Rising Temperatures, Rising Risks: A Three-Decade Analysis of Children's Heat Exposure in China (1990-2020)

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Abstract

We map fine-grained hourly spatiotemporal data on extreme temperature with county-level population census to investigate the unequal distribution of heat exposure burdens among children—a population especially vulnerable to extreme temperatures—in China from 1990 to 2020. In 1990, an average child in China experienced moderate or stronger heat stress (UTCI 26°C degrees and above) for 20.09% of their total hours of the year. By 2020, this percentage had increased by 2.7%. Delving into the population distribution of children, we found that in 1990, only 9.49% of children experienced moderate or stronger heat stress for more than 30% of their hours. By 2020, this proportion had increased to 19.51%, reflecting a rise of 10.02%. Using counterfactual decomposition, we found that effects of escalating temperatures and a growing child population in the heat-affected regions contribute equally to the overall increase in heat exposure among children. In addition, we observed substantial variations across regions. Our approach can be applied to other regions of the world.

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Findings Summary

- In 1990, an ***average*** child in China experienced moderate or stronger heat stress (UTCI 26C and above) for 20.09 % of their hours. By 2020, this percentage had increased by 2.7 percentage points (pp) (Figure 1).
- In 1990, 9.49 % of children experienced moderate or stronger heat stress for over 30 % of their hours. By 2020, this figure had risen to 19.51 %, marking an increase of 10.02 pp (Figure 2).
- Counterfactual decomposition analyses reveal that the effects of escalating temperatures and a growing child population in the heat-affected regions contribute equally to the overall increase in heat exposure among children (Figure 3).
- The substantial increase in children's exposure to heat stress in Eastern China, the nation's most economically developed and densely populated region, is a primary driver behind the overall surge observed at the national level (Figure 4).

1 Introduction

There is a growing evidence base on heat exposure affecting various developmental outcomes for children including education, health, and long-term productivity. This body of work includes emerging literature in China, which is home to more than 253.38 million children ages 0-14 in the year 2020 (National Bureau of Statistics of China 2021). The effect of the thermal environment on children in regards to their school performance has been investigated by studies such as Jiang et al. (2018), Liu et al. (2017), and Wang et al. (2018), finding extreme temperatures affecting student's academic performance. Negative health outcomes such as the common cold; hand, foot, and mouth disease; and asthma have also been associated with extreme temperature exposure (Guo et al. 2012; Lu et al. 2018; Lu et al. 2022; Xu et al. 2015). While it is one of the less developed research trends in China, Lai et al. (2023) and Zivin and Shrader (2016) review evidence that shows extreme temperature experienced at an early age can limit bodily development and thus limit work productivity as an adult. Despite emerging outcome-focused literature, an important question that has not yet been adequately addressed is how children's heat exposure on its own in China is changing over time.

In this paper, we combined county-level census population data on child distribution from 1990 and 2020 with perceived temperature data to study changes in ambient heat exposure facing children over three decades. we develop new methods and framework for measuring the share of children at risk of extreme temperature exposures that jointly considers temperature thresholds and the share of time exposed to such temperature thresholds. Applying our framework, empirically, we find substantial increases in the average heat exposure for children and the share of children at risk and substantial regional heterogeneity. Interestingly, we find that half of the overall changes in child heat exposure is driven by heat increases and the rest is driven by shifts in child population towards locations that have higher temperature.

Literature Review The complexities of living under a dynamic anthropocentric context have necessitated expanding and reconsidering how people experience extreme heat. Arbuthnott et al. (2016) systematically reviews the literature and find evidence to believe that exposure susceptibility to high temperatures, in relation to mortality, has lowered for persons depending on location, pointing to an element of climate adaptation. The Universal Thermal Climate Index (UTCI) is another example of consideration of human-experienced climate change. Developed at the beginning of the 21st century by the International Society of Biometeorology, the UTCI is an index used for comprehensively measuring the interaction of the thermal environment upon the human body (Jendritzky, Dear, and Havenith 2012; Jendritzky and Höppe 2017). The benefit of UTCI over other measures is UTCI's sensitivity to fluctuations while still maintaining high correlations to some, but not all other types of temperature indexes (Blazejczyk et al. 2012; Bröde et al. 2018; Spangler et al. 2023). UTCI lends towards a consideration of ambient temperature that is actually humanly experienced, supporting a greater development in the literature towards recognizing population-weighted exposures rather than defaulting to spatially-based measurements (Gao et al. 2018; Kyaw et al. 2023; Spangler, Liang, and Wellenius 2022).

