heat-attributable mortality in the city of turin, northwest of italy: a time series analysis from 1982 to 2018. *Environmental Health*, 19:1–14.

Flouris, A. D., Dinas, P. C., Ioannou, L. G., Nybo, L., Havenith, G., Kenny, G. P., and Kjellstrom, T. (2018). Workers' health and productivity under occupational heat strain: a systematic review and meta-analysis. *The Lancet Planetary Health*, 2(12):e521–e531.

Gubernot, D. M., Anderson, G. B., and Hunting, K. L. (2014). The epidemiology of occupational heat exposure in the United States: a review of the literature and assessment of research needs in a changing climate. *International journal of biometeorology*, 58(8):1779–1788.

Guha, S. and Chandra, H. (2022). Multivariate small area modelling for measuring micro level earning inequality: Evidence from periodic labour force survey of india. *Social Indicators Research*, pages 1–21.

He, C., Kim, H., Hashizume, M., Lee, W., Honda, Y., Kim, S. E., Kinney, P. L., Schneider, A., Zhang, Y., Zhu, Y., et al. (2022). The effects of night-time warming on mortality burden under future climate change scenarios: a modelling study. *The Lancet Planetary Health*, 6(8):e648–e657.

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., et al. (2020). The era5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society*, 146(730):1999–2049.

Heyes, A. and Saberian, S. (2022). Hot days, the ability to work and climate resilience: Evidence from a representative sample of 42,152 indian households. *Journal of Development Economics*, 155:102786.

Hnatkovska, V., Lahiri, A., and Paul, S. B. (2013). Breaking the caste barrier intergenerational mobility in india. *Journal of Human Resources*, 48(2):435–473.

Islam, A., Pakrashi, D., Vlassopoulos, M., and Wang, L. C. (2021). Stigma and misconceptions in the time of the covid-19 pandemic: A field experiment in india. *Social Science & Medicine*, 278:113966.

ISO, I. O. f. S. (2004). *Ergonomics of the Thermal Environment: Analytical Determination and Interpretation of Heat Stress Using Calculation of the Predicted Heat Strain.* ISO.

Ito, T. (2009). Caste discrimination and transaction costs in the labor market: Evidence from rural north india. *Journal of development Economics*, 88(2):292–300.

Jacklitsch, B. L., Williams, W. J., Musolin, K., Coca, A., Kim, J.-H., and Turner, N. (2016). *Occupational exposure to heat and hot environments: revised criteria 2016.* Centers for Disease Control.

Jajoria, D. and Jatav, M. (2020). Is periodic labour force survey, 2017–18 comparable with employment–unemployment survey, 2011–12? *Economic and Political Weekly*, 55(3):12–16.

Jendritzky, G., de Dear, R., and Havenith, G. (2012). Utci—why another thermal index? *International journal of biometeorology*, 56:421–428.

Jha, M. and Basole, A. (2023). Labour incomes in india: A comparison of two national household surveys. *The Indian Journal of Labour Economics*, 66(1):181–201.

Kawachi, I., Subramanian, S., and Almeida-Filho, N. (2002). A glossary for health inequalities. *Journal of Epidemiology & Community Health*, 56(9):647–652.

Khosla, R., Jani, A., and Perera, R. (2021). Health risks of extreme heat.

Kotsila, P. and Anguelovski, I. (2023). Justice should be at the centre of assessments of climate change impacts on health. *The Lancet Public Health*, 8(1):e11–e12.

Kugler, T. A., Grace, K., Wrathall, D. J., de Sherbinin, A., Van Riper, D., Aubrecht, C., Comer, D., Adamo, S. B., Cervone, G., Engstrom, R., et al. (2019). People and pixels 20 years later: the current data landscape and research trends blending population and environmental data. *Population and Environment*, 41:209–234.

Kuntamalla, V. (2022). As temperatures rise, men descending into hot, noxious sewers are in greater danger than ever. *Article-14*, 22(8):1–17.

Lavetti, K. (2023). Compensating wage differentials in labor markets: Empirical challenges and applications. *Journal of Economic Perspectives*, 37(3):189–212.

LoPalo, M. (2023). Temperature, worker productivity, and adaptation: evidence from survey data production. *American Economic Journal: Applied Economics*, 15(1):192–229.

Mishra, V., Mukherjee, S., Kumar, R., and Stone, D. A. (2017). Heat wave exposure in india in current, 1.5 c, and 2.0 c worlds. *Environmental Research Letters*, 12(12):124012.

Moran, D., Pandolf, K., Shapiro, Y., Laor, A., Heled, Y., and Gonzalez, R. (2003). Evaluation of the environmental stress index for physiological variables. *Journal of thermal biology*, 28(1):43–49.

Moran, D. S. and Pandolf, K. B. (1999). Wet bulb globe temperature (wbgt)–to what extent is gt essential? *Aviation, space, and environmental medicine*, 70(5):480–484.

Moran, D. S., Pandolf, K. B., Shapiro, Y., Heled, Y., Shani, Y., Mathew, W., and Gonzalez, R. (2001). An environmental stress index (esi) as a substitute for the wet bulb globe temperature (wbgt). *Journal of thermal biology*, 26(4-5):427–431.

Moran, D. S., Pandolf, K. B., Vitalis, A., Heled, Y., Parker, R., and Gonzalez, R. R. (2004). Evaluation of the environmental stress index (esi) for the southern hemisphere. *Journal of Thermal Biology*, 29(7-8):535–538.

Mukherjee, S. and Mishra, V. (2018). A sixfold rise in concurrent day and night-time heatwaves in india under 2 c warming. *Scientific Reports*, 8(1):1–9.

Munshi, K. (2019). Caste and the Indian economy. *Journal of Economic Literature*, 57(4):781–834.

Nijman, T. and Verbeek, M. (1990). Estimation of time-dependent parameters in linear models using cross-sections, panels, or both. *Journal of Econometrics*, 46(3):333–346.

NSO (2023). *Annual Report: Periodic Labour Force Survey (July 2018 – June 2019, July 2021 – June 2022)*. National Statistics Office, Ministry of Statistics and Programme Implementation, Government of India.

Obradovich, N., Migliorini, R., Mednick, S. C., and Fowler, J. H. (2017). Nighttime temperature and human sleep loss in a changing climate. *Science advances*, 3(5):e1601555.

Perkins-Kirkpatrick, S. and Lewis, S. (2020). Increasing trends in regional heatwaves. nat. commun. 11, 1–8.

Piil, J. F., Lundbye-Jensen, J., Trangmar, S. J., and Nybo, L. (2017). Performance in complex motor tasks deteriorates in hyperthermic humans. *Temperature*, 4(4):420–428.

Rajan, J. and Malghan, D. (2022). Administrative proliferation and developmental outcomes: Data from india. *IIM Bangalore Research Paper*, 1(658):1–27.

Randell, H., Gray, C., and Shayo, E. H. (2022). Climatic conditions and household food security: Evidence from tanzania. *Food Policy*, 112:102362.

Registrar General of India (2011). Census of india 2011. *Provisional Population Totals. New Delhi: Government of India*, pages 409–413.

Romanello, M., Di Napoli, C., Drummond, P., Green, C., Kennard, H., Lampard, P., Scamman, D., Arnell, N., Ayeb-Karlsson, S., Ford, L. B., et al. (2022). The 2022 report of the lancet countdown on health and climate change: health at the mercy of fossil fuels. *The Lancet*, 400(10363):1619–1654.

Rosen, S. (1986). The theory of equalizing differences. *Handbook of labor economics*, 1:641–692.

Ruggles, S. (2014). Big microdata for population research. *Demography*, 51(1):287–297.

Schulte, P., Bhattacharya, A., Butler, C., Chun, H., Jacklitsch, B., Jacobs, T., Kiefer, M., Lincoln, J., Pendergrass, S., Shire, J., et al. (2016). Advancing the framework for considering the effects of climate change on worker safety and health. *Journal of occupational and environmental hygiene*, 13(11):847–865.

Shah, A., Garg, A., and Mishra, V. (2021). Quantifying the local cooling effects of urban green spaces: Evidence from bengaluru, india. *Landscape and Urban Planning*, 209:104043.

Sharma, M. (2017). *Caste and nature: Dalits and Indian environmental policies*. Oxford University Press.

Somanathan, E., Somanathan, R., Sudarshan, A., and Tewari, M. (2021). The impact of temperature on productivity and labor supply: Evidence from indian manufacturing. *Journal of Political Economy*, 129(6):1797–1827.

Somanchi, A. (2021). Missing the poor, big time: A critical assessment of the consumer pyramids household survey. *SocArXiv*, 11.

Subramanian, S. V. and Kawachi, I. (2003). The association between state income inequality and worse health is not confounded by race. *International Journal of Epidemiology*, 32(6):1022–1028.

Sylla, M. B., Faye, A., Giorgi, F., Diedhiou, A., and Kunstmann, H. (2018). Projected heat stress under 1.5 c and 2 c global warming scenarios creates unprecedented discomfort for humans in west africa. *Earth's Future*, 6(7):1029–1044.

Thorat, S. (2018). Scheduled castes among worst sufferers of india's job problem. *Hindustan Times*, Sep.

Tustin, A. W., Lamson, G. E., Jacklitsch, B. L., Thomas, R. J., Arbury, S. B., Cannon, D. L., Gonzales, R. G., and Hodgson, M. J. (2018). Evaluation of occupational exposure limits for heat stress in outdoor workers—united states, 2011–2016. *Morbidity and Mortality Weekly Report*, 67(26):733.

Vaid, D. (2014). Caste in contemporary india: Flexibility and persistence. *Annual Review of Sociology*, 40:391–410.

Venugopal, V., Chinnadurai, J. S., Lucas, R. A., and Kjellstrom, T. (2016). Occupational heat stress profiles in selected workplaces in india. *International journal of environmental research and public health*, 13(1):89.

Verdin, A., Funk, C., Peterson, P., Landsfeld, M., Tuholske, C., and Grace, K. (2020). Development and validation of the chirts-daily quasi-global high-resolution daily temperature data set. *Scientific Data*, 7(1):303.

Vicedo-Cabrera, A. M., Scovronick, N., Sera, F., Royé, D., Schneider, R., Tobias, A., Astrom, C., Guo, Y., Honda, Y., Hondula, D., et al. (2021). The burden of heat-related mortality attributable to recent human-induced climate change. *Nature climate change*, 11(6):492–500.

Wilkinson, R. G. (2002). *Unhealthy societies: the afflictions of inequality*. Routledge.

Yan, Y., Xu, Y., and Yue, S. (2021). A high-spatial-resolution dataset of human thermal stress indices over south and east asia. *Scientific data*, 8(1):229.

