

Dear Editors,

We enclose a manuscript for consideration by *Science*, titled 'Rising Temperatures, Rising Risks: Changes in Chinese Children's Ambient Heat Exposure from 1990 to 2020.' We believe our paper is well-suited for your journal and will greatly interest its readership.

While a large literature has estimated the effects of heat exposure on child outcomes, this is the first paper to provide empirical evidence on how ambient heat conditions experienced by children have been changing in recent decades at a population level. We accomplish this by considering large-scale child population distribution data jointly with climatic data. Our empirical results focus on China and provide important findings in a country that has the second-largest population of children in the world.

At a methodological level, we develop a framework that addresses an important research gap by examining how the duration and intensity of heat have impacted children's ambient exposure in areas experiencing population and temperature changes. We develop an innovative *double-dual-distributional framework* to calculate two kinds of population-level heat exposure risk statistics for children: 1) A *Share of Time for the Average Child* (STAC) statistic, measuring the share of time exposed to ambient extreme temperature for the average child at any given temperature threshold, and 2) A *Share Exposed by Intensity and Duration Thresholds* (SEIDT) statistic, measuring the share of children exposed to extreme temperature by differing temperature (intensity) and time (duration) thresholds. In short, "dual-double-distributional" refers to the joint consideration of two types of geospatial and temporal distributions (temperature and population) and two types of temperature exposure thresholds (intensity and duration).

Our methodological approach, which accounts for both the geographical and temporal distributions of heat and of child populations, alongside varying temperature thresholds, offers a comprehensive population-level analysis. While we present analysis of extreme temperature exposure for children, the approach is usable for any population subgroup.

Our focus on the case of China is motivated by its large child population and significant demographic and climatic changes over recent decades. Our framework, which requires minimal data, can be easily adapted to other regions where populations are changing. It thus offers extensive applicability.

This research aligns closely with *Science's* commitment to interdisciplinary studies that have a profound impact. We confirm that this paper has not been published or considered elsewhere.

Sincerely,
Kai Feng

Ray Kei

Title Page

Title Rising Temperatures, Rising Risks: Changes in Chinese Children's Ambient Heat Exposure between 1990 and 2020

Author list Kai Feng and Marco M. Laghi are the corresponding authors. Correspondence and requests for materials should be addressed to Kai Feng at kaifeng@sas.upenn.edu.

1. [Kai Feng](#): Department of Sociology and Population Studies Center, University of Pennsylvania, Philadelphia, Pennsylvania, USA
2. [Marco M. Laghi](#): Department of Sociology, New York University, New York, NY, USA; Center for Applied Social and Economic Research, NYU Shanghai, Shanghai, China
3. [Jere R. Behrman](#): Departments of Economics and Sociology and Population Studies Center, University of Pennsylvania, Philadelphia, Pennsylvania, USA
4. [Emily Hannum](#): Department of Sociology and Population Studies Center, University of Pennsylvania, Philadelphia, Pennsylvania, USA
5. [Fan Wang](#): Department of Economics, University of Houston, Houston, Texas, USA

Abstract

The frequency and intensity of heat waves are increasing as the earth's climate warms, but how these trends translate to changes in children's ambient heat exposure is not well established. Existing studies often measure heat exposure using person-time units, which overlook variations in risk levels and exposure durations. Our study addresses this gap by developing a double-dual-distributional (DDD) framework to assess heat exposure among 250 million children in China from 1990 to 2020. We found that children's average annual exposure to moderate or stronger heat stress increased by 238 hours, and the proportion experiencing over 18 weeks of such stress more than doubled. This framework highlights that both rising temperatures and shifts in child population distribution contribute to increased heat exposure, offering new insights for mitigating climate-related risks to children's health.

Keywords: Extreme heat, children, China, geographic distribution of children

Rising Temperatures, Rising Risks: Changes in Chinese Children's Ambient Heat Exposure between 1990 and 2020

Introduction

Extreme-heat exposure is a significant and growing threat to human health and welfare [1, 2, 3, 4, 5], with research increasingly highlighting its disproportionate impacts on vulnerable populations [6, 7, 8, 9, 10]. Children are particularly susceptible to the detrimental effects of heat exposure because of their lower ability to self-thermoregulate, impaired thirst sensation and impaired glomerular filtration rates [11, 12, 13, 14, 15]. Studies have shown that extreme heat directly impacts children by undermining their nutrition [16], impairing cognitive and skill development [11], and escalating rates of heat-related illnesses and mortality [17, 13]. The negative effects of heat exposure can begin as early as the prenatal stage [18]. Research has linked high temperatures to increased instances of preterm births and low birth weights [19, 20, 21]. Additionally, extreme heat indirectly affects children by exacerbating droughts and associated food insecurity [22, 23, 24], intensifying tropical disasters [25, 26], facilitating the spread of infectious diseases [27, 28, 29, 30], and heightening the risk of violent conflicts [31, 32].

Climatic change has both prolonged and intensified extreme-heat exposures [33, 34, 35, 36, 37]. Projections suggest a significant rise in the burden of heat exposure on populations, a trend attributed to both climatic changes and the increased populations exposed to these changes [38, 39]. Yet, only a few studies focus on measuring exposure to heat among the child population despite the great vulnerability of children to heat exposure [40, 41]. While UNICEF 2022 offers one form of evaluation of child heat exposure, their analysis presents limitations in using nationally aggregated population data. Our contribution in comparison is the explicit use of intra-national population distribution data. Further, while UNICEF considers different climate scenarios, their analysis is aggregated at the national level, leaving out crucial information reflective

of the varied climate situations occurring throughout the more than 3,000-mile-wide landscape of China. Despite the substantial research on the effects of extreme heat on children, no study has documented population-level changes in the share of children exposed to extreme heat in recent decades. In addition, the prevalent approach in studies that measure general population heat burdens is to measure the total burden in person-time units, calculated by multiplying the total population by the time that the average person experiences thresholds of heat exposures [33, 39, 37, 35], while overlooking the distribution of population experiencing heat exposures of varying risk levels and diverse durations.

Using the case of China—home to approximately 249.9 million children ages 0–14 in 2020 [42]—this paper provides the first empirical evidence on how heat exposure for children has been changing in recent decades at a population level. We accomplished this by linking county-level child-population data to the hourly Universal Thermal Climate Index (UTCI), a bioclimatic heat index for assessing the physiological comfort of the human body [43, 44, 45], across two censuses spanning 30 years (1990–2020).

We developed a convenient, low-data-demand framework for measuring the share of children at risk of extreme-heat exposure. Using what we call the *double-dual-distributional* (DDD) framework, we measure population-level child-heat-exposure changes by jointly considering two types of geospatial and temporal distributions—that of temperature and that of child population—and two types of temperature-exposure thresholds—for temperature (intensity) and time (duration). In this framework, we compute a *Share of Time for the Average Child* (STAC) statistic, measuring the share of time exposed to ambient extreme temperature for the average child at any given temperature threshold, and a *Share Exposed by Intensity and Duration Thresholds* (SEIDT) statistic, measuring the share of children exposed to extreme temperature by differing temperature (intensity) and time (duration) thresholds.

We found substantial increases in the average heat-stress exposure for children and the share of children at risk. Specifically, the average child was exposed to moderate or higher levels of heat stress for an additional 238 hours in 2020 in comparison to

1990. The share of children subjected to over 18 weeks per year of such heat stress more than doubled, increasing from 6.7% to 13.7%. We also found that approximately half of the overall change in child heat-stress exposure between 1990 and 2020 was driven by heat increases and the rest was driven by cross-location shifts in the child population towards locations that had higher heat stress, illustrating the importance of *both* heat patterns *and* child population distributions. Finally, we highlighted significant regional disparities: In Eastern China, China's most-developed region, there was a marked increase in the duration of children's heat exposure from 1990 to 2020, even though the exposure levels were already high in 1990. Conversely, the Central region, which had comparable exposure levels as the Eastern region in 1990, experienced only a minimal increase in aggregate child-heat exposure from 1990 to 2020.

Results

Increase in the Average Share of Time Exposed to Heat for Children (STAC). The three-colored backgrounds in Figure 1 reflect the heat-stress categories associated with different UTCI thresholds. This figure depicts the *percentage-point changes* (Panel a) and *percentage changes* (Panel b) in the STAC statistics, which measure the average share of time in ambient-heat stress for children from 1990 to 2020 using three different within-year time frames: all annual hours, daytime hours (6 a.m.–10 p.m.), and April-to-September hours as the hot months of the year. Across the three time-frame specifications, children's shares of time in heat stress increased in China from 1990 to 2020 across all UTCI heat thresholds. The largest percentage-point change (Figure 1 Panel a) occurred when considering only hours in hot months, followed by daytime hours, and then all annual hours. The percentage changes (Figure 1 Panel b) largely overlapped across the three time-frame specifications.

When all hours were considered, an average child in China experienced 20.09% of her total hours in 1990 at-or-above 26 °C UTCI. By 2020, this percentage increased to 22.8%, representing a 2.7 percentage-point (Figure 1 Panel a) and 13.5% increase

in annual average exposure duration (Figure 1 Panel b), which corresponded to an average increase over 30 years of 238 hours of additional moderate-or-stronger heat-stress exposure.

Across all heat-stress thresholds, children's average shares of time at risk of heat stress increased. While the percentage-point increases were smaller at higher-heat thresholds, the percentage increases in the average child shares of time exposed to UTCI thresholds between 26 °C to 40 °C were similar and ranged between 14% and 18%. For example, the average duration of children's exposure to UTCI at-or-above 32 °C increased by 1.1 percentage points, reflecting a 14.7% rise as compared to the levels observed in 1990. These results also indicated that approximately 40% (calculated as $1 - \frac{2.7-1.1}{2.7} \approx 0.4$) of the increase in average-heat exposure at the 26 °C threshold can be attributed to the escalation in exposure to strong or above heat stress exceeding the 32 °C threshold. Tables C.1 and C.2 in the online Appendix enumerate levels and changes for average child-heat exposure at additional UTCI thresholds.

Increases in Shares of Children at Risk of Heat Exposure (SEIDT). While the previous results focus on heat exposure for the average child in China, they do not provide information on how many children were increasingly at risk of ambient heat exposure. In this section, given the changing distributions of heat and of children across counties in China, we computed the SEIDT statistics and examined whether the *percentage* of children most affected by heat stress also changed over time.

We computed the share of children at risk by jointly considering two thresholds of risks: a threshold for the level of heat-stress exposure (intensity) and a threshold for the share of annual hours (duration) exposed to heat stress above a particular threshold. Figure 2 presents results for combinations of selected thresholds for the duration of time exposed to heat stress (from 4% to 36%) and the intensity of heat stress (from above 26 °C to above 38 °C). Online Appendix Tables C.3 and C.4 provide tabulations at additional thresholds.

Exposure to at-least-some moderate-heat stress was nearly universal among chil-

dren in China. In 1990 (Figure 2 Panel a) and 2020 (Figure 2 Panel b), respectively, 97.2% and 97.7% of children experienced at least 4% of their hours, or over 2 weeks, in moderate-or-stronger-heat stress (i.e. $UTCI \geq 26^{\circ}\text{C}$). At longer durations of exposure to heat stress, the shares of affected children were lower.

The shares of children enduring prolonged exposure to heat stress increased substantially from 1990 to 2020. In 1990, 6.7% of children experienced moderate or stronger heat stress for more than 36% of their total hours, or equivalently, for over 16 weeks. By 2020, this number rose to 13.7%, marking an increase of 7.0 percentage points (Figure 2 Panel c) or 106%. In other words, the shares of children experiencing *at-least* moderate-heat stress for *at least* 32% of their total hours in 2020 more than doubled compared to 1990.

Similar increases in the shares of children experiencing heat stress were observed along a frontier of higher (or lower) heat-stress intensity and lower (or higher) duration combinations. For example, 11.2% of children had at least 12% of their total hours, or 6 weeks at strong-heat stress or above ($\geq 32^{\circ}\text{C}$). This number rose to 18.6% in 2020, representing a 7.4 percentage-point or 66.3% increase.

Especially alarming were rapid increases in the shares of children at risk for very-strong-heat stress, emerging first for low duration of exposure. In particular, the shares of children experiencing at least 4% of their total hours at very-strong-heat stress ($\geq 38^{\circ}\text{C}$) increased from 0.1% to 1.8%. While the shares of children exposed to these extreme-risk levels remained small, these increases represented approximately an 18-fold jump in the shares of children at these high-exposure-risk levels. With 249.9 million children between ages 0 to 15 in China in 2020, 1.8% amounts to 4.5 million children.

Decomposing the Contributions of Changes in Climate and Population. Our decomposition analysis illustrates the extent to which changes in children's heat exposure over time can be attributed to shifts in the child population distribution, or due to changes in UTCI driven by meteorological changes. In this calculation, we computed

counterfactual STAC statistics after altering one distribution (either children's population or UTCI) to 2020 levels while keeping the other constant at 1990 levels, without modeling mechanisms of change.

Figure 3 demonstrates that the increase in an average child's heat-stress exposure from 1990 to 2020 resulted from both climatic change and shifts in children's population distribution. For at-least-strong ($\geq 32^{\circ}\text{C}$) and at-least-moderate ($\geq 26^{\circ}\text{C}$) heat-stress levels, child population distribution shifts accounted for 48% and 50% of the actual change, respectively. UTCI distribution shifts accounted for 42% and 40% of the actual changes, respectively. The remaining residual changes were due to interactions between shifts in climatic and population distributions.

While both population distribution changes and climatic changes contributed to the rise in the average-child's heat-stress exposures, regional decomposition analysis showed varying contributions within regions. Specifically, changes in the population distribution accounted for about 1/3 of the exposure shifts in the Eastern region and less than 1/5 in the Northeastern region. This suggests that cross-region shifts in children's distribution, due to for example migration to the Eastern region or fertility decline in the Northeastern region, contributed significantly to the national-population-decomposition results. Online Appendix Table C.5 provides additional details on regional-decomposition results.

Figure 3 also indicates that at higher-UTCI thresholds, the influence of changes in population distributions diminished. Nationally, the contribution of population distributions to heat-stress exposure declined with increasing-heat thresholds, from 50% at the 26°C UTCI threshold to 39% at the 36°C UTCI threshold. Similarly, the contribution of population distributions declined from 38% to 19% in the Eastern region and from 16% to 5% in the Northeastern region over the same sets of UTCI-threshold increments. This suggests that the rise in more-extreme heat exposures was primarily a result of climatic changes, rather than population shifts to already hotter areas.