One weakness in the existing literature is the usage of mean temperatures over different spans of time, with little focus on the extreme temperature ranges within the distributions that make up mean measurements. Of the studies that do take note of extreme heat, certain limitations exist. Liu et al. (2022) uses UTCI measures and hourly temperature data from the city of Guangzhou to find a significant negative-outcome association between temperature exposure and birth weight with the mother's education being a possible buffer. A report from the United Nations Children's Fund (2022) focuses on increasing durations of global heatwaves and projections for the future, using daily maximum temperatures to visualize global exposures for children using admittedly low-resolution data. Zhang et al. (2020) also runs multiple projections to examine long-term extreme heat temperature exposure during China's warm season weighed by population growth, using fine-resolution data and finding a projected increase in heat exposure in comparison to projected spatially-weighted temperature data. Spangler, Liang, and Wellenius (2022) in fact presents a relevant meteorological data set in the United States context using hourly temperature extremes and UTCI calculated and weighed at the county-population level for the 21st century. And globally, Kjellstrom et al. (2018) observe heat exposures on working populations using UTCI to find projected falling working capacity, also not further disaggregating the population data. Of these studies, only Liu et al. (2022) and United Nations Children's Fund (2022) specifically consider the effects of temperature exposure on children, and only the former specifically considers the Chinese context. Despite the methodological and topic coverage shortcomings, these studies show the value of considering extreme temperature exposure on populations. The limitations of these and other studies will be noted within the Appendix. In noting these studies' shortcomings, the need for a more comprehensive study and framework becomes clearer.

A limited amount of research exists that considers multiple years of census data in China in relation to temperature exposure. Zeng et al. (2022), which considers age-specific disparities in temperature-driven mortality is an example that uses the 2000 and 2010 censuses. However, Zeng et al. also acknowledge a lack of analysis of children in their study. Liao et al. (2023) and Wang, Luo, and Liu (2015) go further in their analysis of mortality, utilizing up to the 1990 census, and breaking up analysis into China's counties. However, none of these studies focus on children as a special interest group, nor do they consider temperature exposure as a standalone measure.

While Helldén et al. (2021) and Programme Division (2021) provide other examples of globally applicable frameworks for considering children and climate change, these frameworks are largely conceptual and are focused on multiple experienced effects of climate change beyond temperature exposure.

The importance of children as being affected by temperature exposure is two-fold. First, beyond general popular concern for children as a vulnerable population, empirically, children are at more risk compared to their adult counterparts not only in terms of health and daily thermo-regulatory stress (Smith 2019; Xu et al. 2012), but also in terms of vulnerability in fields such as educational development (Park, Behrer, and Goodman 2021). Second, children offer the opportunity for a shorter but more complete understanding of cumulative exposures in their short lifetimes; as opposed to adults or the elderly. This has long been regularly understood as a key complication in aging scholarship (Fries 2000; Olshansky 2018; Olshansky et al. 1991).

2 Method and Data

2.1 Method

Consideration of population weight in understanding exposure is a critical point in researching the effects of climate change. A growing literature studies population-weighted heat and cold distributional shifts by combining location-specific averages aggregated over some span of time with location-specific population counts during the same span of time. While this literature considers population, it is limited in its consideration of how the variations in temperature within location and across time affect population-weighted changes in climatic burdens. Zhang et al. (2023) is one example of weighing thermal comfort by population to find an overall negative impact of climate change, albeit with unequal effects based on national assets. One flaw with Zhang et al. (2023) and much other research is that the used temperature measures are in the format of mean daily temperatures, and thus some nuance in exposure is lost. Population-weighted analysis in China is considered by Gao et al. (2018), showing projected regional variation in population exposure. But this again uses mean daily temperature and so is limited in its depiction of exposure variation. Kyaw et al. (2023) does use hourly ERA5 temperature data, however despite doing this the findings are presented in the context of a number of days under exposure as opposed to using the more exact measure of hours. We also note that Kyaw et al. uses raster data as opposed to our use of more convenient tabular data. A strength of our particular method is the circumvention of data harmonization of geographic boundaries.

In contrast, our framework is the first that considers the variations in exposure across hours within location, jointly with population distributions across time. In our methods discussion (see Appendix Section A), we focus on changing climatic burdens for socio-demographic groups, either across all locations or conditional on subsets of locations. We compute for the first time, measures of shifting climatic risks for population groups while jointly considering temperature thresholds for heat and cold as well as risk thresholds of durations of exposure. While our empirical analysis focuses on children in China between 1990 and 2020, the framework can be applied to any socio-demographic group.