Table 1: Summary statistics using PLFS data for April-June (2019 and 2022)

	April to June 2019									
Social Group	All		OTHERS		OBC		SC		ST	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Count	101510	101510	29914	29914	40539	40539	17182	17182	13875	13875
Work (hrs/day)	2.25	3.41	2.33	3.51	2.24	3.42	2.24	3.38	2.13	3.19
Outdoor (hrs/day)	0.70	2.08	0.55	1.87	0.69	2.08	0.83	2.26	0.92	2.27
% Outdoors	36	48	27	45	35	48	42	49	49	50
Exposure (hrs/day) (UTCI: 26)	0.67	2.03	0.50	1.79	0.68	2.06	0.82	2.22	0.86	2.18
Exposure (hrs/day) (UTCI: 29)	0.66	2.01	0.49	1.77	0.68	2.05	0.80	2.19	0.83	2.13
Exposure (hrs/day) (UTCI: 32)	0.63	1.95	0.46	1.69	0.66	2.01	0.77	2.15	0.74	1.99
Exposure (hrs/day) (UTCI: 35)	0.58	1.83	0.41	1.56	0.62	1.92	0.73	2.07	0.61	1.78
MPCE (INR)	2340	1960	2933	2647	2159	1582	2009	1399	1997	1473
Age (yrs)	30.7	19.5	32.7	20.0	30.4	19.5	29.3	18.9	29.2	18.6
% Female	49		49		49		49		49	
% No education	23		18		25		29		24	
% Upto primary education	25		23		25		26		26	

	April to June 2022									
Social Group	All		OTHERS		OBC		SC		ST	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Count	104164	104164	28414	28414	42292	42292	18187	18187	15271	15271
Work (hrs/day)	2.31	3.32	2.36	3.39	2.31	3.33	2.26	3.28	2.27	3.17
Outdoor (hrs/day)	0.75	2.08	0.60	1.90	0.76	2.09	0.86	2.22	0.90	2.21
% Outdoors	36	48	28	45	36	48	41	49	43	50
Exposure (hrs/day) (UTCI: 26)	0.72	2.03	0.54	1.81	0.75	2.07	0.85	2.20	0.81	2.09
Exposure (hrs/day) (UTCI: 29)	0.70	1.99	0.52	1.77	0.74	2.05	0.84	2.19	0.74	1.96
Exposure (hrs/day) (UTCI: 32)	0.65	1.90	0.48	1.66	0.71	1.99	0.80	2.12	0.61	1.75
Exposure (hrs/day) (UTCI: 35)	0.58	1.78	0.41	1.51	0.66	1.89	0.74	2.03	0.48	1.52
MPCE (INR)	2209	1800	2759	2387	2107	1593	1900	1247	1836	1331
Age (yrs)	31.3	19.8	33.7	20.4	31.2	19.8	29.9	19.2	29.1	19.0
% Female	49		49		50		49		50	
% No education	23		18		24		27		23	
% Upto primary education	25		23		24		26		28	

Table 2: Regression Results for a UTCI threshold of 32°C for April-June (2019, 2022)

	DV: Hours of exposure							
	2019				2022			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OBC	0.015*	−0.078***	−0.147***	−0.121***	0.035***	−0.051*	−0.122***	−0.099***
	(0.007)	(0.022)	(0.021)	(0.021)	(0.008)	(0.024)	(0.023)	(0.022)
SC	0.005	−0.073***	−0.160***	−0.117***	0.020*	−0.063**	−0.164***	−0.124***
	(0.009)	(0.020)	(0.020)	(0.019)	(0.009)	(0.022)	(0.022)	(0.021)
ST	0.018	0.174***	0.077+	0.087*	0.015	0.239***	0.112**	0.118**
	(0.014)	(0.044)	(0.045)	(0.042)	(0.013)	(0.044)	(0.043)	(0.040)
Workhours	0.177***	0.180***	0.172***	0.084***	0.178***	0.179***	0.170***	0.080***
	(0.014)	(0.014)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)
OBC * Workhours	0.095***	0.095***	0.092***	0.077***	0.088***	0.090***	0.086***	0.073***
	(0.015)	(0.015)	(0.014)	(0.014)	(0.016)	(0.016)	(0.015)	(0.015)
SC * Workhours	0.151***	0.152***	0.147***	0.114***	0.144***	0.146***	0.140***	0.114***
	(0.017)	(0.017)	(0.017)	(0.016)	(0.017)	(0.017)	(0.016)	(0.016)
ST * Workhours	0.150***	0.148***	0.144***	0.129***	0.058*	0.062*	0.058*	0.045+
	(0.026)	(0.026)	(0.026)	(0.024)	(0.026)	(0.026)	(0.026)	(0.024)
Gender: Male			0.196***	0.148***			0.218***	0.172***
			(0.016)	(0.010)			(0.016)	(0.010)
No education			0.299***	−0.129***			0.250***	−0.174***
			(0.019)	(0.012)			(0.019)	(0.011)
Upto primary education			0.216***	−0.064***			0.215***	−0.090***
			(0.016)	(0.009)			(0.017)	(0.008)
Age			0.006***	0.004***			0.006***	0.003***
			(0.000)	(0.000)			(0.000)	(0.000)
MPCE			0.000***	0.000***			0.000***	0.000***
			(0.000)	(0.000)			(0.000)	(0.000)
Gender: Male * Workhours				0.047***				0.051***
				(0.010)				(0.008)
No education * Workhours				0.256***				0.239***
				(0.012)				(0.012)
Upto primary education * Workhours				0.129***				0.135***
				(0.009)				(0.009)
Num.Obs.	99255	99255	99255	99255	104164	104164	104162	104162
R2	0.216	0.233	0.251	0.277	0.196	0.218	0.238	0.262
R2 Adj.	0.216	0.233	0.251	0.277	0.196	0.217	0.238	0.261
State Fixed Effects	No	Yes	Yes	Yes	No	Yes	Yes	Yes

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[a] All standard errors are clustered at the district level

[b] OBC - Other backward class, SC - Scheduled caste, ST - Scheduled tribe

[c] Reference category for caste - OTHERS

[d] Reference category for gender - Female

[e] Reference category for education - Greater than primary education

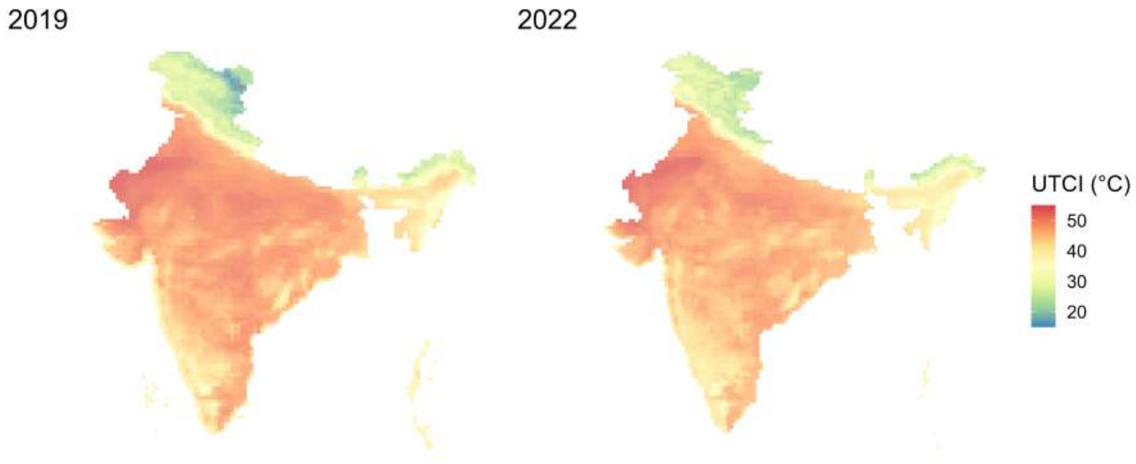

Figure 1: Maximum UTCI

[a] Panel A presents the the maximum UTCI (Universal Thermal Climate Index) recorded in different parts of India between April 01 and June 30, 2019. Panel B presents the same information for April 01 to June 30, 2022.
[b] The maps are based on data from Hersbach et al. (2020)

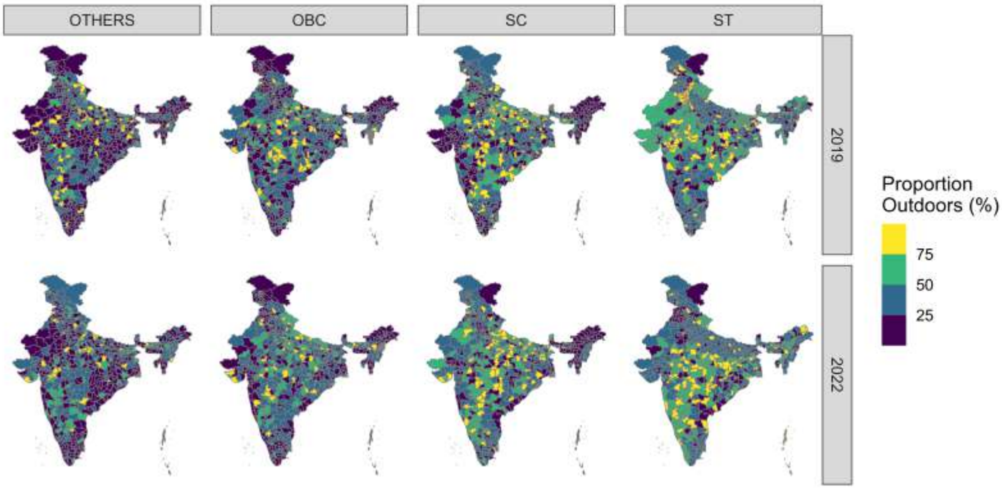

Figure 2: Variation in proportion of work done outdoors by caste group

[a] The plot shows the proportion of working hours spent outdoors by caste at the district level for 2019 and 2022.
[b] The maps are based on a PLFS sample of 101,510 individuals for April to June 2019 (top panel), and 104,164 individuals for April to June 2022 (bottom panel) (NSO, 2023)

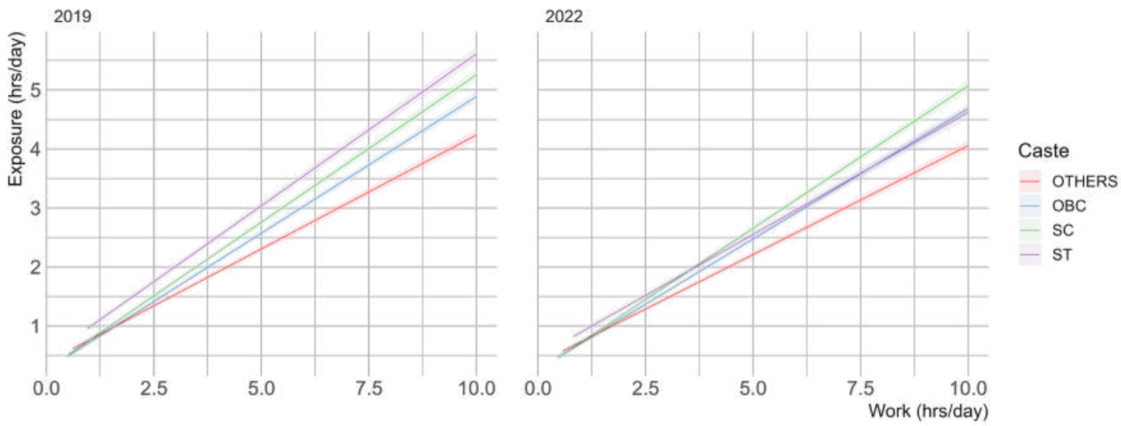

Figure 3: Predicted values of exposure by caste for varying levels of work for entire PLFS sample

[a] The plot shows the predicted exposure to UTCI values above 32°C for varying levels of work for different caste groups for April to June 2019 (left panel) and April to June 2022 (right panel). The sample for the plot includes the entire PLFS sample in the period.
[b] Reference values for the 2019 plot are Gender - Male, Education - No education, State - Uttar Pradesh (most populous state in India), MPCE - INR 2343, Age - 30.
[c] Reference values for the 2022 plot are Gender - Male, Education - No education, State - Uttar Pradesh, MPCE - INR 2209, Age - 31.
[d] The plot is based on Model 4 (April to June 2019) and Model 8 (April to June 2022) in Table 2.