Changes in Children’s Heat Exposure Across Regions. We present in Figure 4 Panels (a) and (b) regional-STAC statistics, which show the average shares of annual time at risk of heat stress for children in 1990 and 2020 across the four major economic regions of China. Figure 4 (c) shows the percentage-point change between 1990 and 2020 across these regions. Tables C.7 and C.8 in the online Appendix detail within-region provincial results.

Children in both the Central and Eastern regions experienced high levels of heat-stress exposure. For instance, in 1990, an average child in the Eastern and Central regions faced at-least-moderate-heat stress ($\geq 26^{\circ}\text{C}$) 23.6% and 23.4% of the time, and at-least-strong heat stress ($\geq 32^{\circ}\text{C}$) 8.4% and 9.3% of the time, respectively. The shares of time exposed to at-least-moderate or at-least-strong heat stress in these two regions remained high in 2020 as shown in Figure 4 Panel (b). The percentage-point increases in the shares of time at risk of heat exposure were notable across various UTCI thresholds in the Eastern region, with a 4.4 percentage-point increase at the 26°C UTCI threshold and a 1.7 percentage-point increase at the 32°C UTCI threshold. In contrast, for the Central region, the increases in the share of time remained at below one percentage point across UTCI thresholds (Figure 4 (c)). The comparison indicates that although Eastern- and Central-region children both have significant exposures to heat, those in the Eastern region have faced a heightened challenge in adapting to heat stress owing to the rapid increase in average exposure duration.

Compared to the Eastern and Central regions, the Northeastern region had relatively low average-child-heat exposure in 1990. However, the average child’s share of annual time in the Northeastern region increased 19% for at-least-moderate-heat stress ($\geq 26^{\circ}\text{C}$) and 106% for at-least-strong-heat stress ($\geq 32^{\circ}\text{C}$). In 2020, the average Northeastern-region child experienced 8.9% and 2.4% of her time under at-least-moderate ($\geq 26^{\circ}\text{C}$) and at-least-strong ($\geq 32^{\circ}\text{C}$) heat stress, respectively. While child-heat stress in the Northeastern region remained much lower than that in the Central and Eastern regions, the rapid increases indicate potential challenges for a population that is not accustomed to heat to protect children from emerging occurrences of heat

stress.

Zooming in to the provincial level, in 2020, Hainan (Eastern), Guangdong (Eastern), Guangxi (Western), Jiangxi (Central), and Fujian (Eastern) were generally ranked as the top one-to-five provinces respectively in terms of the average shares of child time exposed to heat across UTCI thresholds. Specifically, in 2020, children in these provinces had on average 19.2%, 15.2%, 13.2%, 12.8%, and 11.8% shares of time exposed to at-least-strong-heat stress ($UTCI \geq 32^{\circ}\text{C}$), which represented respective increases of 17%, 20%, 8%, 16%, and 54% in shares of time exposed compared to 1990. While Northeastern and Eastern provinces generally experienced substantial increases in heat exposure, provinces in the Central and Western regions experienced limited exposure increases or reductions. Tables C.7 and C.8 in the online Appendix detail within-region provincial results.

Discussion

As climatic change intensifies, the distributions of children's exposure to extreme heat are of critical concern for human development and public health [14, 11, 12, 13], but these distributions have received limited attention in research. This study analyzed children's exposure to extreme heat in China over the past 30 years. Leveraging both geographical and temporal distributions of heat and of children, our study uncovered significant increases in children's exposures to moderate-or-stronger heat by an average of 238 hours from 1990 to 2020. The shares of children experiencing over 18 weeks per year of such heat stress more than doubled, indicating a growing vulnerability to heat exposure among children.

Our results highlighted the compound effect of rising temperatures and shifts in child-population-geographical distributions, particularly in a large nation like China with population and temperature distribution heterogeneities. The exposure to higher heat-stress levels, especially in the Eastern region, underscored the urgency for targeted interventions. This includes enhancing climate resilience and heat-stress miti-

gation strategies, especially in urban areas where "heat island" effects may exacerbate high temperatures [46], as found in cities across China [47]. Additionally, our findings underscored the importance of considering demographic changes in addition to climatic trends, as population shifts contributed significantly to the observed increase in heat exposure [33, 39].

Conceptually, our approach to analyzing population-climatic exposure changes moved from the conventional metric of total person-time for measuring overall heat-exposure burdens to a *double-dual-distributional* framework that considered both exposure intensity and exposure duration given changing population and temperature distributions. This approach enabled comprehensive analysis of the shares of children experiencing 1) varying degrees of heat stress (exposure intensity) over 2) varying spans of time (exposure duration). It allowed for cross-time and cross-location comparisons. Moreover, this approach emphasized shifts in population-spatial distribution rather than changes in total population numbers, making it particularly valuable in identifying populations at risk of exposure in scenarios with substantial migration.

Our framework combined tabular-population-census data with gridded-climatic data across time and space. We provided a framework for integrating population and climatic data for climatic and social scientists and policymakers interested in examining changing exposures of different populations to climatic and environmental hazards. While the availability of subnational and consistent global population data across long time spans is limited, subnational census data are publicly available for many countries across time and could be merged with publicly available global-temperature and other-climatic data to explore changes in population-based climatic exposures over time.

Our study has limitations. First, we examined ambient exposures, and did not explore how the same-ambient-heat stress might impact heterogeneously individuals residing in the same location but coming from varied socio-economic backgrounds. Socioeconomic disparities in access to air conditioning or other adaptive resources

can significantly influence the actual experience of heat stress [48, 13]. At an aggregate level, regions with similar ambient exposures but at different stages of economic development could also have varied levels of adaptabilities to the same heat stress [49]. Future research may benefit from examining the heterogeneities in exposure by exploiting the migratory paths of children and households using panel data or retrospective surveys [50]. Second, the use of county-level data, while detailed, might still miss finer nuances of heat stress, especially in densely populated urban areas where microclimatic variations were significant [51, 52]. Future research can build upon our study by integrating our frameworks with various definitions of heat exposure and using more fine-grained geographic units.

Despite these limitations, our study contributed new insights about the extent of heat-stress-exposure change for children between 1990 and 2020 in the country with the world's largest population of children in 1990. Importantly, we showed that changes in population distributions on the national level, though with variations among regions, were about as important as climatic changes. That the changing-spatial distribution of children is a crucial component of changing-child-heat-exposure risk is potentially relevant globally, given substantial shifts in recent decades in the distribution of the global child population across world regions [53, Appendix A1]. The simple approach that we developed, moreover, permits new insights with minimal-data demands and therefore fruitfully could be easily applied to other countries and regions.

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Author contributions

Conceptualization: JRB, EH, FW

Methodology: FW

Investigation: KF, MML

Visualization: KF

Supervision: JRB, EH, FW

Writing—original draft: KF, MML

Writing—review & editing: JRB, KF, EH, MML, FW

Competing interests

All authors declare they have no competing interests.

Data and materials availability

Data Availability

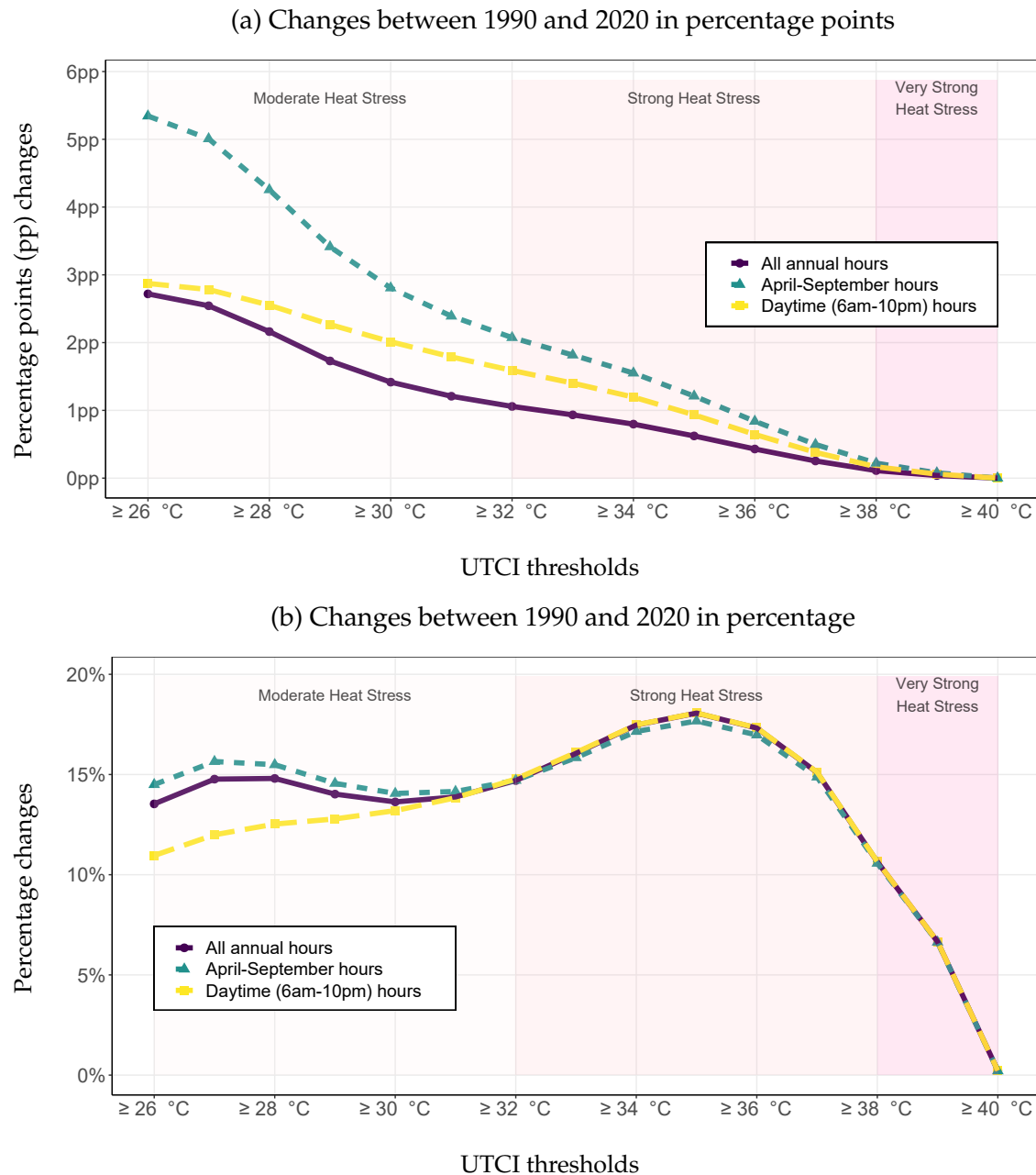
The UTCI data used in this study are publicly available from Napoli [54], at [copernicus-dataset/derived-utci-historical](#). Census data can be accessed from [ClimateInequality/PrjCEC](#). Additionally, this repository also provides code for downloading and linking census data with UTCI.

Code Availability

All analyses presented in this study were conducted using the statistical software R. All corresponding R files are publicly accessible at [ClimateInequality/PrjCEC](#).

Figures

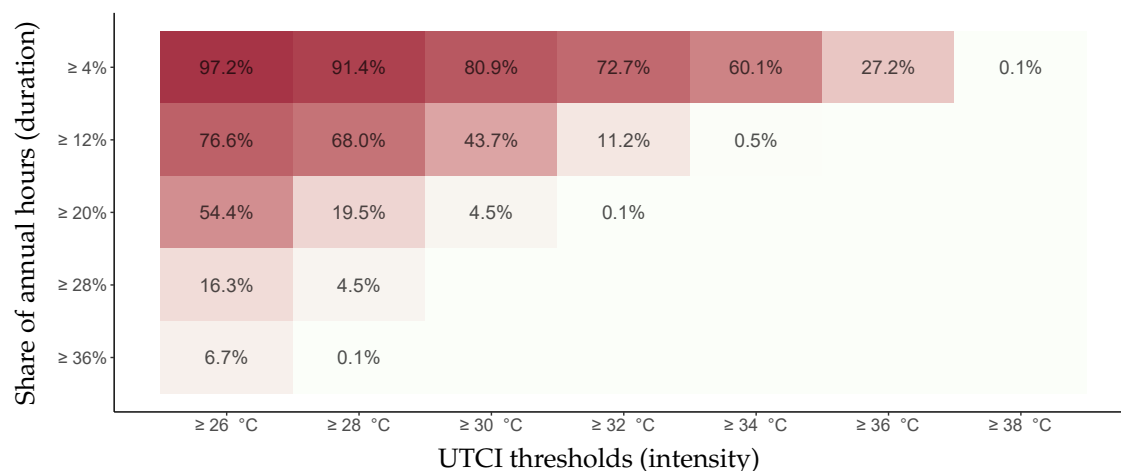
Figure 1: Change in Share of Time for the Average Child at or above UTCI Thresholds for Children 1990-2020



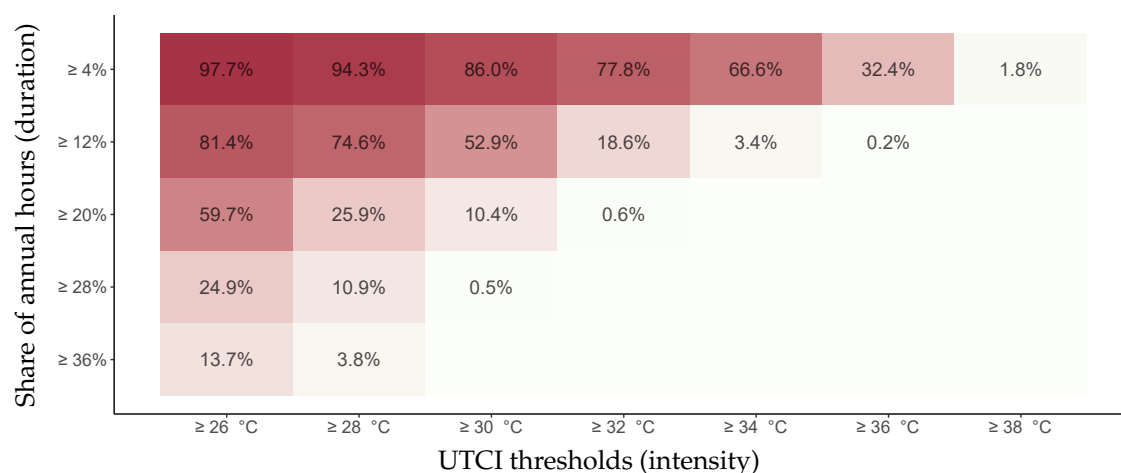
Notes: Panel (a) displays the percentage points (pp) change in the Share of Time for the Average Child at or above UTCI thresholds between 1990 and 2020, while Panel (b) displays the percentage changes in this share. The purple solid line represents results for all annual hours, the green short-dash line for the summer season (April to September), and the yellow long-dash line for daytime hours (6 am to 10 pm). Background colors indicate UTCI heat exposure categories. UTCI values above 26 to 32 degrees Celsius indicate moderate heat stress (light pink), from 32 to 38 degrees Celsius indicate strong heat stress (pink), and from 38 to 46 degrees Celsius indicate very strong heat stress (dark pink). Results above 40 degrees Celsius were not shown because very few children were exposed to such high levels of heat during the observed time periods in China. Tables C.1 and C.2 in the online Appendix tabulate results.