We set $s_l(c^*, t, \tau)$ to show the share of time that temperatures at a specific location and time $c_l(t)$ exceed any given threshold c^*. Share of time exceeding a given threshold is specifically calculated across time from time $\underline{t}$ to time $\underline{t} + \tau$ when observed temperature is above a certain threshold ($c_l(t) > c^*$) using $\frac{1}{\tau}\int_{\underline{t}}^{\underline{t}+\tau} dt$, thus allowing us to calculate from a starting hour to the last hour of exposure.

We then combine a binary calculation to see the presence of a given population in a location at a certain time ($\sum_{l=1}^{L} P_{\underline{t} \leqslant t < \underline{t}+\tau}(l|m) = 1$) with the share of time at a temperature exceeding a threshold ($s_l(c^*, t, \tau)$) to show the share of time where temperature over a certain threshold is experienced by that particular population. Accordingly, we do this across multiple locations in China ($\sum_{l=1}^{L}$).

We take these calculations, and not only use them for comparison amongst themselves but also for consideration of measuring risk. We input a specific percentage measure of hours where a temperature exposure threshold associated with some risk is exceeded ($s^*(\tau)$). We combine these share-of-time thresholds with the specific population in location measures to find the percentage of the population exposed to excess temperature above the inputted percentage of hours in a year. In our case, the inputted measures are 0.10; 0.20; and 0.30 as shares of time above each UTCI temperature between 26 and 32. The difference in these exposure threshold measures can also be used for across year comparisons.

Given the availability of time-varying and location-specific demographic distributional information via tabular census type data across countries, and the availability of temperature data from ERA5 and other sources (Spangler, Liang, and Wellenius 2022), our framework has wide applicability.

2.2 Data

ERA5 data brief summary We utilize the fifth generation of the European Centre for Medium-Range Weather Forecasts (ECMWF) atmospheric reanalyses of the global climate: the ERA5-HEAT dataset. ERA5-HEAT, a distinct advancement from its predecessors, offers hourly data on numerous climate variables with a spatial resolution of 0.1 degrees. One of the critical components we drew from this dataset is the Universal Thermal Climate Index (UTCI). UTCI provides an integrative measure of the human-perceived equivalent temperature, taking into account factors like air temperature, humidity, wind speed, and radiant heat (Jendritzky, Dear, and Havenith 2012; Jendritzky and Höppe 2017).

China Census data brief summary Chinese Census data for the years 1990, 2000, 2010, and 2020 were used from the New York University and Harvard University's Spatial Data Repository. County-level population data, shapefiles, and microdata on demographic characteristics of age and gender were extracted and used to construct the population exposures by county.

For regional analysis, temperature and population data were sorted by province and assigned a region according to the four recognized economic regions of China (National Bureau of Statistics of China 2011).

3 Findings

Aggregate Average Changes in Extreme Temperature Burdens over Time for Cohorts of Children When the UTCI is above 26°C, it indicates a level of thermal stress on the human body. As the UTCI value increases, the level of thermal stress on the human body intensifies. Figure 1 depicts an increase in temperature exposure for children ages 0 to 14 across mainland China from 1990 to 2020. Focusing on 26°C, a temperature level that is considered to be associated with moderate or stronger heat stress, an average child in China experienced 20.09% of her total ambient hours in 1990 at equal to or above this threshold. By 2020, this percentage increased to 22.81% (Figure 1), representing a 2.72 percentage points and 13.54 % increase in annual average exposure duration, which corresponds to be an annual average increase of 238 hours of additional ambient moderate or stronger heat stress exposure over 30 years.

Additionally, on average in 2020, children experience 8.26% and 1.16% of their annual ambient hours—marking 14.70% and 10.64% increases compared to 1990—at over 32°C and 38°C, which are temperature levels marking thresholds for strong and very strong heat stress.

This nationwide increase will be further inspected in the following sections to understand more local implications of UTCI change. Comparing these findings to those found using the methods in Kyaw et al. (2023), we can clearly see a more precise measurement of exposure using hours rather than days.

Increases in Share of Children at Risk of Heat Exposure While the previous results focuses on heat exposure for the average child in China, it does not provide information on how many children are at risk of heat exposure. In this section, given the distribution of heat and children across counties in China, we examine whether the *percentage* of children most affected by heat stress has also changed over time.

As discussed in the methods section, we compute the share of children at risk by considering jointly two thresholds of risks: a threshold for temperature and also a threshold for the share of time (hours) exposed to temperature above a particular threshold. In Figure 2, we consider different levels of temperature as well as share of time thresholds, providing different measures of changes in the share of children at risk depending on plausible considerations of thresholds for risks.