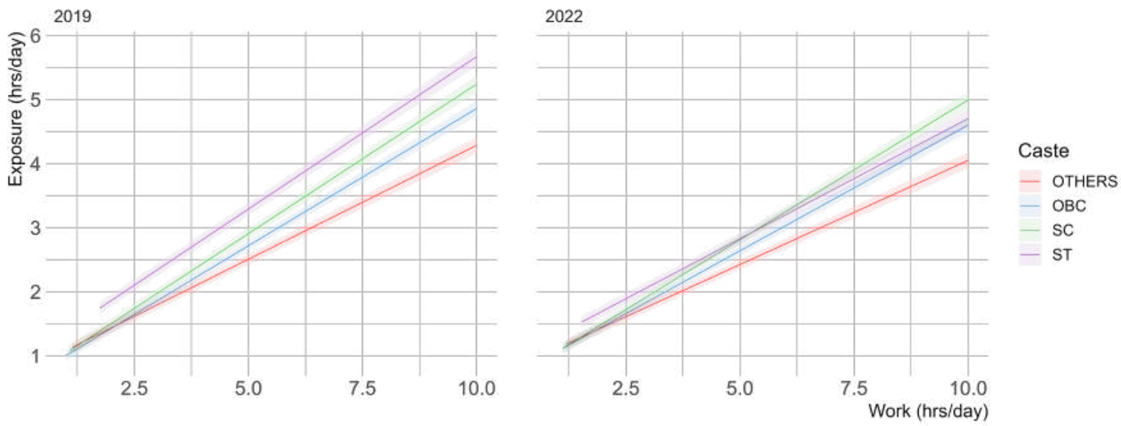

Figure 4: Predicted values of exposure by caste for varying levels of work for working-age adults in the PLFS sample

[a] The plot shows the predicted exposure to UTCI values above 32°C for varying levels of work for different caste groups for April to June 2019 (left panel) and April to June 2022 (right panel). The sample for the plot includes working-age adults (age 18 to 65) in the PLFS sample.
[b] Reference values for the 2019 plot are Gender - Male, Education - No education, State - Uttar Pradesh (most populous state in India), MPCE - INR 2343, Age - 30.
[c] Reference values for the 2022 plot are Gender - Male, Education - No education, State - Uttar Pradesh, MPCE - INR 2209, Age - 31.
[d] The plot is based on Model 4 (April to June 2019) and Model 8 (April to June 2022) in Table A7.

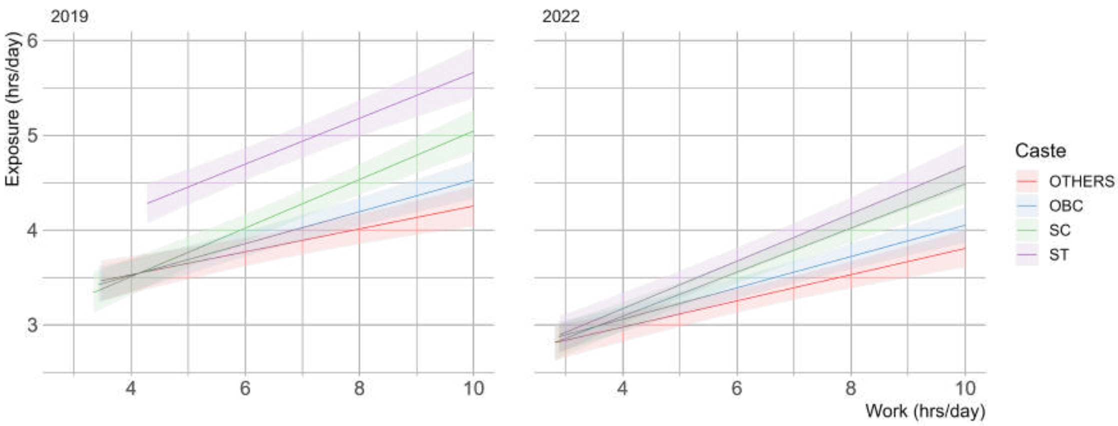

Figure 5: Predicted values of exposure by caste for varying levels of work for individuals in the workforce (non-zero workhours)

[a] The plot shows the predicted exposure to UTCI values above 32°C for varying levels of work for different caste groups for April to June 2019 (left panel) and April to June 2022 (right panel). The sample for the plot includes individuals in the PLFS sample who report non-zero workhours in the respective time period.
[b] Reference values for the 2019 plot are Gender - Male, Education - No education, State - Uttar Pradesh (most populous state in India), MPCE - INR 2343, Age - 30.
[c] Reference values for the 2022 plot are Gender - Male, Education - No education, State - Uttar Pradesh, MPCE - INR 2209, Age - 31.
[d] The plot is based on Model 4 (April to June 2019) and Model 8 (April to June 2022) in Table A8.

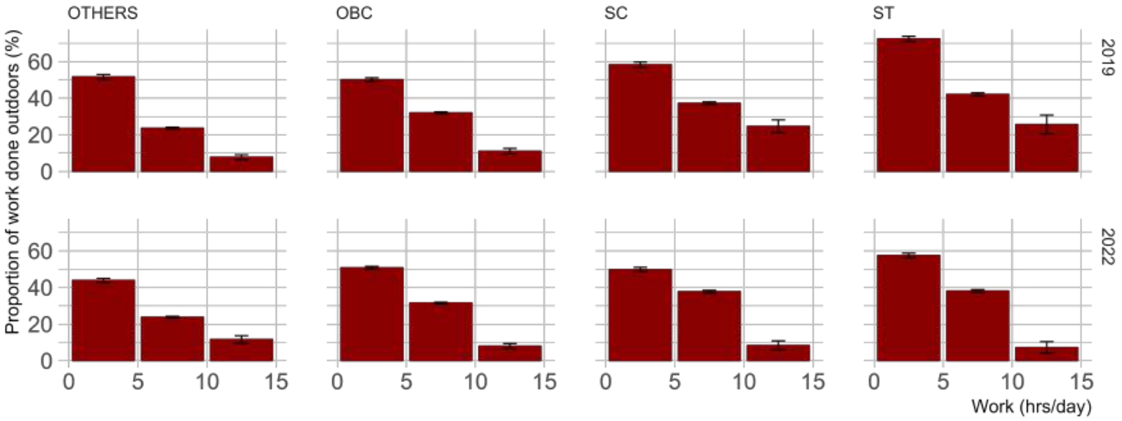

Figure 6: Proportion of time spent working outdoors by working hours for individuals in the workforce (non-zero workhours)

[a] The sample for the plot includes only individuals that have non-zero average daily workhours between April and June reported in PLFS 2018-19 and PLFS 2021-22.

Appendices

Overlap between UTCI and district data

Figure A1 shows the overlap between the UTCI raster data (Hersbach et al., 2020) and the district map for the state of Karnataka, India. The green cells represent the UTCI data, while the gold boundary represents the state and district boundaries for the state of Karnataka. It is clear that the UTCI data does not perfectly overlap with the district boundaries. To extract UTCI values at the district level, we use the procedure of Baston et al. (2022), implemented in the `exactextractr` R package. This procedure allows us to extract UTCI at the district level while accounting for partial overlaps. For instance, consider a district comprised of three raster cells that have UTCI values of 30°C, 25°C, and 20°C in a certain time period. These cells overlap 100%, 100%, and 80% with the district, respectively (20% of the final cell overlaps with a neighboring district). In this case, the average UTCI for the district in that time period will be:

$$UTCI_{district} = (100\% * 30 + 100\% * 25 + 80\% * 20)/(100\% + 100\% + 80\%) \tag{3}$$

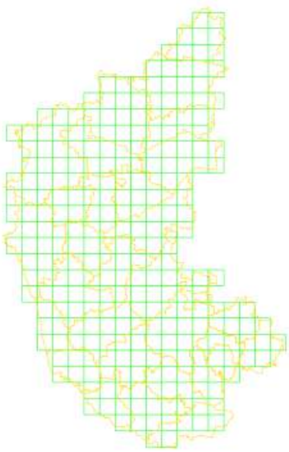

Figure A1: Overlap between district boundary and raster data for the state of Karnataka, India

[a] The green grid represents the UTCI raster pixels from Hersbach et al. (2020). The gold boundary represents the state and district boundaries of Karnataka, India.

UTCI at the district level

The panel on the left in Figure A2 shows the average number of hours for which UTCI exceeded 32°C in the district during daylight hours (8 AM to 6 PM) between April 1, 2019 and June 30, 2019. The panel on the right presents the same information for the period April 1, 2022 to June 30, 2022. The plot is based on data from Hersbach et al. (2020).

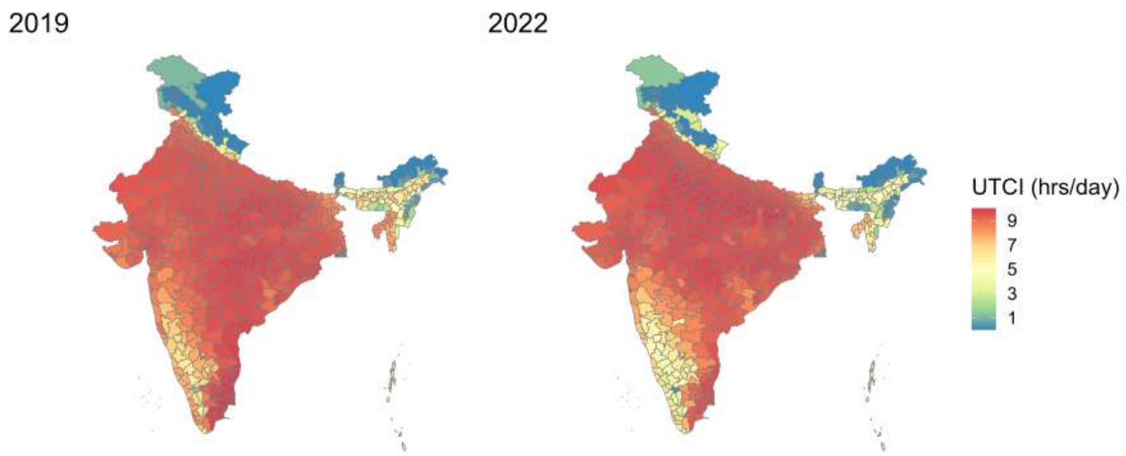

Figure A2: Variation in stressful UTCI at the district level

Inequality in exposure to stressful heat

Figure A3 presents variation in average daily exposure to stressful heat by caste because of outdoor work during the April-June months.