Figure 2: Share of Children Exposed to Heat Stress by Intensity and Duration

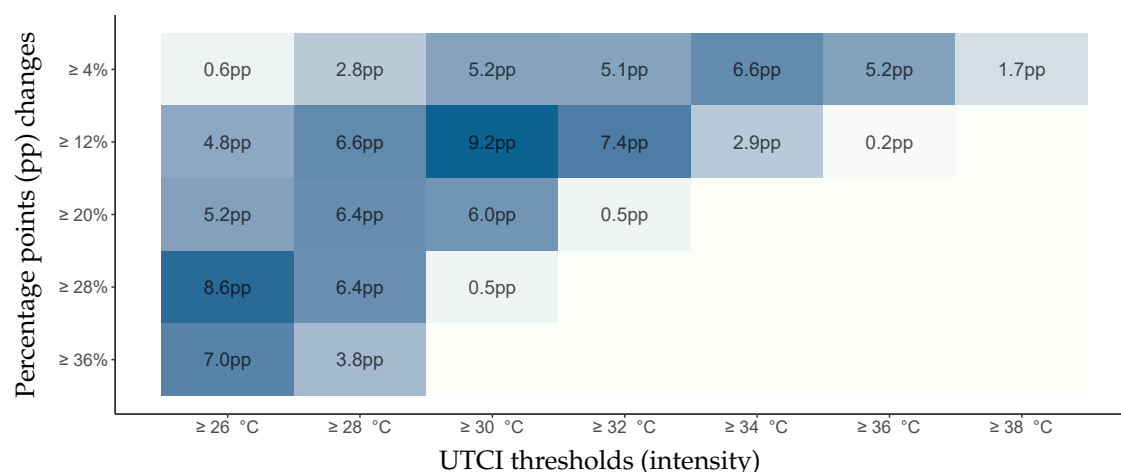
(a) 1990



(b) 2020

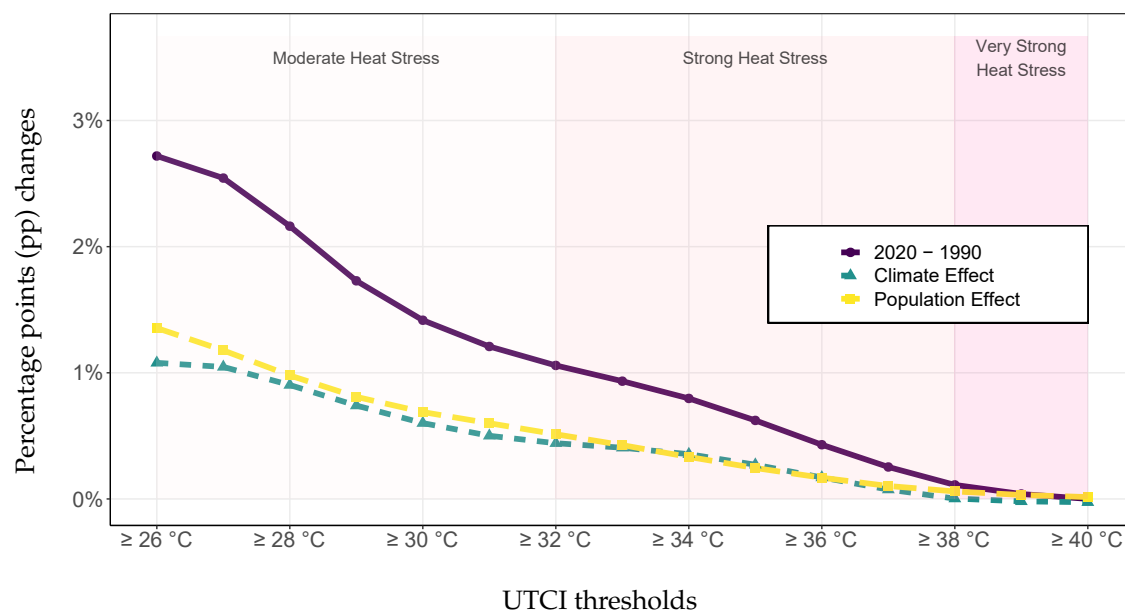


(c) Changes between 1990 and 2020 in percentage points



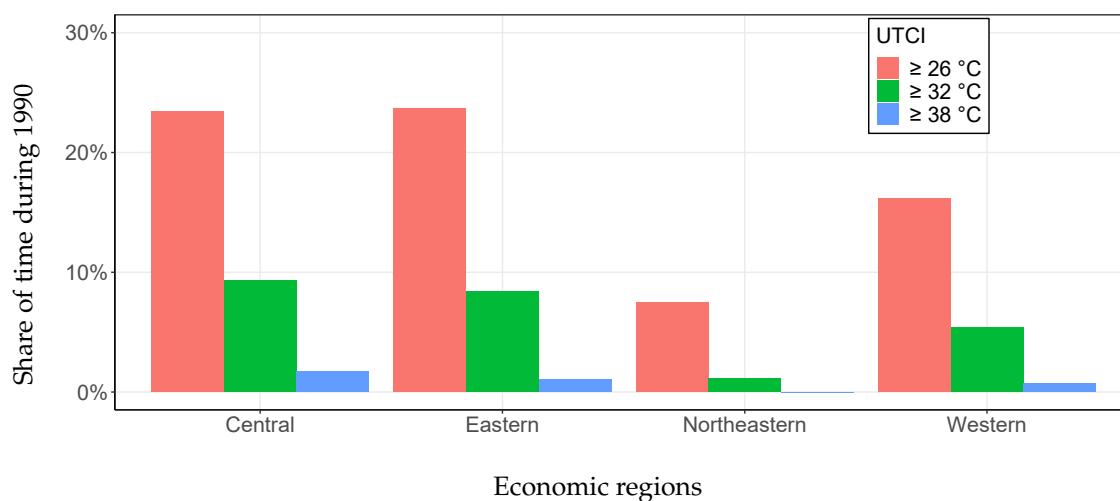
Notes: Panel (a) presents the share of children at risk of heat stress by duration and intensity in 1990. The duration is measured as the share of annual hours, whereas the intensity is measured as being at or above the UTCI threshold. Panel (b) presents the share of children at risk of heat stress by duration and intensity in 2020. Panel (c) presents the percentage points (pp) changes of children at risk of heat stress by duration and intensity between 1990 and 2020. Tables C.3 and C.4 in the online Appendix tabulate results.

Figure 3: Decomposed Change in Share of Time for the Average Child at Risk of Heat Stress

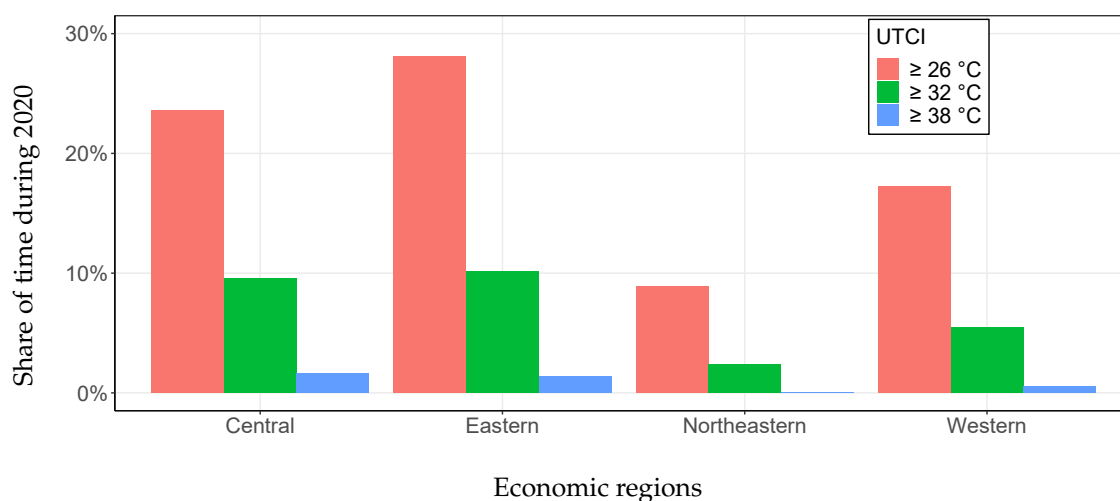


Notes: The purple solid line represents the percentage point difference in the share of time for the average child at risk of exposure to heat stress for children aged 0 to 14 between 1990 and 2020 (with 1990 as the baseline year). In the first counterfactual decomposition, we fix the children's population distribution in 1990 with the observed Universal Thermal Climate Index (UTCI) in 2020. The green short-dash line, or the climate effect, represents the percentage difference between the first counterfactual decomposition results and the baseline (using 1990 children's population distribution with 1990 UTCI). In the second counterfactual decomposition, we fix the UTCI at the 1990 level and use the children's population distribution in 2020. The yellow long-dash line, or the population effect, represents the percentage difference between the second counterfactual decomposition results and the baseline. Tables C.5 and C.6 in the online Appendix tabulate the results.

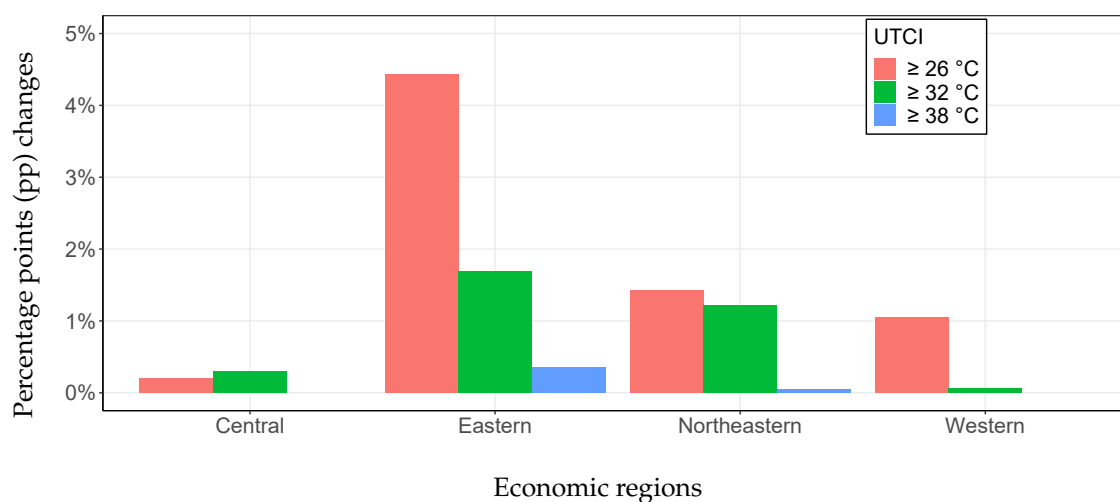
Figure 4: Regional Share of Time for the Average Child at Risk of Heat Stress
(a) 1990



(b) 2020



(c) Changes between 1990 and 2020 in percentage points



Notes: The y-axis depicts the percentage point difference from 2020 and 1990 heat exposure for children ages 0-14. We display these differences across the four economic regions of China and across different thresholds of heat exposure (moderate, strong, and very strong). Tables C.7 and C.8 in the online Appendix tabulate results.

Supplementary Materials for Rising Temperatures, Rising Risks: Changes in Chinese Children’s Ambient Heat Exposure between 1990 and 2020

A Materials and Methods

Methods. In this section, we summarize our *double-dual-distributional* (DDD) framework for measuring child population at risk of heat exposure. Within a particular span of time in a region, our DDD framework develops two statistics for heat-exposure risks building on two types of distributions and two types of thresholds. The two distributions are the distribution of location-specific temperature and the distribution of location-specific population groups (e.g., children). The two thresholds are temperature thresholds (intensity of exposure) for extreme-heat exposure and time thresholds (duration of exposure) for share of time exposed to extreme heat. The first risk statistic, STAC, captures the risk of extreme heat exposure facing the average child, measured in units of *share of time the average child is exposed to extreme heat in a particular period*. The second risk statistic, SEIDT, captures the distribution of risk among children, measured in units of the *share of child population exposed to extreme heat by different intensity and durations thresholds*. While the overall framework allows for the incorporation of additional heat-exposure dimensions—such as the length of specific heat spells—that would require dividing children into more granular cells of exposure experiences. Therefore, we focused on heat-intensity and overall-time-duration as two first-order dimensions of heat-exposure experiences.

Existing studies that consider population heat exposures have computed changes in heat exposure in total person-time units for a particular region or country. The person-days of heat exposure in a place at time t can be computed, for example, by multiplying the days during which the maximum temperature exceeds a threshold level with the total population residing in a place at time t . Aggregate person-time statistics have two limitations. First, when comparing exposures over time, aggregate person-time statistics will capture changes in aggregate population size over time in

addition to changes in average heat exposure burdens. As countries have experienced diverse patterns of declining and increasing child populations in recent decades[1], the resultant person-time estimates may not reflect average child heat-exposure experiences. Second, the person-time aggregate provides a single statistic of exposure for a region or country, overlooking the within-region or within-country heterogeneities in ambient exposure changes across populations residing in locations with differing climatic-change experiences. In addition to considering both climatic and population distributions, as done in person-time statistics, our DDD framework captures heterogeneities across time and space by measuring changes in the percentages of children experiencing different intensities of heat stress (temperature thresholds) for different durations over time (time thresholds).

In the closest-related work, UNICEF estimated for each country the number of children at risk of heat exposure based on the aggregate national population share of children in 2020 [2]. Our framework is the first to compute population-level distributional changes in heat exposure for children over time. By providing—for the first time and in a large economy—measurements on changes in the shares of children at risk of the double-thresholds of heat exposure, our framework and empirical results complement and extend existing research that has shown negative effects of heat exposure on children.