Here we consider two ends of the risk spectrum. First, we consider a lower temperature threshold combined with a higher share of hours, then a higher temperature threshold combined with a lower share of hours. Then, at the bottom left direction of each sub-figure in Figure 2, in 1990, 9.49% of children experienced moderate or stronger heat stress (i.e. UTCI above 26°C) for over 30% of their hours. By 2020, this number had risen to 19.51%, marking an increase of 10.02 percentage points. In other words, the share of children experiencing heat stress for at least 30% of their total hours in 2020 almost doubled compared to 1990. Second, at the top right direction of each sub-figure in Figure 2, in 1990, 17.45% of children have at least 10% of their total hours that are above 32°C. This number rose to 23.55% in 2020, representing a 6.10 percentage point or 34.96% increase. Overall, by both at-risk standards, approximately one-quarter of children in China are at-risk of extreme heat exposure in 2020, increasing from about only one sixth of children in 1990.

Additionally, Figure 2 also shows alarmingly fast increases in the share of children at risk toward the direction (lower right of Figure 2) of increasing risk. In particular, the share of children experiencing at least 30 percent of annual ambient time at over 29°C and 20 percent of time at over 31°C increased from 0.02% and 0.25% in 1990 to 1.37% and 1.39% in 2020, respectively. While the share of children exposed at these extreme risk levels remain small, these increases represent approximately 60-fold and 5-fold jumps in the share of children at these high exposure risk levels, respectively.

Decomposing the Contributions of Changes in Temperature and Population Figure 3 depicts a counterfactual decomposition analysis against the UTCI experienced by populations in 1990 and 2020. This counterfactual decomposition shows the extent to which change in exposure is due to population change, or due to change in UTCI as a result of meteorological change.

We first present the percentage gap between year 2020 and 1990 (as indicated by the red line). As mentioned above, we observed a 2.7% increase in children exposure to moderate or stronger heat stress (the vertical line indicate the critical UTCI threshold of 26°C). We then conduct the first counterfactual analysis (green line: climate effect), which combines the children population distribution in 2020 with the observed temperature in 1990. We take the percentage deviation of the counterfactual results from the original results in 1990. In the second counterfactual analysis (blue line: population effect), we use children population distribution in 1990 with the observed temperature in 2020, and again we take the percentage deviation of the results from the original results in 1990. We find that the population effect and climate effect are almost identical after the 26°C UTCI threshold. It implies that the change in children population distribution and temperature equally contribute to increase in children's exposure to heat stress at this level.

There are multiple approaches that have historically been used for counterfactual analyses in climate change and temperature exposure research. Well-cited counterfactual analysis includes the analysis of exposures that occur with and without migration, and how migration may delay mortality (Deschenes and Moretti 2009). Klein and Anderegg (2021) supports our counterfactual analysis in analysis on population growth and migration in relation to climate change exposure: finding that population, climate change, and the interaction of the two are both primary drivers of exposure. Returning to Gao et al. (2018), simulated scenarios are used to depict different population-weighed thermal exposure scenarios in China into the future, finding a decrease in overall comfort. These examples of counterfactual analyses establish precedence that we build upon in focusing on exposures faced by children using fixed populations and fixed meteorological conditions.

Regional Differences in Variation of Climatic Change Results pictured in Figure 4 depict the difference in regionally experienced UTCI for children ages 0 to 14 across China in the years 1990 and 2020, using hourly temperature data.

While some research exists visualizing exposures across regions of China, they can be limited in scope: not tracking temperature across the year (Sun et al. 2020); focusing immediately on outcomes such as mortality (Sun et al. 2020; Yang et al. 2021); focusing on hourly temperature without considering child or even human-experienced exposure (Shi et al. 2021); or using daily or higher interval mean temperatures rather than hourly (Gao et al. 2022; Xiao et al. 2017; Zhao et al. 2018). To the best of our knowledge, this is the first time regional hourly temperature exposure variation in China for children ages 0 to 14 has been visualized.

4 Discussion and Conclusion

In this paper, we combined county-level census population data on child distribution from 1990 and 2020 with temperature data to study changes in ambient heat exposure facing children over three decades. We find substantial increases in the average heat exposure for children and the share of children at risk and substantial regional heterogeneity. Interesting, we find that half of the overall changes in child heat exposure is driven by heat increases and the rest is driven by shifts in child population towards locations that have higher temperature.

In our first result, we found that In 1990, an ***average*** child in China experienced moderate or stronger heat stress (UTCI 26°C and above) for 20.09 % of their hours. By 2020, this percentage had increased by 2.7 percentage points (pp) (Figure 1). In our second result, we found that in 1990, 9.49 % of children experienced moderate or stronger heat stress for over 30 % of their hours. By 2020, this figure had risen to 19.51 %, marking an increase of 10.02 pp (Figure 2).