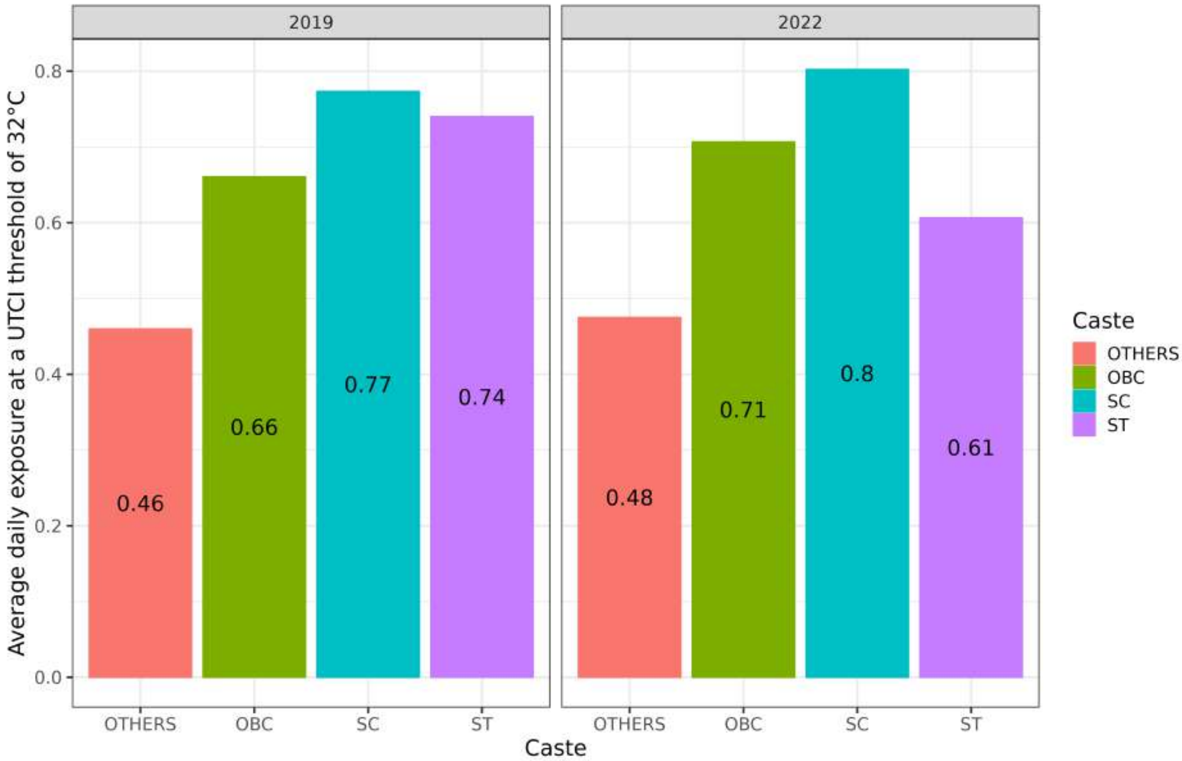

Figure A3: Inequality in exposure to stressful heat by caste

Variations in outdoor work

Table A1 presents the results of an OLS model that tests the impact of caste identity on the number of hours worked outdoors. Figure A4 shows the predicted outdoor work for varying levels of workhours for different caste groups.

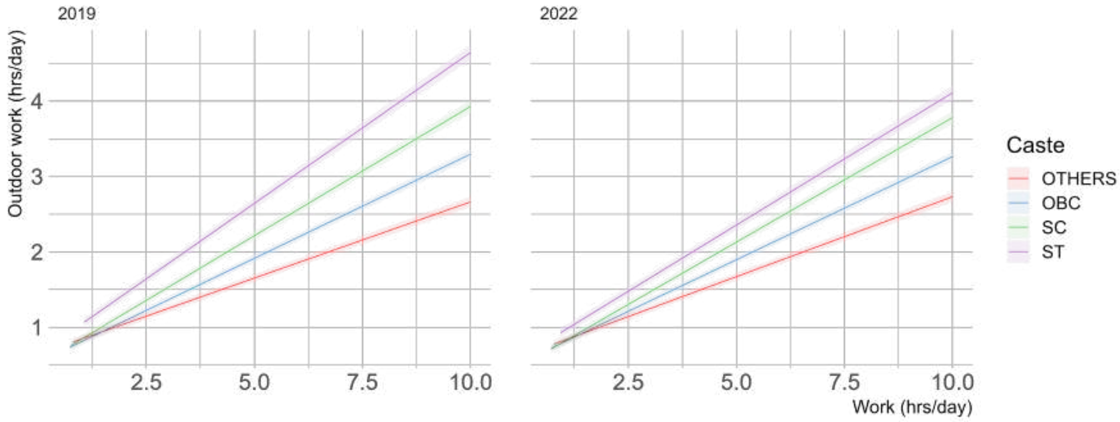

Figure A4: Variation in outdoor work by caste group

[a] Reference values for the 2019 plot are Gender - Male, Education - No education, State - Uttar Pradesh (most populous state in India), MPCE - INR 2343, Age - 30.
[b] Reference values for the 2022 plot are Gender - Male, Education - No education, State - Uttar Pradesh, MPCE - INR 2209, Age - 31.
[c] The plot is based on Model 2 (left panel) and Model 4 (right panel) of Table A1.

Table A1: Regression results for outdoor workhours by caste

	DV: Hours of work done outdoors			
	(1)	(2)	(3)	(4)
	2019	2019	2022	2022
OBC	−0.034	−0.110***	−0.004	−0.084***
	(0.021)	(0.021)	(0.021)	(0.021)
SC	−0.047*	−0.142***	−0.021	−0.135***
	(0.018)	(0.020)	(0.019)	(0.019)
ST	0.107*	−0.001	0.132**	−0.011
	(0.044)	(0.044)	(0.042)	(0.041)
Workhours	0.211***	0.202***	0.223***	0.212***
	(0.015)	(0.014)	(0.014)	(0.014)
OBC * Workhours	0.078***	0.074***	0.066***	0.062***
	(0.015)	(0.015)	(0.016)	(0.015)
SC * Workhours	0.147***	0.141***	0.125***	0.119***
	(0.018)	(0.018)	(0.017)	(0.016)
ST * Workhours	0.204***	0.198***	0.144***	0.139***
	(0.025)	(0.025)	(0.025)	(0.024)
Gender: Male		0.212***		0.250***
		(0.017)		(0.016)
No education		0.328***		0.287***
		(0.019)		(0.020)
Upto primary education		0.244***		0.256***
		(0.016)		(0.019)
Age		0.007***		0.007***
		(0.000)		(0.000)
MPCE		0.000***		0.000***
		(0.000)		(0.000)
Num.Obs.	99255	99255	104164	104162
R2	0.245	0.265	0.230	0.252
R2 Adj.	0.245	0.264	0.229	0.251
RMSE	1.81	1.79	1.83	1.80
Std.Errors	by: DIS_ID	by: DIS_ID	by: DIS_ID	by: DIS_ID
State Fixed Effects	Yes	Yes	Yes	Yes

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[a] All standard errors are clustered at the district level

[b] OBC - Other backward class, SC - Scheduled caste, ST - Scheduled tribe

[c] Reference category for caste - OTHERS

[d] Reference category for gender - Female

[e] Reference category for education - Greater than primary education

Distribution of the dependent variable

The left panel in Figure A5 shows the distribution of the dependent variable (heat stress exposure) for April to June 2019 for all individuals in the data. The right panel in Figure A5 shows the distribution of the depent variable for April to June 2022 for all individuals in the data.

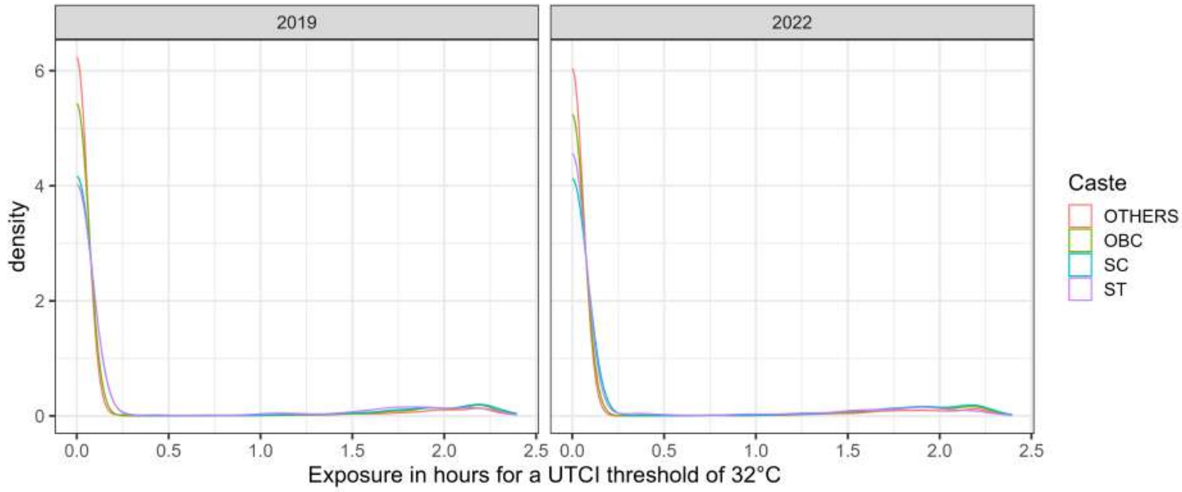

Figure A5: Distribution of the dependent variable (EXP)

[a] The plot is based on a PLFS sample of 101,510 individuals for April to June 2019 (left panel), and 104,164 individuals for April to June 2022 (right panel).

The left and right panels in Figure A6 show the distribution of the dependent variable for a subset of individuals that are working (workhours more than 0) for April to June 2019, and April to June 2022, respectively.

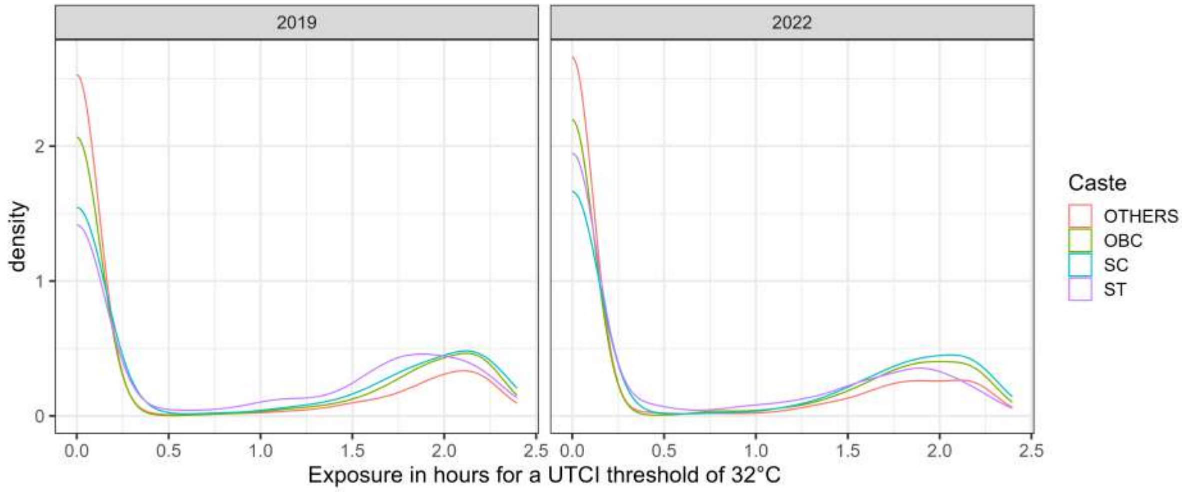

Figure A6: Distribution of the dependent variable (EXP) for working individuals

[a] The plot is based on a PLFS sample of 33,838 individuals for April to June 2019 (left panel), and 37,613 individuals for April to June 2022 (right panel).