We implemented our framework in the setting of China between 1990 and 2020. In this empirical application, we considered each span of time as one year, we approximated continuous-ambient-temperature exposures based on hourly estimates of temperature, and we approximated fine-grained measures of locations with counties (3rd level administrative units) in China. For the exposure-intensity thresholds, we considered a range of UTCI thresholds but focused our analysis on key thresholds for extreme-heat commonly used in the literature. For exposure-duration thresholds, we considered different shares of time during the course of a year that a child is exposed to temperatures above the intensity-thresholds considered. Our method is also straightforward to implement in other settings where tabular population data at a relatively

fine-grained level and location-specific climate data are available.

We now formalize our temperature-exposure analysis framework across time and space. Specifically, let $c_l(t)$ be the UTCI temperature experienced by an individual at a moment in time t at a location l . Between period t and $t + \tau$, the share of time that individuals at location l experience temperature $c_l(t)$ over threshold c^* is, $s_l(c^*, t, \tau)$:

$$s_l(c^*, t, \tau) = \frac{1}{\tau} \int_t^{t+\tau} \mathbf{1}\{c_l(t) > c^*\} dt . \quad (1)$$

Depending on the analysis, our definition of time period includes all time during the day, all day time hours (6 am to 10 pm), or all hours within different seasons (e.g., April–September, October–March). Additionally, let $P_{t \leq t < t+\tau}(l|m)$ be the share of population for socio-demographic group m in a location l , among L locations in total between time t and $t + \tau$. Total population shares across locations sum up to 1: $\sum_{l=1}^L P_{t \leq t < t+\tau}(l|m) = 1$.

Average share of time of heat exposure We compute two key sets of statistics. First, we compute $\mathcal{S}_m(c^*, t, \tau)$, which measures, during a particular interval of time, the average share of time individuals of socio-demographic group m are exposed to temperature over threshold c^* :

$$\mathcal{S}_m(c^*, t, \tau) = \sum_{l=1}^L P_{t \leq t < t+\tau}(l|m) \cdot s_l(c^*, t, \tau) . \quad (2)$$

$\mathcal{S}_m(c^*, t, \tau)$ is the *Share of Time for the Average Child* (STAC) statistic, which measures, for the average child, the share of time exposed to ambient extreme temperature during a particular time-frame across temperature thresholds.

Since $\mathcal{S}_m(c^*, t, \tau)$ is a statistics for share of time, it varies between 0 and 1. In particular, $\lim_{c^* \rightarrow \infty} \mathcal{S}_m(c^*, t, \tau) = 0$ and $\lim_{c^* \rightarrow -\infty} \mathcal{S}_m(c^*, t, \tau) = 1$. A key aggregate statistic for how temperature exposure shifts between period t' and t is the following differ-

ence:

$$\Delta \mathcal{S}_{m,t',t}(c^*, \tau) = \mathcal{S}_m(c^*, t', \tau) - \mathcal{S}_m(c^*, t, \tau). \quad (3)$$

$\Delta \mathcal{S}_{m,t',t}(c^*, \tau)$ is the population-weighted average increase in the share of time exposed to the potential key temperature threshold c^* between time t and t' for population group m . $\Delta \mathcal{S}_{m,t',t}(c^*, \tau)$ shifts due to both shifts in the population distribution as well as the distribution of temperature between t and t' , thus taking into account both population and meteorological changes across time and space.

Share of children by duration and intensity of heat exposure Second, we compute the share of individuals at risk, based on a joint consideration of the relevant temperature threshold that might be considered risky for human development, and the share of time exposed to such temperature that would put individuals at risk of non-transitory impacts.

We consider these two joint dimensions of risks in computing population exposure statistics. Specifically, let $s^*(\tau)$ be a particular share-of-time threshold within span of time τ above a specific temperature risk threshold. We define the m -, c^* -, and s^* -specific at-risk measure $\mathcal{R}_m(c^*, s^*, t, \tau)$ between time t and $t + \tau$ as:

$$\mathcal{R}_m(c^*, s^*, t, \tau) = \sum_{l=1}^L P_{t \leq t < t+\tau}(l|m) \cdot \mathbf{1}\{s_l(c^*, t, \tau) > s^*(\tau)\}. \quad (4)$$

$\mathcal{R}_m(c^*, s^*, t, \tau)$ is the *Share Exposed by Intensity and Duration Thresholds* (SEIDT) statistic, which measures the share of children exposed to extreme temperature by differing temperature (intensity) and time (duration) thresholds.

By construction, $\mathcal{R}_m(c^*, s^* = 0, t, \tau) \leq 1$ and $\mathcal{R}_m(c^*, s^* = 1, t, \tau) = 0$. Additionally, the share of individuals experiencing greater than s^* share of time over c^* threshold converges to 0 as c^* increases: $\lim_{c^* \rightarrow \infty} \mathcal{R}_m(c^*, s^*, t, \tau) = 0$.

For the socio-demographic group indexed by m , given temperature threshold c^* and share of time threshold s^* , the percentage increase over time in the share of indi-

viduals from this group at risk of excess heat exposure is:

$$\Delta \mathcal{R}_{m,t',t}(c^*, s^*, \tau) = \mathcal{R}_m(c^*, s^*, t', \tau) - \mathcal{R}_m(c^*, s^*, t, \tau). \quad (5)$$

One important aspect of our framework is that computing $\mathcal{R}_m(c^*, s^*, t, \tau)$ and $\Delta \mathcal{R}_{m,t',t}(c^*, s^*, \tau)$ do not require the use of harmonized geographic data overtime. This is often a constraint in the analysis of temperature changes over time, due to shifting administrative boundaries, especially across large spans of time. In our framework, we consider all $l \in \{1, \dots, L\}$ locations within a region, and generate time-specific population-temperature cumulative distribution functions by sorting locations along the gradient of heat exposures and summing up the share of population for socio-demographic group m along ascending levels of heat exposures. While our distributions are discretized by location-level administrative units, when there are large number of locations with dispersed population, the population-temperature distributions tend to be approximately smooth. Cross-time comparisons, especially at higher levels of regional aggregation, are based on these approximately smooth distributions over time. Hence moments and percentiles of these population-temperature distributions are robust to shifts in sub-region location boundaries.

Framework and empirical results In our empirical application, t is 1990 and, t' is 2020, τ is one calendar year, and m is children between ages 0 and 14. Additionally, we approximate continuous time with hourly measurements. As an example, $\Delta \mathcal{R}_{\text{children}, 2020, 1990}$ with $c^* = 28$ and $s^* = 0.1$ provides the change in the percentage points of children exposed to temperature over 28 degrees for greater than 10 percent of their time during a year.

Results for $\Delta \mathcal{S}_{m=\text{ages 0 to 15}, t'=\text{year 2020}, t=\text{year 1990}}(c^*, \tau = 1 \text{ year})$ are summarized in Figure 1 and Tables C.1 and C.2. These capture changes in the average share of time children are exposed to temperature over a range of heat thresholds— $23^\circ\text{C} \leq c^* \leq 40^\circ\text{C}$ —considering all hours, day time hours, or hours during hotter and colder seasons.

Results for $\Delta\mathcal{R}_{m=\text{ages 0 to 15}, t'=\text{year 2020}, t=\text{year 1990}}(c^*, s^*, \tau = 1 \text{ year})$ are summarized in Figure 2 and Tables C.3 and C.4. These capture changes in the share of children experiencing ambient heat exposure for over a range of c^* heat *intensity* thresholds— $23^\circ\text{C} \leq c^* \leq 40^\circ\text{C}$ —and s^* heat exposure *duration* thresholds— $4\% \text{ of year} \leq s^* \leq 36\% \text{ of year}$.

Additionally, Figure 3 and Tables C.5 and C.6 summarize decompositional results that compute changes in the average share of time of child exposure, but combining 1990 population distribution with 2020 heat exposure distribution, and also 1990 heat exposure distribution with 2020 population distribution. Finally, Figure 4 and Tables C.7 and C.8 provide regional results on the changes in the average share of time of child exposure.

Data.

Universal Thermal Climate Index To measure heat, we used the fifth generation of the European Centre for Medium-Range Weather Forecasts (ECMWF) atmospheric reanalyses of the global climate: the ERA5-HEAT dataset [3]. ERA5-HEAT provides hourly data on UTCI with a spatial resolution of 0.25 degrees. The UTCI index provides an integrative measure of the perceived thermal stress on the human body, taking into account factors such as air temperature, humidity, wind speed, and radiant heat [4, 5, 6]. When UTCI is between 26 °C and 32 °C, it indicates moderate-heat stress on the human body, signifying warm conditions where individuals may start to feel uncomfortable, especially if engaging in physical activity. As the UTCI value increases, the level of thermal stress on the human body intensifies. UTCI values between 32 °C and 38 °C indicate strong-heat stress, whereas UTCI values between 38 °C and 46 °C indicate very-strong-heat stress [4]. We utilized these UTCI stress categories in this study.

UTCI is not simply a temperature measure. UTCI from ERA5-HEAT incorporates ambient temperature, humidity, wind, and radiation [3]. The incorporation of these measures provides a more reflective measure of physiological experience as a result of exposure than simple temperature. Other popular indices used by weather services (e.g. RealFeel) similarly consider factors beyond just temperature in producing an exposure experience measurement that so happens to use temperature unit labels [7]. ERA5-Land is one alternative to UTCI with extensive data availability, but ERA5-Land as a measure lacks consideration of humidity [8]. We maintain that UTCI data is the preferred unit of measure to examine child heat exposure.

Population Census For population data, we utilized Chinese-census data for the years 1990 and 2020 [9, 10, 11, 12]. County-level child population data and county-level administrative boundary files were extracted and used to construct ages 0–14 populations by county. For regional analysis, we considered the child population and UTCI distributions within each one of the four recognized economic regions of China

[13].

Rather than projecting future climate scenarios based on extending trends of existing national data, we focus on historical heat exposure using past census data. Granular historical environmental analysis is dependent on existing data. Historical national-level population aggregates vary in the level depending on the year observed. We use the detailed censuses from 1990 onward in our analysis to analyze historic child heat exposure on the county level to capture and best contextualize the specific population movements for children.

Census 1990 We use information from 2,369 geographical units at the county level nested in 31 provincial administrative units from the Tabulation on 1990 China Population Census by County. We start with the 1990 Chinese Census as it is the first to offer county-level population counts for individuals between ages 0 to 14. We only include mainland China and do not include special administrative regions. Within each county, we calculate the sum of ages 0 to 14 child population regardless of gender. In 1990, the total number of children across all counties included for analysis was 312,995,886.

Census 2020 We use information from 2,853 geographical units at the county level nested in 31 provincial administrative units from the Tabulation on 2020 China Population Census by County. We only include mainland China and do not include special administrative regions. We again calculate the population counts for children between ages 0 to 14, regardless of gender, in our analysis. In 2020, the total number of children across all counties included for analysis was 249,260,992.

B Integrating Climatic and Population Data

All project data processing, integration, and analysis code are shared at our project repository: <https://github.com/ClimateInequality/PrjCEC>. In this section, we summarize key aspects of how we integrate climatic and population data to enable the

analysis of changes over time in heat burden facing children. Specifically, code for generating computing population-weighted exposure statistics are included in the [R](#) folder, and integrated population-climate data outputs for each analysis included in the paper are stored in the [data-res](#) folder.

B.1 ERA5-HEAT data input specification

To capture the entire mainland China area, we employ China’s far-east (135°E), far-west (53°E), far-south (4°N), and far-north (54°N) points as spatial references in our API request to extract a rectangle area that contains gridded data covering latitude and longitude coordinates that encompass mainland China from the ERA5-HEAT data. We specify all months, dates, and hours in calendar years 1990 and 2020 in our API request. After downloading coordinate-specific hourly UTCI from all dates, we consolidate them into data files by year. For example, in the 2020 data file, corresponding to each coordinate in the gridded map (data rows), we include UTCI values for all hours between January 1, 2020 to December 31, 2020 (data columns).

B.2 Population data input specification

We obtain county-level demographic data from census tabulations. In each census file, there is one unique identification number for each county-level administrative unit. Each county includes demographic data by age group and gender for the corresponding census year. The county-level shapefile for each census year provides geometries defining the boundaries of each county. The geometry information for each county—summarized by county-specific sets of polygon-bounding vertices in longitude and latitude units—is important for linking the population data with the gridded UTCI data.

The final population input consists of a data matrix. In this matrix, the first column identifies a distinct county-level administrative unit ID, while other columns store the proportion of the population between ages 0 to 14 in each county relative to the total population between ages 0 to 14 during one census year. While our focus is on

children between ages 0 to 14, our approach has the flexibility to be extended to any demographic group as needed.

B.3 Specifying key files

There are three key files necessary for linking population data input and UTCI input: (1) key file that links the coordinates to counties. (2) key file that links county to province and regions. (3) key file that links population input column variables to the original labels (e.g., age groups and gender), and grouping variables for aggregation purposes (i.e., age groups 0-14, 15-64, 65+).

Coordinates to counties. We use spatial join from the "sf" package in R [14] to identify coordinates from UTCI data that fall within each county boundary. Some county units are too small to include any coordinates. In this case, we use the nearest coordinate to the centroid of the county geometry. The final key file includes a list of coordinates, with each coordinate matched with the corresponding county-level administrative code in China. The county code provides linkages to the county-level population census, while the coordinates provides linkages to the gridded ERA5-HEAT data.

County to province/region. Each county code can be linked back to the province and economic regions that the county belong to. In addition to province, we can easily aggregate the county to other higher level units.

Population input columns to labels. This key file provides label names to the population input columns.

B.4 Location boundaries and population-weighted temperature distributions

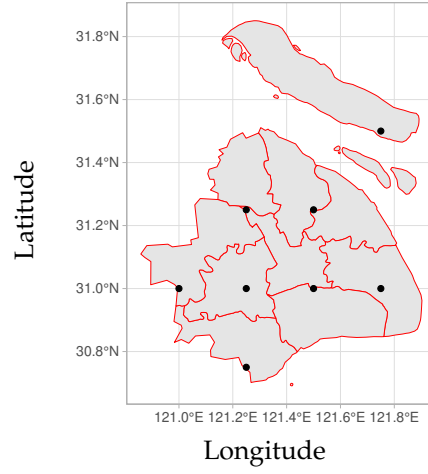
As stated previously, for geo-based analysis over time, harmonizing location boundaries that may change over time is often challenging. This can be difficult to deal with when analyses use county-level boundaries, as Chinese administrative names and boundaries have changed substantially over 30 years. Our child-population based

analysis does not compare each county-level unit over time, instead, we compare child-population-weighted temperature distributions using cross-county information.