Predicted exposure at the state level

The maps in Figure A7 show the predicted exposure to UTCI values above 32°C for different caste groups for each state. The panel on the top presents the predicted exposure for April to June 2019, while the panel on the bottom presents the predicted exposure for April to June 2022.

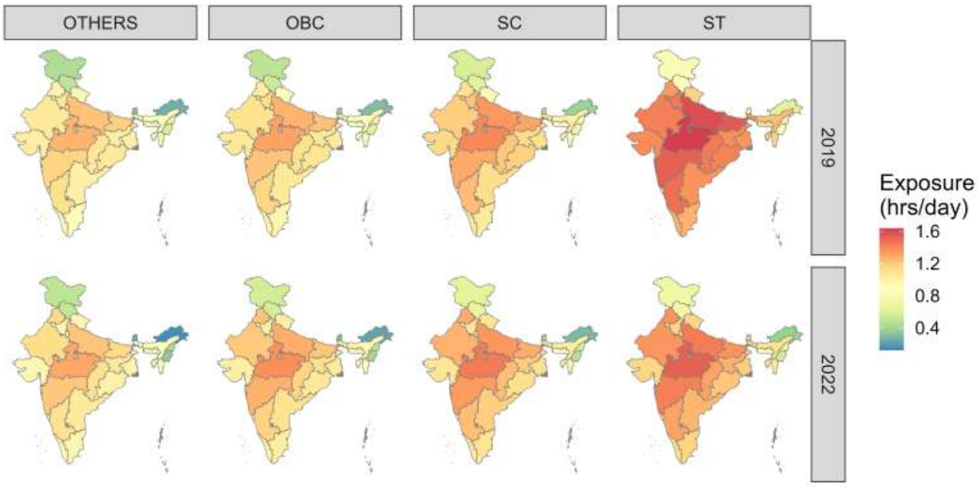

Figure A7: Predicted values of exposure by caste for different states

[a] Reference values for the 2019 plot are Gender - Male, Education - No education, MPCE - INR 2343, Age - 30, Work - 2.17 hours/day.
[b] Reference values for the 2022 plot are Gender - Male, Education - No education, MPCE - INR 2209, Age - 31, Work - 2.31 hours/day.
[c] The plot is based on Model 4 (April to June 2019) and Model 8 (April to June 2022) in Table 2. For MPCE and Age, the reference values are based on average values for the respective years

Robustness checks

Table A2: Pooled Regression Results for a UTCI threshold of 32°C for April-June (2019 and 2022)

	DV: Hours of exposure			
	(1)	(2)	(3)	(4)
OBC	0.025***	−0.066**	−0.134***	−0.110***
	(0.006)	(0.020)	(0.019)	(0.019)
SC	0.013+	−0.068***	−0.161***	−0.119***
	(0.007)	(0.018)	(0.018)	(0.018)
ST	0.014	0.204***	0.097*	0.105**
	(0.011)	(0.040)	(0.040)	(0.037)
Workhours	0.178***	0.180***	0.171***	0.081***
	(0.012)	(0.012)	(0.012)	(0.011)
Year (2022)	−0.009	−0.005	−0.019	−0.014
	(0.022)	(0.021)	(0.019)	(0.019)
OBC * Workhours	0.091***	0.092***	0.089***	0.075***
	(0.013)	(0.012)	(0.012)	(0.012)
SC * Workhours	0.148***	0.149***	0.143***	0.114***
	(0.013)	(0.013)	(0.013)	(0.013)
ST * Workhours	0.102***	0.103***	0.099***	0.085***
	(0.023)	(0.023)	(0.023)	(0.022)
Gender: Male			0.209***	0.160***
			(0.013)	(0.008)
No education			0.276***	−0.152***
			(0.015)	(0.009)
Upto primary education			0.217***	−0.076***
			(0.013)	(0.006)
Age			0.006***	0.004***
			(0.000)	(0.000)
MPCE			0.000***	0.000***
			(0.000)	(0.000)
Gender: Male * Workhours				0.050***
				(0.007)
No education * Workhours				0.247***
				(0.010)
Upto primary education * Workhours				0.133***
				(0.007)
Num.Obs.	203419	203419	203417	203417
R2	0.206	0.224	0.243	0.268
R2 Adj.	0.206	0.224	0.243	0.268
State Fixed Effects	No	Yes	Yes	Yes

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

[a] All standard errors are clustered at the district level

[b] OBC - Other backward class, SC - Scheduled caste, ST - Scheduled tribe

[c] Reference category for caste - OTHERS

[d] Reference category for gender - Female

[e] Reference category for education - Greater than primary education

[f] Reference category for Year - 2019

Table A3: Regression Results for a UTCI threshold of 26°C for April-June (2019, 2022)

	DV: Hours of exposure							
	2019				2022			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OBC	0.008	−0.058**	−0.131***	−0.104***	0.028**	−0.028	−0.105***	−0.081***
	(0.008)	(0.022)	(0.021)	(0.020)	(0.009)	(0.023)	(0.022)	(0.022)
SC	0.005	−0.057**	−0.149***	−0.104***	0.014	−0.041*	−0.150***	−0.107***
	(0.009)	(0.019)	(0.020)	(0.019)	(0.010)	(0.020)	(0.021)	(0.020)
ST	0.014	0.120**	0.017	0.029	0.010	0.153***	0.016	0.022
	(0.015)	(0.042)	(0.043)	(0.039)	(0.013)	(0.043)	(0.042)	(0.039)
Workhours	0.194***	0.196***	0.188***	0.097***	0.204***	0.205***	0.195***	0.094***
	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)	(0.014)	(0.014)
OBC * Workhours	0.088***	0.088***	0.085***	0.069***	0.079***	0.080***	0.076***	0.062***
	(0.015)	(0.015)	(0.015)	(0.014)	(0.016)	(0.016)	(0.015)	(0.015)
SC * Workhours	0.152***	0.153***	0.147***	0.113***	0.137***	0.138***	0.132***	0.104***
	(0.018)	(0.018)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
ST * Workhours	0.188***	0.188***	0.183***	0.167***	0.120***	0.124***	0.120***	0.106***
	(0.025)	(0.025)	(0.025)	(0.023)	(0.026)	(0.025)	(0.025)	(0.024)
Gender: Male			0.199***	0.152***			0.236***	0.177***
			(0.016)	(0.010)			(0.016)	(0.010)
No education			0.322***	−0.128***			0.273***	−0.171***
			(0.019)	(0.012)			(0.020)	(0.011)
Upto primary education			0.234***	−0.070***			0.244***	−0.097***
			(0.016)	(0.009)			(0.019)	(0.008)
Age			0.007***	0.004***			0.007***	0.004***
			(0.000)	(0.000)			(0.000)	(0.000)
MPCE			0.000***	0.000***			0.000***	0.000***
			(0.000)	(0.000)			(0.000)	(0.000)
Gender: Male * Workhours				0.047***				0.060***
				(0.011)				(0.009)
No education * Workhours				0.267***				0.250***
				(0.013)				(0.012)
Upto primary education * Workhours				0.141***				0.154***
				(0.009)				(0.010)
Num.Obs.	99255	99255	99255	99255	104164	104164	104162	104162
R2	0.229	0.240	0.258	0.285	0.213	0.225	0.246	0.270
R2 Adj.	0.229	0.240	0.258	0.285	0.213	0.225	0.246	0.269
State Fixed Effects	No	Yes	Yes	Yes	No	Yes	Yes	Yes

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
[a] All standard errors are clustered at the district level
[b] OBC - Other backward class, SC - Scheduled caste, ST - Scheduled tribe
[c] Reference category for caste - OTHERS
[d] Reference category for gender - Female
[e] Reference category for education - Greater than primary education

Table A4: Regression Results for a UTCI threshold of 29°C for April-June (2019, 2022)

	DV: Hours of exposure							
	2019				2022			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OBC	0.011	−0.066**	−0.138***	−0.111***	0.030***	−0.036	−0.111***	−0.088***
	(0.008)	(0.022)	(0.021)	(0.020)	(0.009)	(0.024)	(0.023)	(0.023)
SC	0.006	−0.062**	−0.152***	−0.108***	0.016+	−0.050*	−0.157***	−0.115***
	(0.009)	(0.020)	(0.020)	(0.019)	(0.010)	(0.021)	(0.022)	(0.021)
ST	0.017	0.132**	0.030	0.041	0.012	0.176***	0.043	0.049
	(0.015)	(0.043)	(0.044)	(0.040)	(0.013)	(0.043)	(0.042)	(0.039)
Workhours	0.189***	0.191***	0.183***	0.093***	0.196***	0.197***	0.187***	0.092***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)	(0.014)	(0.014)
OBC * Workhours	0.091***	0.091***	0.088***	0.073***	0.083***	0.084***	0.080***	0.066***
	(0.015)	(0.015)	(0.014)	(0.014)	(0.016)	(0.016)	(0.015)	(0.015)
SC * Workhours	0.151***	0.152***	0.146***	0.112***	0.142***	0.143***	0.137***	0.110***
	(0.018)	(0.018)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
ST * Workhours	0.179***	0.178***	0.173***	0.158***	0.096***	0.100***	0.096***	0.082***
	(0.026)	(0.025)	(0.025)	(0.023)	(0.025)	(0.024)	(0.024)	(0.023)
Gender: Male			0.198***	0.151***			0.227***	0.176***
			(0.016)	(0.010)			(0.016)	(0.010)
No education			0.315***	−0.126***			0.263***	−0.171***
			(0.019)	(0.012)			(0.020)	(0.011)
Upto primary education			0.229***	−0.068***			0.235***	−0.096***
			(0.016)	(0.009)			(0.018)	(0.008)
Age			0.007***	0.004***			0.006***	0.004***
			(0.000)	(0.000)			(0.000)	(0.000)
MPCE			0.000***	0.000***			0.000***	0.000***
			(0.000)	(0.000)			(0.000)	(0.000)
Gender: Male * Workhours				0.047***				0.054***
				(0.011)				(0.009)
No education * Workhours				0.262***				0.244***
				(0.013)				(0.012)
Upto primary education * Workhours				0.138***				0.149***
				(0.009)				(0.010)
Num.Obs.	99255	99255	99255	99255	104164	104164	104162	104162
R2	0.225	0.238	0.256	0.283	0.207	0.223	0.243	0.267
R2 Adj.	0.225	0.238	0.256	0.282	0.207	0.222	0.243	0.266
State Fixed Effects	No	Yes	Yes	Yes	No	Yes	Yes	Yes

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001
[a] All standard errors are clustered at the district level
[b] OBC - Other backward class, SC - Scheduled caste, ST - Scheduled tribe
[c] Reference category for caste - OTHERS
[d] Reference category for gender - Female
[e] Reference category for education - Greater than primary education

Table A5: Regression Results for a UTCI threshold of 35°C for April-June (2019, 2022)

	DV: Hours of exposure							
	2019				2022			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OBC	0.019**	−0.089***	−0.152***	−0.127***	0.041***	−0.064**	−0.128***	−0.107***
	(0.007)	(0.023)	(0.021)	(0.021)	(0.007)	(0.024)	(0.024)	(0.023)
SC	0.010	−0.083***	−0.162***	−0.121***	0.025**	−0.081***	−0.173***	−0.135***
	(0.009)	(0.021)	(0.021)	(0.020)	(0.008)	(0.022)	(0.023)	(0.022)
ST	0.014	0.214***	0.125**	0.136**	0.024+	0.279***	0.163***	0.168***
	(0.014)	(0.045)	(0.045)	(0.041)	(0.013)	(0.045)	(0.046)	(0.041)
Workhours	0.156***	0.159***	0.151***	0.070***	0.152***	0.153***	0.145***	0.064***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.013)	(0.013)
OBC * Workhours	0.098***	0.098***	0.096***	0.082***	0.093***	0.095***	0.091***	0.079***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)	(0.015)
SC * Workhours	0.154***	0.155***	0.150***	0.119***	0.146***	0.148***	0.143***	0.118***
	(0.017)	(0.017)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
ST * Workhours	0.110***	0.108***	0.104***	0.090***	0.026	0.032	0.028	0.016
	(0.027)	(0.027)	(0.027)	(0.025)	(0.024)	(0.025)	(0.024)	(0.023)
Gender: Male			0.184***	0.142***			0.198***	0.159***
			(0.015)	(0.010)			(0.016)	(0.010)
No education			0.278***	−0.133***			0.232***	−0.174***
			(0.019)	(0.012)			(0.019)	(0.011)
Upto primary education			0.192***	−0.059***			0.186***	−0.081***
			(0.015)	(0.009)			(0.016)	(0.008)
Age			0.006***	0.004***			0.005***	0.003***
			(0.000)	(0.000)			(0.000)	(0.000)
MPCE			0.000***	0.000***			0.000***	0.000***
			(0.000)	(0.000)			(0.000)	(0.000)
Gender: Male * Workhours				0.042***				0.045***
				(0.010)				(0.008)
No education * Workhours				0.246***				0.230***
				(0.012)				(0.011)
Upto primary education * Workhours				0.114***				0.116***
				(0.008)				(0.009)
Num.Obs.	99255	99255	99255	99255	104164	104164	104162	104162
R2	0.202	0.227	0.243	0.270	0.181	0.213	0.232	0.256
R2 Adj.	0.202	0.226	0.243	0.270	0.181	0.212	0.231	0.255
State Fixed Effects	No	Yes	Yes	Yes	No	Yes	Yes	Yes

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[a] All standard errors are clustered at the district level

[b] OBC - Other backward class, SC - Scheduled caste, ST - Scheduled tribe

[c] Reference category for caste - OTHERS

[d] Reference category for gender - Female

[e] Reference category for education - Greater than primary education

Table A6: Regression Results for different values of flexibility to avoid work during heat for April-June (2019, 2022)

	DV: Hours of exposure									
	2019					2022				
	1 hr	2 hrs	3 hrs	4 hrs	5 hrs	1 hr	2 hrs	3 hrs	4 hrs	5 hrs
OBC	−0.098***	−0.084***	−0.071***	−0.057***	−0.043***	−0.080***	−0.070***	−0.060***	−0.047***	−0.034***
	(0.017)	(0.015)	(0.012)	(0.009)	(0.007)	(0.019)	(0.016)	(0.013)	(0.010)	(0.007)
SC	−0.101***	−0.093***	−0.083***	−0.071***	−0.055***	−0.104***	−0.092***	−0.079***	−0.064***	−0.048***
	(0.017)	(0.014)	(0.012)	(0.009)	(0.007)	(0.018)	(0.015)	(0.012)	(0.009)	(0.007)
ST	0.025	0.010	−0.002	−0.010	−0.008	0.023	0.003	−0.008	−0.009	−0.006
	(0.034)	(0.028)	(0.023)	(0.017)	(0.012)	(0.033)	(0.028)	(0.022)	(0.017)	(0.012)
Workhours	0.075***	0.058***	0.042***	0.027***	0.015***	0.074***	0.056***	0.039***	0.023***	0.012**
	(0.012)	(0.010)	(0.008)	(0.006)	(0.004)	(0.012)	(0.010)	(0.008)	(0.006)	(0.005)
Gender: Male	0.107***	0.065***	0.028***	−0.003	−0.022***	0.125***	0.076***	0.031***	−0.004	−0.024***
	(0.008)	(0.006)	(0.005)	(0.004)	(0.003)	(0.008)	(0.006)	(0.005)	(0.004)	(0.003)
No education	−0.108***	−0.090***	−0.072***	−0.053***	−0.035***	−0.144***	−0.116***	−0.089***	−0.063***	−0.040***
	(0.010)	(0.008)	(0.007)	(0.005)	(0.004)	(0.009)	(0.007)	(0.006)	(0.004)	(0.003)
Upto primary education	−0.056***	−0.045***	−0.034***	−0.023***	−0.014***	−0.079***	−0.061***	−0.045***	−0.030***	−0.018***
	(0.007)	(0.006)	(0.005)	(0.004)	(0.003)	(0.007)	(0.005)	(0.004)	(0.003)	(0.002)
Age	0.003***	0.002***	0.001***	0.000	0.000*	0.003***	0.001***	0.001**	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MPCE	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
OBC * Workhours	0.064***	0.054***	0.044***	0.034***	0.024***	0.057***	0.048***	0.038***	0.029***	0.019***
	(0.012)	(0.010)	(0.008)	(0.007)	(0.005)	(0.013)	(0.011)	(0.009)	(0.007)	(0.005)
SC * Workhours	0.097***	0.082***	0.067***	0.052***	0.038***	0.095***	0.080***	0.064***	0.049***	0.034***
	(0.014)	(0.012)	(0.010)	(0.008)	(0.006)	(0.015)	(0.012)	(0.010)	(0.008)	(0.006)
ST * Workhours	0.132***	0.106***	0.080***	0.055***	0.033***	0.066***	0.050**	0.035*	0.024*	0.014+
	(0.020)	(0.017)	(0.014)	(0.010)	(0.008)	(0.020)	(0.017)	(0.015)	(0.011)	(0.008)
Gender: Male * Workhours	0.048***	0.049***	0.049***	0.046***	0.039***	0.055***	0.055***	0.054***	0.050***	0.042***
	(0.009)	(0.007)	(0.006)	(0.005)	(0.004)	(0.008)	(0.006)	(0.005)	(0.004)	(0.003)
No education * Workhours	0.223***	0.184***	0.146***	0.109***	0.075***	0.205***	0.167***	0.129***	0.093***	0.061***
	(0.011)	(0.009)	(0.008)	(0.006)	(0.005)	(0.010)	(0.009)	(0.007)	(0.006)	(0.004)
Upto primary education * Workhours	0.117***	0.096***	0.076***	0.056***	0.037***	0.126***	0.103***	0.081***	0.059***	0.039***
	(0.008)	(0.007)	(0.005)	(0.004)	(0.003)	(0.008)	(0.007)	(0.006)	(0.005)	(0.003)
Num.Obs.	99255	99255	99255	99255	99255	104162	104162	104162	104162	104162
R2	0.282	0.279	0.271	0.256	0.231	0.266	0.263	0.255	0.238	0.211
R2 Adj.	0.282	0.279	0.271	0.256	0.230	0.266	0.263	0.254	0.238	0.211
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

[a] All standard errors are clustered at the district level

[b] OBC - Other backward class, SC - Scheduled caste, ST - Scheduled tribe

[c] Reference category for caste - OTHERS

[d] Reference category for gender - Female

[e] Reference category for education - Greater than primary education

Table A7: Regression Results for a UTCI threshold of 32°C for adults for April-June (2019, 2022)

	DV: Hours of exposure							
	2019				2022			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OBC	0.044**	−0.085*	−0.222***	−0.153***	0.085***	−0.039	−0.183***	−0.121***
	(0.014)	(0.035)	(0.033)	(0.032)	(0.016)	(0.038)	(0.036)	(0.035)
SC	0.016	−0.086**	−0.281***	−0.155***	0.054**	−0.067+	−0.275***	−0.165***
	(0.019)	(0.033)	(0.033)	(0.031)	(0.018)	(0.035)	(0.035)	(0.035)
ST	0.047	0.322***	0.102	0.186**	0.053+	0.363***	0.087	0.155*
	(0.032)	(0.072)	(0.075)	(0.070)	(0.028)	(0.067)	(0.069)	(0.062)
Workhours	0.168***	0.173***	0.141***	0.096***	0.166***	0.169***	0.131***	0.094***
	(0.013)	(0.014)	(0.013)	(0.014)	(0.014)	(0.014)	(0.013)	(0.013)
OBC * Workhours	0.092***	0.090***	0.091***	0.073***	0.083***	0.083***	0.083***	0.067***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.016)	(0.015)	(0.015)	(0.015)
SC * Workhours	0.151***	0.149***	0.150***	0.111***	0.141***	0.142***	0.142***	0.111***
	(0.017)	(0.018)	(0.017)	(0.016)	(0.016)	(0.017)	(0.016)	(0.016)
ST * Workhours	0.143***	0.139***	0.142***	0.120***	0.052*	0.065*	0.070**	0.050*
	(0.026)	(0.026)	(0.025)	(0.024)	(0.025)	(0.025)	(0.025)	(0.024)
Gender: Male			0.456***	0.426***			0.511***	0.545***
			(0.032)	(0.029)			(0.032)	(0.028)
No education			0.564***	−0.229***			0.521***	−0.278***
			(0.041)	(0.032)			(0.040)	(0.031)
Upto primary education			0.422***	−0.044+			0.467***	−0.027
			(0.033)	(0.023)			(0.035)	(0.023)
Age			0.004***	0.008***			0.002*	0.005***
			(0.001)	(0.001)			(0.001)	(0.001)
MPCE			0.000***	0.000***			0.000***	0.000***
			(0.000)	(0.000)			(0.000)	(0.000)
Gender: Male * Workhours				0.002				−0.009
				(0.011)				(0.009)
No education * Workhours				0.258***				0.240***
				(0.013)				(0.012)
Upto primary education * Workhours				0.123***				0.126***
				(0.009)				(0.010)
Num.Obs.	60184	60184	60184	60184	63765	63765	63763	63763
R2	0.167	0.195	0.224	0.246	0.142	0.177	0.211	0.230
R2 Adj.	0.167	0.195	0.223	0.245	0.142	0.177	0.211	0.229
State Fixed Effects	No	Yes	Yes	Yes	No	Yes	Yes	Yes

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[a] All standard errors are clustered at the district level

[b] OBC - Other backward class, SC - Scheduled caste, ST - Scheduled tribe

[c] Reference category for caste - OTHERS

[d] Reference category for gender - Female

[e] Reference category for education - Greater than primary education

Table A8: Regression Results for a UTCI threshold of 32°C for working individuals for April-June (2019, 2022)