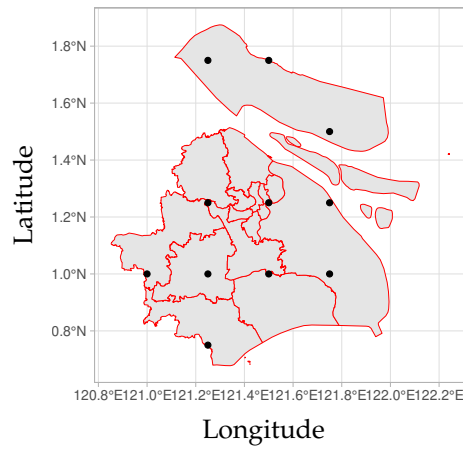
Depending on our analysis, we consider all counties in China, in a region, or in a province, and generate year-specific population-temperature cumulative distribution functions by sorting counties along the gradient of heat exposures and summing up the share of child population along ascending levels of heat exposures. While our distributions are discretized by county-level administrative units, at regional and national aggregation levels, given that there are 2369 (in 1990) and 2853 (in 2020) county-level administrative units in China, the population-temperature distributions are approximately smooth. Cross-time comparisons, especially at the national and regional levels, are based on these fine-grained discrete distribution.

Figure B.1: Chinese Counties and UTCI Grids, Shanghai

(a) 1990 districts/counties



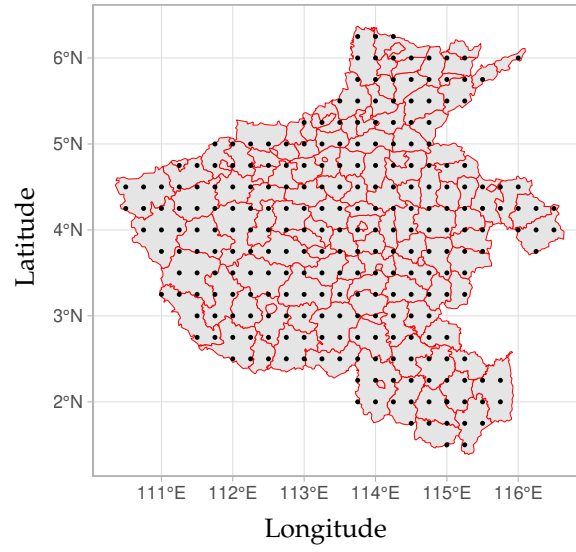
(b) 2020 districts/counties



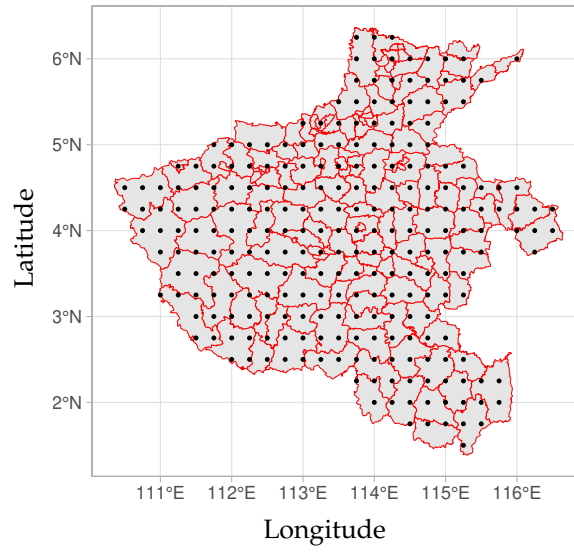
Notes: We superimpose UTCI grid points ($0.25^\circ \times 0.25^\circ$ longitude–latitude grid) over 1990 and 2020 district/county-level administrative boundaries (red boundary lines) from Shanghai, China. We show grid points (shown as black dots) that fall within the boundary of at least one district/county-level administrative unit. We associate county-level child population data with the average hourly temperature of grid points that fall within the boundaries of the county-level administrative unit. For Shanghai counties that do not overlap with any grid points, we associate children in the county with hourly temperatures from the spatial grid point that is the closest to the centroid location for the county.

Figure B.2: Chinese Counties and UTCI Grids, Henan

(a) 1990 counties

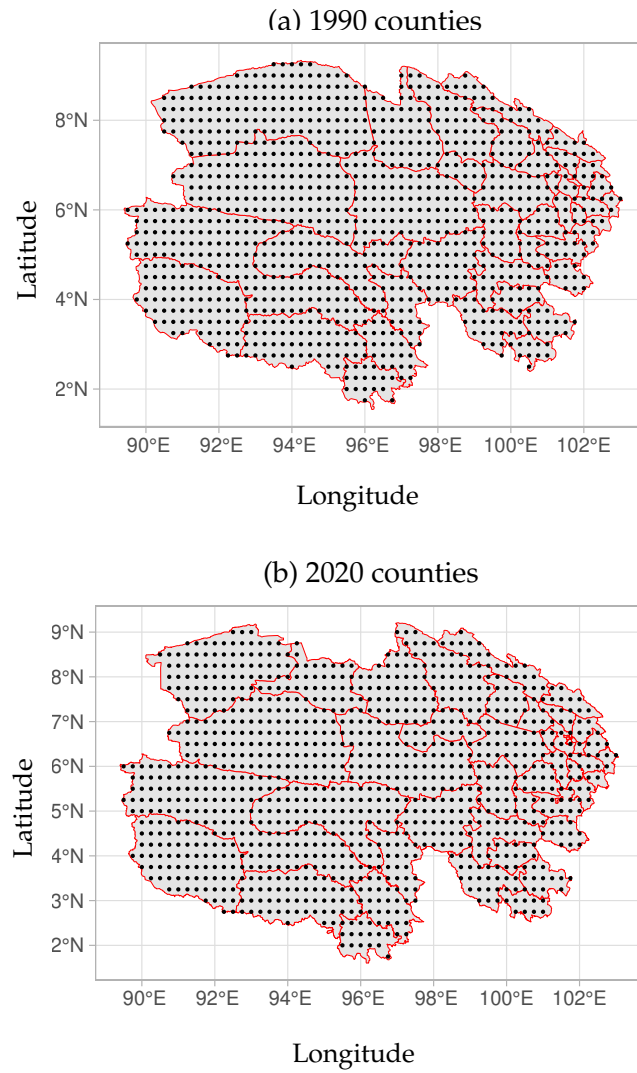


(b) 2020 counties



Notes: We superimpose UTCI grid points ($0.25^\circ \times 0.25^\circ$ longitude–latitude grid) over 1990 and 2020 county-level administrative boundaries (red boundary lines) from Henan, China. We show grid points (shown as black dots) that fall within the boundary of at least one county-level administrative unit. We associate county-level child population data with the average hourly temperature of grid points that fall within the boundaries of the county-level administrative unit.

Figure B.3: Chinese Counties and UTCI Grids, Qinghai



Notes: We superimpose UTCI grid points ($0.25^\circ \times 0.25^\circ$ longitude–latitude grid) over 1990 and 2020 county-level administrative boundaries (red boundary lines) from Qinghai, China. We show grid points (shown as black dots) that fall within the boundary of at least one county-level administrative unit. We associate county-level child population data with the average hourly temperature of grid points that fall within the boundaries of the county-level administrative unit.

Table B.1: The Distribution of the Number of Overlapping Grid Points ($0.25^\circ \times 0.25^\circ$ longitude–latitude grid) and the Distribution of Children (ages 0–14) among the 2369 Chinese Counties in 1990 and 2853 Chinese Counties in 2020

Number of grid points	Number of counties		Percent of children		Cumulative % of children	
	1990	2020	1990	2020	1990	2020
Panel A: Less than 6 grid points falling within a county						
1	503	957	19.89%	34.51%	19.89%	34.51%
2	467	508	21.29%	20.18%	41.19%	54.68%
3	378	382	17.58%	15.51%	58.77%	70.19%
4	307	309	16.08%	12.94%	74.84%	83.13%
5	171	167	8.10%	6.23%	82.94%	89.36%
Panel B: Between 6 and 50 grid points falling within a county						
6 to 10	280	275	12.65%	7.42%	95.59%	96.77%
11 to 20	135	131	2.77%	1.77%	98.36%	98.54%
21 to 30	46	41	0.75%	0.68%	99.11%	99.22%
31 to 40	29	27	0.34%	0.27%	99.46%	99.50%
41 to 50	14	15	0.19%	0.13%	99.65%	99.63%
Panel C: 51 or more grid points falling within a county						
51 to 100	24	27	0.25%	0.27%	99.90%	99.89%
101 to 200	12	11	0.09%	0.09%	99.99%	99.99%
201 to 330	3	3	0.01%	0.01%	100.00%	100.00%

Note: We overlay boundaries for Chinese counties (administrative level 3) in 1990 and 2020 with $0.25^\circ \times 0.25^\circ$ longitude–latitude spatial grids, which is the spatial resolution for the Universal Thermal Climate Index (UTCI) data that we use. We count the number of grid points that intersect (fall within the boundary) with each Chinese county. For county boundaries that do not intersect with points on the grid, we associate the county to the spatial grid point that is the closest to the centroid location for the county, and count that county as having 1 grid point. In the first column, we present categorizations of counties by the number of $0.25^\circ \times 0.25^\circ$ spatial grid points. In the second and third columns, we count the number of counties intersecting with different numbers of spatial grid points in 1990 and 2020. In the fourth and fifth columns, we show the percentage of children, as a share of the overall child (ages 0–14) population, that reside in the counties categorized in the second and third columns. In the sixth and seventh columns, we show the corresponding cumulative percentage of children. The statistics show, for example, that in 1990, 467 counties intersect with two $0.25^\circ \times 0.25^\circ$ spatial grid points, these counties account for 21.3% of the child population in 1990, and 41.2% of children reside in counties with equal or less than two intersecting UTCI spatial grid points.

Table B.2: The Distribution of Chinese Children (ages 0-14) Across Counties in 1990 and 2020

Statistics	Year	Percentiles						
		1	10	25	50	75	90	99
Panel A: National								
Number	1990	27.5K	79.3K	117.0K	185.7K	291.0K	405.5K	1240.1K
Percent	1990	0.008%	0.024%	0.036%	0.057%	0.09%	0.125%	0.382%
Number	2020	15.5K	47.9K	77.4K	128.3K	201.7K	296.0K	689.6K
Percent	2020	0.006%	0.019%	0.031%	0.051%	0.081%	0.118%	0.276%
Panel B: Central region								
Number	1990	39.6K	89.9K	140.9K	215.7K	312.4K	404.9K	540.0K
Percent	1990	0.012%	0.028%	0.043%	0.066%	0.096%	0.125%	0.166%
Number	2020	20.3K	54.7K	86.7K	142.7K	209.3K	270.6K	374.3K
Percent	2020	0.008%	0.022%	0.035%	0.057%	0.084%	0.108%	0.15%
Panel C: Eastern region								
Number	1990	52.2K	94.3K	138.1K	206.0K	320.9K	486.7K	1453.2K
Percent	1990	0.016%	0.029%	0.043%	0.063%	0.099%	0.15%	0.448%
Number	2020	33.3K	67.8K	97.9K	150.8K	239.1K	378.8K	1376.4K
Percent	2020	0.013%	0.027%	0.039%	0.06%	0.096%	0.152%	0.551%
Panel D: Northeastern region								
Number	1990	25.2K	83.9K	116.8K	165.4K	249.8K	332.4K	984.1K
Percent	1990	0.008%	0.026%	0.036%	0.051%	0.077%	0.102%	0.303%
Number	2020	6.0K	21.5K	33.4K	51.5K	76.4K	116.9K	233.0K
Percent	2020	0.002%	0.009%	0.013%	0.021%	0.031%	0.047%	0.093%
Panel E: Western region								
Number	1990	14.6K	54.9K	90.1K	137.3K	238.4K	350.5K	563.6K
Percent	1990	0.004%	0.017%	0.028%	0.042%	0.073%	0.108%	0.174%
Number	2020	10.6K	37.1K	62.4K	99.4K	164.9K	235.4K	405.0K
Percent	2020	0.004%	0.015%	0.025%	0.04%	0.066%	0.094%	0.162%

Note: Drawing on the 1990 and 2020 Chinese census, we present key percentiles of county-level distribution of child population (ages 0–14) in China in 1990 and 2020. In the rows where the statistics are “Number”, we show the number of children in units of thousands of children. In the rows where the statistics are “Percent”, we show the percent of children in a county as a share of the overall child (ages 0–14) population in the country. We present national and regional results. The statistics show, for example, that in 1990, the median county in China had 185.7 thousand children, which is equivalent to 0.057% of the overall child (ages 0–14) population in the country.

C Additional Results on heat exposure for children

Code and results for the additional results in this section as well as in the main text of the paper are accessible at: <https://github.com/ClimateInequality/PrjCEC>.

C.1 Average shares of time of heat exposure for children (STAC)

In Tables C.1 and C.2, we present additional details on changes in the average shares of time that Chinese children (ages 0–14) are at risk of heat exposure, between the years 1990 and 2020. Selected STAC results are visualized in Figure 1. We compute the annual average share of time that Chinese children are exposed to UTCI temperatures at or above various thresholds z °C. We group thresholds by panels focusing at least borderline thermal stress (23 °C–25 °C), at least moderate heat stress (26 °C–31 °C), at least strong heat stress (32 °C–37 °C), and very strong heat stress (38 °C–40 °C).

Table C.1's first four columns contain our main results where we consider ambient exposure during all hours of 1990 and 2020. The remaining four columns in Table C.1 present results considering only daytime (between 6 am and 10 pm) hours. Table C.2 presents results where we compare average exposures in the warmer months of April, May, June, July, August, and September with exposures during the colder months of January, February, March, October, November, and December in 1990 and 2020.

Tables C.1 and C.2 show that children's share of time at or above various UTCI heat stress thresholds increased across all heat stress thresholds. Specifically, Tables C.1 and C.2 show that there are between 14 and 18 percent increases the average share of time that children experienced at least moderate and strong heat stress for all hours, daytime hours only, as well as all hours between April and September. Interestingly, despite their low levels (less than 0.5% share of time), Table C.2 shows that heat exposure increased substantially during the colder months by 14% to 476% across thresholds between 1990 and 2020.