	DV: Hours of exposure							
	2019				2022			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OBC	0.289	−0.077	−0.337*	−0.197	0.569***	0.118	−0.118	−0.025
	(0.196)	(0.167)	(0.156)	(0.154)	(0.170)	(0.151)	(0.145)	(0.141)
SC	−0.110	−0.526*	−0.873***	−0.559**	0.295	−0.195	−0.480**	−0.262
	(0.231)	(0.222)	(0.211)	(0.194)	(0.181)	(0.169)	(0.165)	(0.162)
ST	0.478	0.377	−0.092	0.201	0.091	−0.122	−0.518**	−0.253
	(0.368)	(0.299)	(0.289)	(0.286)	(0.223)	(0.196)	(0.197)	(0.187)
Workhours	−0.028	−0.075***	−0.068***	−0.034	0.018	−0.022	−0.027	0.023
	(0.022)	(0.021)	(0.019)	(0.024)	(0.024)	(0.022)	(0.022)	(0.025)
OBC * Workhours	0.054*	0.061*	0.067**	0.047*	0.010	0.039	0.041+	0.027
	(0.026)	(0.025)	(0.023)	(0.023)	(0.028)	(0.026)	(0.025)	(0.024)
SC * Workhours	0.159***	0.178***	0.182***	0.135***	0.100**	0.134***	0.129***	0.094***
	(0.037)	(0.037)	(0.034)	(0.032)	(0.031)	(0.029)	(0.028)	(0.028)
ST * Workhours	0.063	0.142**	0.164***	0.121**	0.034	0.152***	0.156***	0.112**
	(0.052)	(0.048)	(0.046)	(0.045)	(0.039)	(0.036)	(0.037)	(0.035)
Gender: Male			0.653***	1.220***			0.740***	1.551***
			(0.061)	(0.140)			(0.051)	(0.113)
No education			1.197***	−0.433*			0.919***	−0.651***
			(0.078)	(0.181)			(0.068)	(0.131)
Upto primary education			0.722***	0.207			0.682***	−0.092
			(0.057)	(0.140)			(0.056)	(0.108)
Age			0.007***	0.008***			0.003+	0.004*
			(0.002)	(0.002)			(0.001)	(0.001)
MPCE			0.000***	0.000***			0.000***	0.000***
			(0.000)	(0.000)			(0.000)	(0.000)
Gender: Male * Workhours				−0.095***				−0.145***
				(0.022)				(0.019)
No education * Workhours				0.249***				0.260***
				(0.030)				(0.024)
Upto primary education * Workhours				0.074***				0.118***
				(0.022)				(0.018)
Num.Obs.	31583	31583	31583	31583	37613	37613	37612	37612
R2	0.017	0.095	0.146	0.151	0.016	0.092	0.147	0.156
R2 Adj.	0.017	0.093	0.145	0.150	0.015	0.091	0.146	0.155
State Fixed Effects	No	Yes	Yes	Yes	No	Yes	Yes	Yes

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

[a] All standard errors are clustered at the district level

[b] OBC - Other backward class, SC - Scheduled caste, ST - Scheduled tribe

[c] Reference category for caste - OTHERS

[d] Reference category for gender - Female

[e] Reference category for education - Greater than primary education

Table A9: Regression Results for a UTCI threshold of 32°C for July-September 2021

	DV: Hours of exposure			
	(1)	(2)	(3)	(4)
OBC	0.028***	−0.054*	−0.127***	−0.106***
	(0.007)	(0.023)	(0.023)	(0.022)
SC	0.021**	−0.089***	−0.182***	−0.144***
	(0.008)	(0.023)	(0.022)	(0.022)
ST	0.033*	0.171***	0.059	0.067+
	(0.014)	(0.042)	(0.040)	(0.037)
Workhours	0.142***	0.146***	0.138***	0.076***
	(0.011)	(0.011)	(0.011)	(0.011)
OBC * Workhours	0.102***	0.102***	0.099***	0.084***
	(0.013)	(0.013)	(0.012)	(0.012)
SC * Workhours	0.139***	0.141***	0.137***	0.112***
	(0.014)	(0.014)	(0.014)	(0.014)
ST * Workhours	0.121***	0.117***	0.110***	0.093***
	(0.022)	(0.021)	(0.021)	(0.019)
Gender: Male			0.166***	0.149***
			(0.014)	(0.009)
No education			0.219***	−0.144***
			(0.020)	(0.010)
Upto primary education			0.175***	−0.076***
			(0.015)	(0.008)
Age			0.006***	0.004***
			(0.000)	(0.000)
MPCE			0.000***	0.000***
			(0.000)	(0.000)
Gender: Male * Workhours				0.028***
				(0.008)
No education * Workhours				0.198***
				(0.012)
Upto primary education * Workhours				0.112***
				(0.008)
Num.Obs.	104691	104691	104684	104684
R2	0.205	0.234	0.252	0.272
R2 Adj.	0.205	0.234	0.252	0.272
State Fixed Effects	No	Yes	Yes	Yes

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

[a] All standard errors are clustered at the district level

[b] OBC - Other backward class, SC - Scheduled caste, ST - Scheduled tribe

[c] Reference category for caste - OTHERS

[d] Reference category for gender - Female

[e] Reference category for education - Greater than primary education

Table A10: Regression Results for a UTCI threshold of 32°C for October-December 2021

	DV: Hours of exposure			
	(1)	(2)	(3)	(4)
OBC	0.037***	−0.029+	−0.072***	−0.059***
	(0.006)	(0.016)	(0.015)	(0.015)
SC	0.042***	−0.013	−0.077***	−0.052***
	(0.008)	(0.015)	(0.015)	(0.014)
ST	0.029*	0.168***	0.103***	0.103***
	(0.011)	(0.032)	(0.031)	(0.029)
Workhours	0.089***	0.088***	0.084***	0.068***
	(0.007)	(0.007)	(0.007)	(0.008)
OBC * Workhours	0.060***	0.060***	0.056***	0.047***
	(0.008)	(0.008)	(0.008)	(0.007)
SC * Workhours	0.068***	0.070***	0.066***	0.050***
	(0.008)	(0.008)	(0.008)	(0.008)
ST * Workhours	0.086***	0.082***	0.076***	0.063***
	(0.015)	(0.015)	(0.015)	(0.014)
Gender: Male			0.095***	0.139***
			(0.010)	(0.007)
No education			0.172***	−0.074***
			(0.014)	(0.007)
Upto primary education			0.131***	−0.045***
			(0.010)	(0.005)
Age			0.005***	0.003***
			(0.000)	(0.000)
MPCE			0.000***	0.000***
			(0.000)	(0.000)
Gender: Male * Workhours				−0.014**
				(0.005)
No education * Workhours				0.124***
				(0.007)
Upto primary education * Workhours				0.073***
				(0.005)
Num.Obs.	105029	105029	105025	105025
R2	0.178	0.207	0.229	0.250
R2 Adj.	0.178	0.207	0.229	0.249
State Fixed Effects	No	Yes	Yes	Yes

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[a] All standard errors are clustered at the district level

[b] OBC - Other backward class, SC - Scheduled caste, ST - Scheduled tribe

[c] Reference category for caste - OTHERS

[d] Reference category for gender - Female

[e] Reference category for education - Greater than primary education

Table A11: Regression Results for a UTCI threshold of 32°C for January-March 2022

	DV: Hours of exposure			
	(1)	(2)	(3)	(4)
OBC	0.039***	−0.036*	−0.091***	−0.077***
	(0.006)	(0.016)	(0.015)	(0.015)
SC	0.034***	−0.002	−0.075***	−0.053***
	(0.007)	(0.015)	(0.014)	(0.014)
ST	0.016	0.226***	0.148***	0.151***
	(0.012)	(0.035)	(0.033)	(0.030)
Workhours	0.089***	0.089***	0.082***	0.058***
	(0.007)	(0.007)	(0.007)	(0.008)
OBC * Workhours	0.063***	0.062***	0.060***	0.051***
	(0.007)	(0.007)	(0.007)	(0.007)
SC * Workhours	0.072***	0.071***	0.068***	0.052***
	(0.009)	(0.009)	(0.008)	(0.008)
ST * Workhours	0.070***	0.068***	0.063***	0.049**
	(0.018)	(0.017)	(0.017)	(0.015)
Gender: Male			0.119***	0.148***
			(0.011)	(0.007)
No education			0.163***	−0.081***
			(0.014)	(0.007)
Upto primary education			0.142***	−0.038***
			(0.011)	(0.005)
Age			0.005***	0.003***
			(0.000)	(0.000)
MPCE			0.000***	0.000***
			(0.000)	(0.000)
Gender: Male * Workhours				−0.004
				(0.005)
No education * Workhours				0.133***
				(0.008)
Upto primary education * Workhours				0.078***
				(0.005)
Num.Obs.	103841	103841	103833	103833
R2	0.160	0.197	0.220	0.239
R2 Adj.	0.160	0.196	0.219	0.239
State Fixed Effects	No	Yes	Yes	Yes

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[a] All standard errors are clustered at the district level

[b] OBC - Other backward class, SC - Scheduled caste, ST - Scheduled tribe

[c] Reference category for caste - OTHERS

[d] Reference category for gender - Female

[e] Reference category for education - Greater than primary education

Table A12: Regression Results for a UTCI threshold of 32°C for July 2021-June 2022

	DV: Hours of exposure			
	(1)	(2)	(3)	(4)
OBC	0.039***	−0.048**	−0.115***	−0.094***
	(0.005)	(0.017)	(0.016)	(0.016)
SC	0.034***	−0.050**	−0.141***	−0.105***
	(0.005)	(0.015)	(0.015)	(0.015)
ST	0.022*	0.240***	0.136***	0.141***
	(0.010)	(0.037)	(0.035)	(0.032)
Workhours	0.136***	0.138***	0.130***	0.079***
	(0.009)	(0.009)	(0.009)	(0.009)
OBC * Workhours	0.090***	0.090***	0.086***	0.073***
	(0.009)	(0.009)	(0.009)	(0.009)
SC * Workhours	0.118***	0.119***	0.115***	0.091***
	(0.009)	(0.009)	(0.009)	(0.009)
ST * Workhours	0.099***	0.097***	0.090***	0.073***
	(0.020)	(0.020)	(0.019)	(0.017)
Gender: Male			0.171***	0.183***
			(0.011)	(0.007)
No education			0.231***	−0.138***
			(0.013)	(0.007)
Upto primary education			0.181***	−0.074***
			(0.009)	(0.005)
Age			0.006***	0.004***
			(0.000)	(0.000)
MPCE			0.000***	0.000***
			(0.000)	(0.000)
Gender: Male * Workhours				0.012*
				(0.005)
No education * Workhours				0.200***
				(0.007)
Upto primary education * Workhours				0.110***
				(0.005)
Num.Obs.	417725	417725	417704	417704
R2	0.200	0.225	0.247	0.271
R2 Adj.	0.200	0.225	0.247	0.271
State Fixed Effects	No	Yes	Yes	Yes

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[a] All standard errors are clustered at the district level