Table C.1: Change in Average Share of Time at or above UTCI Heat Thresholds for Chinese Children (ages 0-14), 1990 to 2020

UTCI thresholds	All annual hours \geq UTCI thresholds				Day time (6 am-10 pm) hours \geq UTCI thresholds			
	Share of time		Changes		Share of time		Changes	
	1990	2020	Level	%	1990	2020	Level	%
Panel A: Very strong heat stress								
$\geq 40^{\circ}\text{C}$	0.3%	0.3%	0.0007pp	0.2%	0.4%	0.4%	0.001pp	0.2%
$\geq 39^{\circ}\text{C}$	0.6%	0.6%	0.0pp	6.7%	0.9%	0.9%	0.1pp	6.7%
$\geq 38^{\circ}\text{C}$	1.0%	1.2%	0.1pp	10.6%	1.6%	1.7%	0.2pp	10.7%
Panel B: At least strong heat stress								
$\geq 37^{\circ}\text{C}$	1.7%	1.9%	0.3pp	15.1%	2.5%	2.9%	0.4pp	15.1%
$\geq 36^{\circ}\text{C}$	2.5%	2.9%	0.4pp	17.3%	3.7%	4.4%	0.6pp	17.3%
$\geq 35^{\circ}\text{C}$	3.4%	4.1%	0.6pp	18.1%	5.2%	6.1%	0.9pp	18.1%
$\geq 34^{\circ}\text{C}$	4.6%	5.4%	0.8pp	17.5%	6.8%	8.0%	1.2pp	17.5%
$\geq 33^{\circ}\text{C}$	5.8%	6.7%	0.9pp	16.1%	8.7%	10.1%	1.4pp	16.1%
$\geq 32^{\circ}\text{C}$	7.2%	8.3%	1.1pp	14.7%	10.8%	12.3%	1.6pp	14.8%
Panel C: At least moderate heat stress								
$\geq 31^{\circ}\text{C}$	8.7%	9.9%	1.2pp	13.9%	12.9%	14.7%	1.8pp	13.8%
$\geq 30^{\circ}\text{C}$	10.4%	11.8%	1.4pp	13.6%	15.2%	17.3%	2.0pp	13.2%
$\geq 29^{\circ}\text{C}$	12.3%	14.1%	1.7pp	14.0%	17.7%	20.0%	2.3pp	12.8%
$\geq 28^{\circ}\text{C}$	14.6%	16.8%	2.2pp	14.8%	20.4%	22.9%	2.6pp	12.5%
$\geq 27^{\circ}\text{C}$	17.2%	19.8%	2.5pp	14.8%	23.2%	26.0%	2.8pp	12.0%
$\geq 26^{\circ}\text{C}$	20.1%	22.8%	2.7pp	13.5%	26.2%	29.1%	2.9pp	11.0%
Panel D: At least borderline thermal stress								
$\geq 25^{\circ}\text{C}$	23.0%	25.7%	2.7pp	11.8%	29.3%	32.1%	2.8pp	9.7%
$\geq 24^{\circ}\text{C}$	25.9%	28.6%	2.6pp	10.1%	32.3%	35.1%	2.7pp	8.5%
$\geq 23^{\circ}\text{C}$	28.7%	31.3%	2.6pp	9.0%	35.3%	38.1%	2.7pp	7.7%

Note: Columns 1, 2, 5, and 6 show the annual average share of time at or above various UTCI thresholds (UTCI temperatures at $\geq z^{\circ}\text{C}$) for children in China (ages 0–14). Columns 3, 4, 7, and 8 show 1990 to 2020 changes in percentage points (level) or percentage (%) of the average shares of time at or above UTCI heat thresholds. We consider both all hourly as well as only daytime hourly (between 6 am and 10 am) UTCI temperature data.

Table C.2: Change in Average Share of Time at or above UTCI Heat Thresholds for Chinese Children (ages 0-14), during Warmer and Colder Months, 1990 to 2020

UTCI thresholds	April–September hours \geq UTCI thresholds				October–March hours \geq UTCI thresholds			
	Share of time		Changes		Share of time		Changes	
	1990	2020	Level	%	1990	2020	Level	%
Panel A: Very strong heat stress								
$\geq 40^{\circ}\text{C}$	0.6%	0.6%	0.001pp	0.2%	0.00002%	0.00008%	0.00006pp	334.3%
$\geq 39^{\circ}\text{C}$	1.2%	1.2%	0.1pp	6.6%	0.0001%	0.0004%	0.0002pp	159.0%
$\geq 38^{\circ}\text{C}$	2.1%	2.3%	0.2pp	10.6%	0.0004%	0.002%	0.001pp	373.7%
Panel B: At least strong heat stress								
$\geq 37^{\circ}\text{C}$	3.3%	3.8%	0.5pp	14.9%	0.002%	0.010%	0.008pp	476.0%
$\geq 36^{\circ}\text{C}$	4.9%	5.8%	0.8pp	17.0%	0.006%	0.02%	0.0pp	291.4%
$\geq 35^{\circ}\text{C}$	6.9%	8.1%	1.2pp	17.7%	0.02%	0.05%	0.0pp	144.1%
$\geq 34^{\circ}\text{C}$	9.0%	10.6%	1.6pp	17.1%	0.06%	0.10%	0.0pp	67.0%
$\geq 33^{\circ}\text{C}$	11.5%	13.3%	1.8pp	15.8%	0.1%	0.2%	0.0pp	35.1%
$\geq 32^{\circ}\text{C}$	14.1%	16.2%	2.1pp	14.7%	0.3%	0.3%	0.0pp	14.1%
Panel C: At least moderate heat stress								
$\geq 31^{\circ}\text{C}$	16.9%	19.3%	2.4pp	14.2%	0.5%	0.5%	0.0pp	4.2%
$\geq 30^{\circ}\text{C}$	20.0%	22.8%	2.8pp	14.1%	0.8%	0.8%	0.0pp	2.5%
$\geq 29^{\circ}\text{C}$	23.4%	26.9%	3.4pp	14.6%	1.2%	1.2%	0.0pp	3.0%
$\geq 28^{\circ}\text{C}$	27.5%	31.7%	4.3pp	15.5%	1.7%	1.7%	0.1pp	3.4%
$\geq 27^{\circ}\text{C}$	32.0%	37.0%	5.0pp	15.6%	2.4%	2.4%	0.1pp	2.8%
$\geq 26^{\circ}\text{C}$	36.9%	42.2%	5.3pp	14.5%	3.2%	3.3%	0.1pp	2.5%
Panel D: At least borderline thermal stress								
$\geq 25^{\circ}\text{C}$	41.7%	47.0%	5.3pp	12.7%	4.2%	4.4%	0.1pp	2.7%
$\geq 24^{\circ}\text{C}$	46.3%	51.4%	5.1pp	11.0%	5.4%	5.6%	0.2pp	3.0%
$\geq 23^{\circ}\text{C}$	50.6%	55.5%	4.9pp	9.7%	6.8%	7.1%	0.3pp	4.0%

Note: Columns 1, 2, 5, and 6 show the annual average share of time at or above various UTCI thresholds (UTCI temperatures at $\geq z^{\circ}\text{C}$) for children in China (ages 0–14). Columns 3, 4, 7, and 8 show 1990 to 2020 changes in percentage points (level) or percentage (%) of the average shares of time at or above UTCI heat thresholds. We compare UTCI temperatures in 1990 and 2020 during April, May, June, July, August and September and during January, February, March, October, November and December. We consider all 24 hours.

C.2 Share of children at risk of heat exposure (SEIDT)

In Tables C.3 and C.4, we present additional details from the SEIDT statistics analysis of the share of children at risk of exposure to heat stress thresholds, considering the dual thresholds of intensity (UTCI temperature thresholds $z^{\circ}\text{C}$) and duration (share of time-in-year thresholds $y\%$). Selected results are visualized in Figure 2. In each scenario, the share of children is computed by aggregating the child population from locations (counties) that experienced a particular combination of intensity and duration of exposures. In Table C.3, Panels A and B present shares of children at risk in 1990 and 2020. In Table C.3, Panels A and B present percentage points and percentage changes between 1990 and 2020.

We find that the shares of children experiencing long duration of moderate heat stress increased substantially between 1990 and 2020. In particular, the share of children experiencing at least 3 months of $\geq 26^{\circ}\text{C}$ UTCI temperature increased by about one tenth from 31.1% to 34.8%, at least 3 months of $\geq 28^{\circ}\text{C}$ UTCI temperature more than doubled from 7.5% to 17.4%, and at least 3 months of $\geq 30^{\circ}\text{C}$ increased by more than six times from 0.4% to 3.0%.

We also find a growing share of children experiencing at least strong and very strong heat stress. In particular, the share of children experiencing $\geq 34^{\circ}\text{C}$ UTCI temperature for at least 1.5 months increased by about six times from 0.5% to 3.4%, experiencing $\geq 36^{\circ}\text{C}$ for at least 1 month increased by 23 times from less than 0.1% to 2.1%, and experiencing $\geq 38^{\circ}\text{C}$ UTCI temperature for at least 2 weeks increased by 18 times from less than 0.1% to 1.8%.

Finally, not only did more children experience high intensities and long duration of heat exposure in 2020 compared to 1990, children experienced in 2020 new exposure combinations at higher intensities and with longer duration beyond the 1990 frontier. Specifically, in 1990, no children experienced at least 1 month of $\geq 38^{\circ}\text{C}$, at least 2 months of $\geq 34^{\circ}\text{C}$, or at least 4 months of $\geq 30^{\circ}\text{C}$ UTCI heat exposures, but about 0.1%, 0.4%, and 0.1% of children experienced these in 2020, respectively.

Table C.3: Share of Children at Risk of Heat Stress, 1990 to 2020

	Share of time in year thresholds and corresponding number of weeks								
	$\geq 4\%$	$\geq 8\%$	$\geq 12\%$	$\geq 16\%$	$\geq 20\%$	$\geq 24\%$	$\geq 28\%$	$\geq 32\%$	$\geq 36\%$
UTCI thresholds	2 weeks	4 weeks	6 weeks	8 weeks	10 wks	12 wks	14 wks	16 wks	18 wks
Panel A: 1990									
x% (cell) of children with at least y% (column) of time in year 1990 experiencing $\geq z^{\circ}\text{C}$ (row) UTCI temperature.									
Very strong heat stress									
$\geq 38^{\circ}\text{C}$	0.1%								
At least strong heat stress									
$\geq 36^{\circ}\text{C}$	27.2%	0.1%							
$\geq 34^{\circ}\text{C}$	60.1%	15.1%	0.5%						
$\geq 32^{\circ}\text{C}$	72.7%	52.1%	11.2%	1.4%	0.1%				
At least moderate heat stress									
$\geq 30^{\circ}\text{C}$	80.9%	69.0%	43.7%	13.1%	4.5%	0.4%			
$\geq 28^{\circ}\text{C}$	91.4%	77.5%	68.0%	44.6%	19.5%	7.5%	4.5%	1.4%	0.1%
$\geq 26^{\circ}\text{C}$	97.2%	87.0%	76.6%	68.5%	54.4%	31.1%	16.3%	8.6%	6.7%
At least borderline thermal stress									
$\geq 24^{\circ}\text{C}$	98.8%	96.0%	84.9%	76.6%	70.8%	63.2%	44.2%	25.3%	13.9%
Panel B: 2020									
x% (cell) of children with at least y% (column) of time in year 2020 experiencing $\geq z^{\circ}\text{C}$ (row) UTCI temperature.									
Very strong heat stress									
$\geq 38^{\circ}\text{C}$	1.8%	0.1%							
At least strong heat stress									
$\geq 36^{\circ}\text{C}$	32.4%	2.1%	0.2%						
$\geq 34^{\circ}\text{C}$	66.6%	20.1%	3.4%	0.4%					
$\geq 32^{\circ}\text{C}$	77.8%	59.1%	18.6%	6.1%	0.6%				
At least moderate heat stress									
$\geq 30^{\circ}\text{C}$	86.0%	75.6%	52.9%	20.7%	10.4%	3.0%	0.5%	0.1%	
$\geq 28^{\circ}\text{C}$	94.3%	83.5%	74.6%	53.6%	25.9%	17.4%	10.9%	7.4%	3.8%
$\geq 26^{\circ}\text{C}$	97.7%	91.9%	81.4%	74.5%	59.7%	34.8%	24.9%	17.9%	13.7%
At least borderline thermal stress									
$\geq 24^{\circ}\text{C}$	98.7%	97.0%	89.7%	81.2%	76.4%	65.6%	45.1%	32.4%	23.3%

Note: Cells show the shares of Chinese children (ages 0–14) experiencing at least y% of their time in a year to $\geq z^{\circ}\text{C}$ UTCI temperature. Shares of children are computed based on aggregating population shares from locations (counties) experiencing the various combinations of heat stress duration (share of time) and intensity (UTCI temperature) thresholds. For shares of time in a year, the correspondence between the share of time and the number of weeks is based on the fact that the average of N weeks of time and $\frac{N}{4}$ months of time is approximately $(N \cdot 2)\%$ of total share of time in a year. To enhance contrast, values are rounded and cells with values less than 0.05% or 0.05pp are left empty. We consider all 24 hours and 12 months.

Table C.4: Change in Share of Children at Risk of Exposure to Heat Stress Thresholds, 2020–1990

	Minimal share of time in year thresholds and corresponding number of weeks								
	≥ 4%	≥ 8%	≥ 12%	≥ 16%	≥ 20%	≥ 24%	≥ 28%	≥ 32%	≥ 36%
UTCI thresholds	2 weeks	4 weeks	6 weeks	8 weeks	10 wks	12 wks	14 wks	16 wks	18 wks
Panel a: 2020% – 1990%									
Increases in percentage points (cell) of children with at least y% (column) of time at ≥ z °C (row) heat threshold									
Very strong heat stress									
≥ 38 °C	1.7pp	0.1pp							
At least strong heat stress									
≥ 36 °C	5.2pp	2.0pp	0.2pp						
≥ 34 °C	6.6pp	5.0pp	2.9pp	0.4pp					
≥ 32 °C	5.1pp	6.9pp	7.4pp	4.7pp	0.5pp				
At least moderate heat stress									
≥ 30 °C	5.2pp	6.5pp	9.2pp	7.6pp	6.0pp	2.6pp	0.5pp	0.1pp	
≥ 28 °C	2.8pp	6.0pp	6.6pp	8.9pp	6.4pp	9.9pp	6.4pp	6.0pp	3.8pp
≥ 26 °C	0.6pp	5.0pp	4.8pp	6.0pp	5.2pp	3.7pp	8.6pp	9.3pp	7.0pp
At least borderline thermal stress									
≥ 24 °C	-0.2pp	1.0pp	4.8pp	4.6pp	5.5pp	2.5pp	0.9pp	7.2pp	9.4pp
Panel b: $\frac{2020\% - 1990\%}{1990\%} \cdot 100$									
Percentage increases (cell) of children with at least y% (column) of time at ≥ z °C (row) heat threshold									
Very strong heat stress									
≥ 38 °C	1.8k%								
At least strong heat stress									
≥ 36 °C	19.2%	2.3k%							
≥ 34 °C	10.9%	33.1%	606%						
≥ 32 °C	7.0%	13.3%	66.3%	330%	792%				
At least moderate heat stress									
≥ 30 °C	6.4%	9.4%	20.9%	58.5%	133%	654%			
≥ 28 °C	3.1%	7.7%	9.7%	20.0%	32.9%	131%	141%	414%	5.2k%
≥ 26 °C	0.6%	5.7%	6.3%	8.7%	9.6%	11.7%	52.9%	109%	106%
At least borderline thermal stress									
≥ 24 °C	-0.2%	1.0%	5.7%	6.0%	7.8%	3.9%	2.1%	28.5%	67.5%

Note: Cells show changes between 1990 and 2020 in percentage points (Panel A) and percentage (Panel B) of the shares of Chinese children (ages 0–14) experiencing at least y% of their time in a year to ≥ z °C UTCI temperature. Shares of children are computed based on aggregating population shares from locations (counties) experiencing the various combinations of heat stress duration (share of time) and intensity (UTCI temperature) thresholds. For shares of time in a year, the correspondence between the share of time and the number of weeks is based on the fact that the average of N weeks of time and $\frac{N}{4}$ months of time is approximately $(N \cdot 2)\%$ of total share of time in a year. To enhance contrast, values are rounded and cells with values less than 0.05% or 0.05pp are left empty. We consider all 24 hours and 12 months.

C.3 Decomposing shifts in population and temperature distributions

In Tables C.5 and C.6, we provide details on the relative contributions of shifts in the child population distribution and the temperature distribution to overall changes in the average shares of time of heat exposure for children. Selected results are visualized in Figure 3. Columns 1–3 of the tables follow from Table C.1. In columns 4–6 of the tables, we use the 1990 population distribution jointly with the 2020 UTCI temperature distribution. In columns 7–9, we consider exposures if the 2020 population distribution faced the 1990 UTCI temperature distribution. Residual unexplained changes are attributed to population and temperature shift interactions. Our STAC-based decomposition analysis is statistical in nature: We shift one distribution while holding the other constant and do not model mechanisms of change.

In Table C.5, nationally, we show that shifts in the child population distribution between 1990 and 2020 account for 39% to 50% of the increases in the average shares of time of that children are exposed to at least moderate or at least strong heat stress. In contrast, within the Eastern and Northeastern regions, child population distribution shifts account for 5% to 38% of the aggregate regional increases in average child heat exposure. The national results are due to both within- and across-region shifts, whereas the regional results are attributed to only within-region shifts.

In the last column of Tables C.5 we note the decreased importance of population effects in explaining overall changes at higher UTCI thresholds. For example, nationally, the population-shift contributions to overall changes decreased from 61% for at least borderline heat stress ($\geq 24^{\circ}\text{C}$) to 39% for the upper-bound of at least strong heat stress ($\geq 36^{\circ}\text{C}$); for the Eastern region, the corresponding numbers decreased from 61% to 19%. These mean that increases at higher heat exposure thresholds come more from increasing temperatures rather than from populations moving to locations that were already hotter in 1990.

For completeness, in Table C.6, we also present decompositions of regional changes from the Central and Western regions. Child population shifts also help to explain the

relatively limited aggregate heat exposures changes in these regions.

Table C.5: Decompose Changes in Average Share of Time Exposed to Heat

UTCI thresholds	Actual 2020 vs 1990			2020 UTCI with 1990 population			1990 UTCI with 2020 population		
	Share of time		Changes	Share-time	Decompose changes		Share-time	Decompose changes	
	1990	2020	Δ	Prediction	Vs. 1990	% of Δ	Prediction	Vs. 1990	% of Δ
Panel A: National									
At least strong heat stress									
$\geq 36^\circ\text{C}$	2.5%	2.9%	0.43pp	2.7%	0.17pp	40%	2.7%	0.17pp	39%
$\geq 34^\circ\text{C}$	4.6%	5.4%	0.80pp	4.9%	0.35pp	45%	4.9%	0.33pp	42%
$\geq 32^\circ\text{C}$	7.2%	8.3%	1.06pp	7.6%	0.44pp	42%	7.7%	0.51pp	48%
At least moderate heat stress									
$\geq 30^\circ\text{C}$	10.4%	11.8%	1.42pp	11.0%	0.60pp	42%	11.1%	0.69pp	49%
$\geq 28^\circ\text{C}$	14.6%	16.8%	2.16pp	15.5%	0.90pp	42%	15.6%	0.98pp	45%
$\geq 26^\circ\text{C}$	20.1%	22.8%	2.72pp	21.2%	1.08pp	40%	21.4%	1.35pp	50%
At least borderline thermal stress									
$\geq 24^\circ\text{C}$	25.9%	28.6%	2.63pp	26.8%	0.88pp	33%	27.5%	1.60pp	61%
Panel B: Eastern region									
At least strong heat stress									
$\geq 36^\circ\text{C}$	2.7%	3.5%	0.85pp	3.3%	0.59pp	70%	2.9%	0.16pp	19%
$\geq 34^\circ\text{C}$	5.3%	6.6%	1.35pp	6.1%	0.89pp	66%	5.6%	0.31pp	23%
$\geq 32^\circ\text{C}$	8.4%	10.1%	1.70pp	9.5%	1.03pp	61%	8.9%	0.50pp	29%
At least moderate heat stress									
$\geq 30^\circ\text{C}$	12.1%	14.3%	2.26pp	13.4%	1.33pp	59%	12.8%	0.73pp	32%
$\geq 28^\circ\text{C}$	17.0%	20.7%	3.70pp	19.0%	2.02pp	55%	18.2%	1.18pp	32%
$\geq 26^\circ\text{C}$	23.6%	28.1%	4.44pp	25.9%	2.27pp	51%	25.3%	1.69pp	38%
At least borderline thermal stress									
$\geq 24^\circ\text{C}$	30.6%	34.2%	3.54pp	32.0%	1.36pp	38%	32.5%	1.87pp	53%
Panel C: Northeastern region									
At least strong heat stress									
$\geq 36^\circ\text{C}$	0.04%	0.3%	0.27pp	0.3%	0.24pp	89%	0.05%	0.01pp	5%
$\geq 34^\circ\text{C}$	0.3%	1.1%	0.79pp	1%	0.72pp	91%	0.3%	0.05pp	6%
$\geq 32^\circ\text{C}$	1.1%	2.4%	1.22pp	2.3%	1.12pp	92%	1.3%	0.11pp	9%
At least moderate heat stress									
$\geq 30^\circ\text{C}$	2.8%	4.1%	1.35pp	4.0%	1.23pp	91%	2.9%	0.17pp	13%
$\geq 28^\circ\text{C}$	5.0%	6.4%	1.39pp	6.2%	1.21pp	87%	5.2%	0.21pp	15%
$\geq 26^\circ\text{C}$	7.5%	8.9%	1.43pp	8.7%	1.16pp	81%	7.7%	0.24pp	16%
At least borderline thermal stress									
$\geq 24^\circ\text{C}$	10.4%	11.8%	1.45pp	11.4%	1.06pp	73%	10.7%	0.29pp	20%

Note: Columns (cols) 1–3 include actual annual average share of time that children in China (ages 0–14) are exposed to UTCI temperatures at $\geq z^\circ\text{C}$ (same as cols 1–3 in Table C.1). In cols 4–6, the 1990 population distribution face the 2020 UTCI temperature distribution. In cols 7–9, 2020 population face 1990 UTCI temperatures. Cols 4 and 7 show annual average share of time that children are exposed to heat given decomposition scenarios. Cols 5 and 8 show differences between predictions and 1990 actual average shares. Cols 6 and 9 show the share of column 3 actual changes that the predictions from cols 5 and 8 account for. We consider all 24 hours and 12 months.

Table C.6: Decompose Changes in Average Share of Time Exposed to Heat

UTCI thresholds	Actual 2020 vs 1990			2020 UTCI with 1990 population			1990 UTCI with 2020 population		
	Share of time		Changes	Share-time	Decompose changes		Share-time	Decompose changes	
	1990	2020	Δ	Prediction	Vs. 1990	% of Δ	Prediction	Vs. 1990	% of Δ
Panel A: Central region									
At least strong heat stress									
$\geq 36^{\circ}\text{C}$	3.7%	3.7%	0.08pp	3.6%	-0.03pp	-33%	3.7%	0.02pp	27%
$\geq 34^{\circ}\text{C}$	6.2%	6.5%	0.25pp	6.4%	0.11pp	45%	6.3%	0.03pp	14%
$\geq 32^{\circ}\text{C}$	9.3%	9.6%	0.30pp	9.4%	0.13pp	43%	9.3%	0.04pp	14%
At least moderate heat stress									
$\geq 30^{\circ}\text{C}$	12.9%	13.3%	0.39pp	13.1%	0.21pp	53%	12.9%	0.04pp	10%
$\geq 28^{\circ}\text{C}$	17.6%	17.9%	0.38pp	17.8%	0.19pp	51%	17.6%	0.03pp	9%
$\geq 26^{\circ}\text{C}$	23.4%	23.6%	0.21pp	23.4%	0.04pp	22%	23.4%	0.04pp	21%
At least borderline thermal stress									
$\geq 24^{\circ}\text{C}$	29.2%	29.6%	0.42pp	29.5%	0.27pp	64%	29.3%	0.08pp	19%
Panel B: Western region									
At least strong heat stress									
$\geq 36^{\circ}\text{C}$	1.7%	1.7%	-0.04pp	1.6%	-0.12pp	284%	1.7%	0.05pp	-112%
$\geq 34^{\circ}\text{C}$	3.2%	3.3%	0.03pp	3.2%	-0.09pp	-312%	3.4%	0.10pp	345%
$\geq 32^{\circ}\text{C}$	5.4%	5.4%	0.07pp	5.3%	-0.09pp	-133%	5.5%	0.16pp	247%
At least moderate heat stress									
$\geq 30^{\circ}\text{C}$	8.0%	8.2%	0.19pp	8.1%	0.01pp	7%	8.2%	0.19pp	102%
$\geq 28^{\circ}\text{C}$	11.5%	12.1%	0.52pp	11.8%	0.29pp	55%	11.8%	0.24pp	47%
$\geq 26^{\circ}\text{C}$	16.2%	17.2%	1.06pp	16.9%	0.77pp	73%	16.5%	0.30pp	28%
At least borderline thermal stress									
$\geq 24^{\circ}\text{C}$	21.5%	22.7%	1.13pp	22.4%	0.91pp	81%	21.8%	0.30pp	26%

Note: Columns (cols) 1–3 include actual annual average share of time that children in the Central and Western regions of China (ages 0–14) are exposed to UTCI temperatures at $\geq z^{\circ}\text{C}$ (same as cols 1–3 in Table C.1). In cols 4–6, the 1990 population distribution face the 2020 UTCI temperature distribution. In cols 7–9, 2020 population face 1990 UTCI temperatures. Cols 4 and 7 show annual average share of time that children are exposed to heat given decomposition scenarios. Cols 5 and 8 show differences between predictions and 1990 actual average shares. Cols 6 and 9 show the share of column 3 actual changes that the predictions from cols 5 and 8 account for. We consider all 24 hours and 12 months.

C.4 Additional regional analysis

In Tables C.7 and C.8, we present details on region- and province-specific STAC child heat exposure analysis. Selected regional results are visualized in Figure 4. Sub-national analyses show which areas have experienced greater changes in heat exposures and also shed light on whether aggregate changes are due to population shifts across provinces within regions or across regions.^{C.1} Table C.7 presents results for at least strong and very strong heat stress and Table C.8 focuses on at least moderate heat stress.

Between 1990 and 2020, while Central (C) and Western (W) heat exposures stagnated, children in the heated Eastern (E) and colder Northeastern (NE) regions experienced increases of 19%–35% and 19%–7.4k% in average heat exposure time. In 2020, the average E, NE, C, and W region child experienced 10.1%, 2.4%, 9.5%, and 5.4% of her time under at least strong ($\geq 32^\circ\text{C}$) heat stress.

In 2020, we find that children in Hainan (E), Guangdong (E), Guangxi (W), Jiangxi (C), and Fujian (E) had the highest heat exposures with 19.2%, 15.2%, 13.2%, 12.8%, and 11.8% of their average shares of time exposed to at least strong heat stress ($\geq 32^\circ\text{C}$), which represented respective increases of 17%, 20%, 8%, 16%, and 54% compared to 1990.

Lastly, we note the importance of considering both changes and levels. While Hebei (E), Zhejiang (E) and NE provinces experienced similar percentage point increases in the average share of heat exposure time, the percentage increases in the NE provinces are 3 to 15 times larger due to lower starting levels. Additionally, Hebei (E) and Jiangsu (E) arrived at similar levels of average child heat exposure in 2020 with a 17% increase and an 11% reduction in average share of heat exposure time, respectively. Locations with similar levels or changes of exposure might require different societal and physical adjustments depending on prior levels and the magnitudes of recent changes.

^{C.1}Even when there are no changes in temperatures and within-region population distributions, average national child exposure could increase due to shifts in child population to hotter regions.