[b] OBC - Other backward class, SC - Scheduled caste, ST - Scheduled tribe

[c] Reference category for caste - OTHERS

[d] Reference category for gender - Female

[e] Reference category for education - Greater than primary education

Table A13: Regression Results for an ESI threshold of 30°C for April-June 2022 using PLFS data

	DV: Hours of exposure			
	(1)	(2)	(3)	(4)
OBC	0.031***	−0.042+	−0.113***	−0.090***
	(0.008)	(0.022)	(0.022)	(0.021)
SC	0.017+	−0.053**	−0.154***	−0.114***
	(0.009)	(0.020)	(0.020)	(0.020)
ST	0.011	0.202***	0.076+	0.082*
	(0.013)	(0.041)	(0.040)	(0.037)
Workhours	0.181***	0.182***	0.172***	0.086***
	(0.013)	(0.013)	(0.013)	(0.013)
OBC * Workhours	0.083***	0.084***	0.080***	0.067***
	(0.015)	(0.015)	(0.014)	(0.014)
SC * Workhours	0.138***	0.139***	0.134***	0.108***
	(0.016)	(0.016)	(0.016)	(0.015)
ST * Workhours	0.075**	0.079***	0.075**	0.061**
	(0.023)	(0.023)	(0.023)	(0.022)
Gender: Male			0.225***	0.186***
			(0.016)	(0.009)
No education			0.250***	−0.170***
			(0.019)	(0.010)
Upto primary education			0.215***	−0.093***
			(0.017)	(0.008)
Age			0.006***	0.004***
			(0.000)	(0.000)
MPCE			0.000***	0.000***
			(0.000)	(0.000)
Gender: Male * Workhours				0.046***
				(0.008)
No education * Workhours				0.236***
				(0.011)
Upto primary education * Workhours				0.137***
				(0.009)
Num.Obs.	104164	104164	104162	104162
R2	0.202	0.220	0.241	0.265
R2 Adj.	0.202	0.220	0.241	0.265
State Fixed Effects	No	Yes	Yes	Yes

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[a] All standard errors are clustered at the district level

[b] OBC - Other backward class, SC - Scheduled caste, ST - Scheduled tribe

[c] Reference category for caste - OTHERS

[d] Reference category for gender - Female

[e] Reference category for education - Greater than primary education

Table A14: Summary statistics using CPHS data for April-June 2022

Social Group	All		OTHERS		OBC		SC		ST	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Count	284491	284491	76436	76436	126164	126164	65903	65903	15988	15988
Work (hrs/day)	2.45	3.71	2.33	3.66	2.42	3.70	2.55	3.75	2.90	3.85
Outdoor (hrs/day)	1.01	2.66	0.49	1.91	1.02	2.67	1.36	3.03	1.88	3.37
% Outdoors	41	49	22	41	43	49	53	50	65	48
Exposure (hrs/day) (UTCI: 32)	0.96	2.56	0.48	1.87	0.98	2.58	1.30	2.93	1.65	3.17
MPCE (INR)	4101	2240	4797	2892	3987	2013	3614	1675	3676	1477
Age (yrs)	35.0	17.9	36.7	18.2	34.9	17.9	33.6	17.5	32.6	17.4
% Female	46		46		46		46		46	
% No education	2		2		2		3		4	
% Upto primary education	86		77		88		92		92	

Table A15: Regression Results for a UTCI threshold of 32°C for April-June 2022

	DV: Hours of exposure			
	(1)	(2)	(3)	(4)
OBC	0.002	−0.037+	−0.170***	−0.066***
	(0.004)	(0.021)	(0.021)	(0.019)
SC	−0.016***	−0.037*	−0.223***	−0.083***
	(0.005)	(0.016)	(0.019)	(0.016)
ST	0.008	0.098	−0.074	0.067
	(0.011)	(0.094)	(0.092)	(0.091)
Workhours	0.195***	0.196***	0.211***	−0.034+
	(0.011)	(0.011)	(0.012)	(0.020)
OBC * Workhours	0.199***	0.199***	0.183***	0.134***
	(0.012)	(0.012)	(0.012)	(0.011)
SC * Workhours	0.312***	0.312***	0.289***	0.223***
	(0.016)	(0.016)	(0.015)	(0.015)
ST * Workhours	0.365***	0.368***	0.345***	0.275***
	(0.048)	(0.046)	(0.045)	(0.043)
Gender: Male			0.126***	0.068***
			(0.020)	(0.010)
No education			1.208***	0.016
			(0.047)	(0.025)
Upto primary education			1.164***	−0.076***
			(0.042)	(0.014)
Age			0.006***	0.004***
			(0.000)	(0.000)
MPCE			0.000***	0.000***
			(0.000)	(0.000)
Gender: Male * Workhours				0.002
				(0.021)
No education * Workhours				0.466***
				(0.117)
Upto primary education * Workhours				0.338***
				(0.011)
Num.Obs.	280592	280592	280592	280592
R2	0.353	0.364	0.390	0.416
R2 Adj.	0.353	0.364	0.390	0.416
State Fixed Effects	No	Yes	Yes	Yes

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[a] All standard errors are clustered at the district level

[b] OBC - Other backward class, SC - Scheduled caste, ST - Scheduled tribe

[c] Reference category for caste - OTHERS

[d] Reference category for gender - Female

[e] Reference category for education - Greater than primary education

Night-time LST

Inequality in exposure to occupational heat stress during the daytime could potentially be exacerbated by heat stress during the night. Ambient temperatures during the night can interrupt the normal physiology of sleep and increase susceptibility to a range of illnesses (Obradovich et al., 2017). Higher ambient night-time temperatures can also affect circadian thermoregulation, and recent research has indicated significant excess health risks to humans (including mortality) because of night-time heat (Royé et al., 2021).

To understand whether night-time LST exacerbates inequality, we analyze exposure to night-time Land Surface Temperature (LST) for the summer heat wave of 2022 by caste group. We use data from the Census of India 2011 to get population by caste group at the block-level (Registrar General of India, 2011). The block is an administrative unit at the sub-district level in India. India had 6,612 blocks as per the Census of India 2011. We extract block-level night-time LST from the MODIS satellite for the period April to June 2022. MODIS LST products have been used in a range of academic studies around the world (Wan et al., 2004; Benali et al., 2012). The MODIS Aqua satellite provides a night-time temperature reading at approximately 1.30 AM every 1 to 2 days. We use the MODIS MOD21A2 product that uses a physics-based temperature-emissivity separation algorithm to dynamically retrieve LST from the satellite reading. The algorithm uses all available cloud-free readings to calculate the 8-day average LST for every pixel. We use Google Earth Engine to retrieve all 8-day average readings for the time period of interest, and then use a simple averaging method to calculate the average night-time LST for every pixel during April-June 2022. Subsequently, we use a block-level map to extract the average night-time LST for every block in India.

The results of this analysis are presented in Tables A16 and A17. Since the Census of India provides population information at the block level only for three caste groups (SC, ST and OTHERS), we do not include the OBC group in this analysis. ST groups experience the lowest night-time LST on average, as one might expect given that they tend to live in forested/hilly districts. The regression results in Table A17 show that the difference between OTHERS and SC is not significant when the models use district-level fixed effects, while ST groups experience significantly lower night-time LST with and without geographical fixed effects.

However, the findings from the national block-level analysis may not translate into urban areas in India. Cities have different dynamics, and are characterized by strong heat island effects that can have negative health and economic impacts (Heaviside et al., 2017). As an additional test, we examine variations in exposure to night-time LST by caste group for the metropolitan city of Bengaluru, India. Bengaluru is one of India's fastest growing cities, and mutiple researchers have documented heat island effects in Bangalore (Shah et al., 2021). We conduct our analysis at the ward-level in Bengaluru. A ward is the smallest unit of urban governance in India, and Bengaluru had 198 wards as per the Census of 2011. We obtain the ward map for Bengaluru from the website of the city's municipal corporation. The Census provides population information for SC, ST and OTHERS at the ward level. Our analytical approach is similar to that followed in the block-level night-time LST analysis for India. The results are presented in Table A18. We do not find significant variation in temperature across caste groups in Bengaluru. While ST groups tend to live in cooler blocks at the national level, the difference between STs and other caste groups does not exist within the context of a city.

The findings provide context to the main argument in the paper. We find that night-time LST does not exacerbate the inequality in occupational heat stress that we observe during the day. However, it is important to note that these findings also show that the inequality in daytime exposure is not being driven by the fact that SC/ST groups tend to live in hotter regions. Rather, the daytime occupational heat stress inequality that we observe is driven by occupational segregation, with lower caste groups facing higher heat stress because they are more likely to be engaged in outdoor work.

Table A16: Variation in average nightime LST values across caste groups at the block (sub-district) level for India

Caste	LST (°C)
OTHERS	22.96
SC	23.17
ST	22.59

Table A17: Regression Results for Nightime LST at the block (sub-district) level for India

	(1)	(2)	(3)
Proportion SC (%)	5.104***	2.951***	0.028
	(0.497)	(0.328)	(0.253)
Proportion ST (%)	−3.322***	−1.730***	−1.498***
	(0.292)	(0.149)	(0.130)
Num.Obs.	6595	6595	6595
R2	0.131	0.662	0.907
R2 Adj.	0.131	0.660	0.897
Log.Lik.	−17016.061	−13902.989	−9650.385
RMSE	3.19	1.99	1.05
Std.Errors	HC3	HC3	HC3
Fixed Effects	No	State	District

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A18: Variation in nighttime LST across caste groups in Bengaluru at the ward level

Caste	LST (°C)
OTHERS	21.53
SC	21.47
ST	21.61

Table A19: Variation in access to cooling equipment at home across caste groups for India using NFHS data

Caste	Has Fan	Has AC/Cooler
OTHERS	94%	36%
OBC	90%	24%
SC	86%	18%
ST	69%	12%

References: Appendix

Benali, A., Carvalho, A., Nunes, J., Carvalhais, N., and Santos, A. (2012). Estimating air surface temperature in portugal using modis lst data. *Remote Sensing of Environment*, 124:108–121.

Heaviside, C., Macintyre, H., and Vardoulakis, S. (2017). The urban heat island: implications for health in a changing environment. *Current environmental health reports*, 4:296–305.

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., et al. (2020). The era5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society*, 146(730):1999–2049.

Obradovich, N., Migliorini, R., Mednick, S. C., and Fowler, J. H. (2017). Nighttime temperature and human sleep loss in a changing climate. *Science advances*, 3(5):e1601555.

Registrar General of India (2011). Census of india 2011. *Provisional Population Totals. New Delhi: Government of India*, pages 409–413.

Royé, D., Sera, F., Tobías, A., Lowe, R., Gasparrini, A., Pascal, M., de'Donato, F., Nunes, B., and Teixeira, J. P. (2021). Effects of hot nights on mortality in southern europe. *Epidemiology*, 32(4):487–498.

Shah, A., Garg, A., and Mishra, V. (2021). Quantifying the local cooling effects of urban green spaces: Evidence from bengaluru, india. *Landscape and Urban Planning*, 209:104043.

Wan, Z., Zhang, Y., Zhang, Q., and Li, Z.-L. (2004). Quality assessment and validation of the modis global land surface temperature. *International journal of remote sensing*, 25(1):261–274.