Table C.7: Regional Average Share of Time at Risk of Exposure to at least **Strong** and **Very Strong** Heat Stress Thresholds for Children (ages 0-14), 1990 to 2020

Location	At least strong heat stress								Very strong heat stress			
	≥ UTCI 32° C				≥ UTCI 35° C				≥ UTCI 38° C			
	Share of time		Changes		Share of time		Changes		Share of time		Changes	
	1990	2020	Level	%	1990	2020	Level	%	1990	2020	Level	%
Panel A: Regions												
Eastern	8.4%	10.1%	1.7pp	20%	3.9%	5.0%	1.1pp	29%	1.0%	1.4%	0.4pp	35%
Northeastern	1.1%	2.4%	1.2pp	106%	0.1%	0.6%	0.5pp	457%	0.0%	0.1%	0.1pp	7.4k%
Central	9.3%	9.6%	0.3pp	3%	4.9%	5.1%	0.2pp	4%	1.7%	1.6%	-0.1pp	-3%
Western	5.4%	5.4%	0.1pp	1%	2.4%	2.4%	0.0pp	0%	0.7%	0.6%	-0.1pp	-18%
Panel B: Eastern region												
Beijing	2.9%	6.3%	3.4pp	117%	0.5%	2.8%	2.3pp	424%	0.0%	0.6%	0.6pp	1.2k%
Fujian	7.7%	11.8%	4.1pp	54%	2.9%	5.6%	2.7pp	94%	0.5%	1.3%	0.9pp	175%
Guangdong	12.7%	15.2%	2.5pp	20%	5.7%	7.5%	1.8pp	31%	1.3%	2.0%	0.7pp	56%
Hainan	16.3%	19.2%	2.8pp	17%	6.4%	10.0%	3.6pp	57%	0.9%	3.4%	2.4pp	261%
Hebei	6.5%	7.6%	1.1pp	17%	2.9%	3.9%	1.0pp	34%	0.8%	1.0%	0.2pp	31%
Jiangsu	8.7%	7.8%	-0.9pp	-11%	4.7%	3.8%	-0.9pp	-20%	1.7%	1.3%	-0.4pp	-25%
Shandong	6.8%	7.1%	0.4pp	6%	2.9%	3.3%	0.4pp	13%	0.5%	0.9%	0.3pp	58%
Shanghai	6.8%	6.1%	-0.7pp	-10%	3.1%	2.7%	-0.4pp	-14%	1.0%	0.6%	-0.4pp	-40%
Tianjin	5.6%	7.3%	1.7pp	31%	2.1%	3.8%	1.7pp	84%	0.2%	0.9%	0.7pp	308%
Zhejiang	8.2%	9.2%	1.0pp	12%	4.6%	4.9%	0.4pp	8%	1.9%	1.6%	-0.3pp	-14%
Panel C: Northeastern region												
Heilongjiang	0.6%	1.7%	1.1pp	175%	0.0%	0.4%	0.4pp	1.6k%	0.0%	0.0%	0.0pp	
Jilin	0.8%	2.1%	1.3pp	148%	0.0%	0.5%	0.5pp	2.7k%	0.0%	0.0%	0.0pp	
Liaoning	1.9%	2.9%	1.1pp	56%	0.3%	0.8%	0.6pp	216%	0.0%	0.1%	0.1pp	4.5k%
Panel D: Central region												
Anhui	10.1%	9.3%	-0.8pp	-7%	5.8%	5.0%	-0.9pp	-15%	2.2%	1.8%	-0.4pp	-18%
Henan	8.9%	9.5%	0.6pp	7%	4.5%	5.1%	0.5pp	12%	1.4%	1.6%	0.2pp	13%
Hubei	10.2%	9.3%	-0.9pp	-9%	5.5%	4.9%	-0.6pp	-10%	2.0%	1.3%	-0.7pp	-35%
Hunan	10.2%	10.6%	0.4pp	4%	5.0%	5.4%	0.4pp	7%	1.6%	1.6%	0.0pp	0%
Jiangxi	11.0%	12.8%	1.8pp	16%	6.1%	7.4%	1.2pp	20%	2.4%	2.9%	0.5pp	19%
Shanxi	2.6%	2.8%	0.1pp	5%	0.8%	0.7%	-0.1pp	-18%	0.2%	0.1%	-0.1pp	-53%
Panel E: Western region												
Gansu	0.8%	0.8%	0.0pp	-1%	0.1%	0.1%	0.0pp	-17%	0.0%	0.0%	0.0pp	-17%
Guangxi	12.3%	13.2%	1.0pp	8%	5.5%	6.6%	1.1pp	20%	1.5%	1.4%	-0.1pp	-7%
Guizhou	2.8%	2.1%	-0.7pp	-26%	0.7%	0.3%	-0.4pp	-53%	0.1%	0.0%	0.0pp	-54%
Neimenggu	0.9%	2.0%	1.1pp	116%	0.1%	0.6%	0.4pp	296%	0.0%	0.1%	0.1pp	268%

Continued on next page

Table C.7: Regional Average Share of Time at Risk of Exposure to at least **Strong** and **Very Strong** Heat Stress Thresholds for Children (ages 0-14), 1990 to 2020

Location	At least strong heat stress								Very strong heat stress			
	\geq UTCI 32° C				\geq UTCI 35° C				\geq UTCI 38° C			
	Share of time		Changes		Share of time		Changes		Share of time		Changes	
	1990	2020	Level	%	1990	2020	Level	%	1990	2020	Level	%
Ningxia	2.1%	2.8%	0.7pp	31%	0.7%	0.9%	0.2pp	35%	0.1%	0.1%	0.0pp	17%
Qinghai	0.0%	0.0%	0.0pp		0.0%	0.0%	0.0pp		0.0%	0.0%	0.0pp	
Shaanxi	4.6%	4.3%	-0.4pp	-8%	1.9%	1.5%	-0.4pp	-23%	0.6%	0.2%	-0.3pp	-58%
Sichuan	8.0%	7.4%	-0.7pp	-8%	4.2%	3.6%	-0.6pp	-14%	1.3%	1.0%	-0.3pp	-23%
Xinjiang	4.3%	5.2%	0.9pp	22%	2.0%	2.4%	0.4pp	19%	0.7%	0.7%	0.0pp	0%
Xizang	0.0%	0.0%	0.0pp		0.0%	0.0%	0.0pp		0.0%	0.0%	0.0pp	
Yunnan	0.9%	1.2%	0.3pp	33%	0.1%	0.1%	0.0pp	53%	0.0%	0.0%	0.0pp	-7%

Note: We present similar statistics as in Table C.1, but now compute exposures separately for the four economic regions and provincial-level administrative units in China. Columns (cols) 1–3 and 4–6 focus on at least strong UTCI heat exposure at $\geq 32^{\circ}\text{C}$ and $\geq 35^{\circ}\text{C}$, respectively. Cols 7–9 focus on very strong UTCI heat exposure at $\geq 38^{\circ}\text{C}$. Cols 1 and 2, 5 and 6, and 9 and 10 show the annual average share of time at or above various UTCI thresholds (UTCI temperatures at $\geq z^{\circ}\text{C}$) for children in China (ages 0–14). Cols 3 and 4, 7 and 8, and 11 and 12 show 1990 to 2020 changes in percentage points (level) or percentage (%) of the average shares of time at or above UTCI heat thresholds. Cells are empty for percentage changes when the denominator is equal to zero. We consider all 24 hours and 12 months.

Table C.8: Regional Average Share of Time at Risk of Exposure to at Least **Moderate** Heat Stress Thresholds for Children (ages 0-14), 1990 to 2020

Location	At least borderline thermal stress				At least moderate heat stress							
	\geq UTCI 23° C				\geq UTCI 26° C				\geq UTCI 29° C			
	Share of time		Changes		Share of time		Changes		Share of time		Changes	
	1990	2020	Level	%	1990	2020	Level	%	1990	2020	Level	%
Panel A: Regions												
Eastern	33.8%	37.0%	3.2pp	9%	23.6%	28.1%	4.4pp	19%	14.3%	17.1%	2.8pp	20%
Northeastern	12.0%	13.5%	1.5pp	13%	7.5%	8.9%	1.4pp	19%	3.8%	5.2%	1.4pp	36%
Central	32.0%	32.7%	0.7pp	2%	23.4%	23.6%	0.2pp	1%	15.1%	15.5%	0.4pp	3%
Western	24.3%	25.3%	1.0pp	4%	16.2%	17.2%	1.1pp	7%	9.7%	10.0%	0.3pp	3%
Panel B: Eastern region												
Beijing	19.0%	23.2%	4.3pp	23%	12.1%	16.2%	4.1pp	34%	7.0%	10.7%	3.7pp	53%
Fujian	38.9%	45.6%	6.7pp	17%	24.6%	32.5%	7.9pp	32%	14.1%	19.0%	4.9pp	35%
Guangdong	51.9%	55.5%	3.7pp	7%	37.5%	45.3%	7.8pp	21%	21.6%	26.3%	4.7pp	22%
Hainan	63.5%	63.4%	0.0pp	0%	47.1%	51.8%	4.7pp	10%	27.7%	31.5%	3.9pp	14%
Hebei	24.4%	25.1%	0.7pp	3%	17.0%	18.0%	1.0pp	6%	10.8%	12.3%	1.5pp	14%
Jiangsu	30.5%	29.7%	-0.8pp	-3%	22.5%	21.5%	-1.0pp	-4%	14.3%	13.7%	-0.6pp	-4%
Shandong	26.7%	25.3%	-1.4pp	-5%	18.1%	18.2%	0.0pp	0%	11.4%	12.1%	0.7pp	6%

Continued on next page

Table C.8: Regional Average Share of Time at Risk of Exposure to at Least **Moderate** Heat Stress Thresholds for Children (ages 0-14), 1990 to 2020

Location	At least borderline thermal stress				At least moderate heat stress							
	\geq UTCI 23° C				\geq UTCI 26° C				\geq UTCI 29° C			
	Share of time		Changes		Share of time		Changes		Share of time		Changes	
	1990	2020	Level	%	1990	2020	Level	%	1990	2020	Level	%
Shanghai	27.9%	29.7%	1.8pp	7%	19.7%	20.7%	1.0pp	5%	12.3%	11.3%	-1.0pp	-8%
Tianjin	23.5%	25.2%	1.7pp	7%	15.8%	17.8%	1.9pp	12%	9.7%	12.1%	2.3pp	24%
Zhejiang	33.4%	36.0%	2.6pp	8%	22.6%	26.5%	3.9pp	17%	13.6%	15.4%	1.8pp	13%
Panel C: Northeastern region												
Heilongjiang	10.2%	11.2%	1.0pp	9%	6.3%	7.3%	0.9pp	15%	2.9%	4.0%	1.1pp	38%
Jilin	11.1%	12.2%	1.1pp	10%	6.9%	8.5%	1.5pp	22%	3.4%	4.9%	1.5pp	45%
Liaoning	14.4%	15.8%	1.4pp	10%	9.1%	10.3%	1.3pp	14%	5.1%	6.2%	1.1pp	21%
Panel D: Central region												
Anhui	32.7%	32.3%	-0.4pp	-1%	25.2%	23.4%	-1.8pp	-7%	16.2%	15.5%	-0.7pp	-5%
Henan	29.6%	29.4%	-0.2pp	-1%	21.5%	21.1%	-0.4pp	-2%	13.9%	14.5%	0.6pp	4%
Hubei	33.3%	33.9%	0.6pp	2%	25.1%	24.2%	-0.9pp	-3%	16.7%	15.4%	-1.3pp	-8%
Hunan	36.2%	37.6%	1.4pp	4%	25.7%	26.8%	1.1pp	4%	16.5%	17.1%	0.5pp	3%
Jiangxi	38.8%	41.8%	3.0pp	8%	28.1%	31.7%	3.6pp	13%	17.9%	20.9%	3.1pp	17%
Shanxi	16.1%	16.6%	0.5pp	3%	10.6%	11.1%	0.6pp	5%	6.0%	6.6%	0.5pp	9%
Panel E: Western region												
Gansu	11.1%	10.7%	-0.4pp	-3%	6.6%	6.4%	-0.2pp	-3%	3.0%	2.9%	0.0pp	-1%
Guangxi	47.5%	49.2%	1.7pp	4%	33.3%	36.8%	3.4pp	10%	20.2%	21.4%	1.2pp	6%
Guizhou	19.5%	19.4%	-0.1pp	0%	12.2%	11.6%	-0.6pp	-5%	7.0%	6.1%	-0.9pp	-13%
Neimenggu	9.9%	12.0%	2.1pp	21%	6.0%	8.2%	2.2pp	36%	2.9%	4.7%	1.8pp	62%
Ningxia	12.9%	14.1%	1.1pp	9%	8.8%	9.6%	0.8pp	10%	5.0%	5.7%	0.7pp	13%
Qinghai	4.9%	3.8%	-1.1pp	-23%	1.4%	1.0%	-0.4pp	-30%	0.1%	0.0%	-0.1pp	-71%
Shaanxi	19.5%	19.3%	-0.2pp	-1%	13.3%	13.1%	-0.3pp	-2%	8.6%	8.2%	-0.3pp	-4%
Sichuan	28.5%	29.4%	0.8pp	3%	19.3%	19.7%	0.4pp	2%	12.5%	12.2%	-0.3pp	-3%
Xinjiang	16.3%	18.0%	1.6pp	10%	11.4%	13.1%	1.7pp	14%	7.4%	8.8%	1.4pp	18%
Xizang	1.3%	1.4%	0.1pp	5%	0.1%	0.1%	0.0pp	-32%	0.0%	0.0%	0.0pp	159%
Yunnan	19.2%	21.0%	1.8pp	9%	11.0%	12.3%	1.3pp	12%	4.6%	5.3%	0.8pp	17%

Note: We present similar statistics as in Table C.1, but now compute exposures separately for the four economic regions and provincial-level administrative units in China. Columns (cols) 4–6 and 7–9 focus on at least moderate UTCI heat exposure at $\geq 26^\circ\text{C}$ and $\geq 29^\circ\text{C}$, respectively. Cols 1–3 provide UTCI heat exposure at $\geq 23^\circ\text{C}$ —UTCI 23°C is a temperature level that is just below the UTCI 25°C threshold for moderate heat stress. Cols 1 and 2, 5 and 6, and 9 and 10 show the annual average share of time at or above various UTCI thresholds (UTCI temperatures at $\geq z^\circ\text{C}$) for children in China (ages 0–14). Cols 3 and 4, 7 and 8, and 11 and 12 show 1990 to 2020 changes in percentage points (level) or percentage (%) of the average shares of time at or above UTCI heat thresholds. Cells are empty for percentage changes when the denominator is equal to zero. We consider all 24 hours and 12 months.

C.5 Main and Additional Results Replication

Code and results for the additional results in this section as well as in the main text of the paper are accessible at: <https://github.com/ClimateInequality/PrjCEC>.

Code for generating the statistics shown in tables and figures are stored in the [R-script](#) folder, and code and output for visualizaing and tabularization are stored in the [res](#) folder.

1. Section [C.1](#) and main text Figure 1 results and code:

- Generate statistics: [R-script/run_1a_mean_child_all24](#), [R-script/run_1b_mean_child_6t22](#), and [R-script/run_1c_mean_child_seasons](#)
- Tabulate and visualize: [R-script/tabfig_1_mean_child](#)
- Tables and figures: [res/res_mean_child](#)

2. Section [C.2](#) and main text Figure 2 results and code:

- Generate statistics: [R-script/run_2a_atrisk_child](#)
- Tabulate and visualize: [R-script/tabfig_2_at_risk](#)
- Tables and figures: [res/res_atrisk](#)

3. Section [C.3](#) and main text Figure 3 results and code:

- Generate statistics: [R-script/run_3a_decompose](#) and [R-script/run_3b_decompose_regional](#)
- Tabulate and visualize: [R-script/tabfig_3_decompose](#)
- Tables and figures: [res/res_decompose](#)

4. Section [C.4](#) and main text Figure 4 results and code:

- Generate statistics: [R-script/run_4a_mean_child_all24_by_region](#) and [R-script/run_4b_mean_child_all24_by_province](#)
- Tabulate and visualize: [R-script/tabfig_4_region_prov](#)
- Tables and figures: [res/res_region_prov](#)

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