For our third result, counterfactual decomposition analyses reveal that the effects of escalating temperatures and a growing child population in the heat-affected regions contribute equally to the overall increase in heat exposure among children (Figure 3). For the fourt result, the substantial increase in children's exposure to heat stress in Eastern China, the nation's most economically developed and densely populated region, is a primary driver behind the overall surge observed at the national level (Figure 4).

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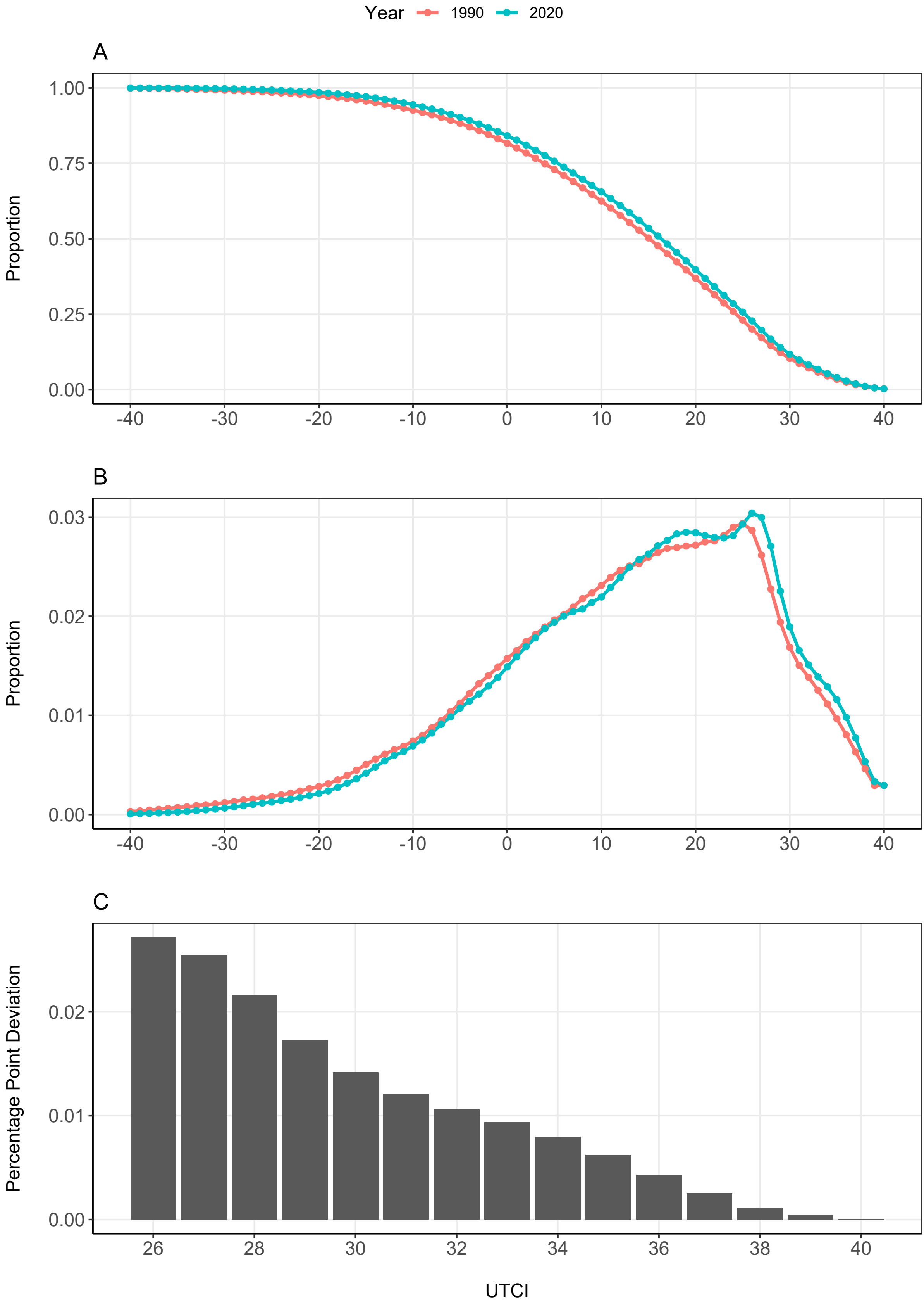
Zivin, Joshua Graff, and Jeffrey Shrader. 2016. "Temperature Extremes, Health, and Human Capital." *The Future of Children,* 31–50.

Figure 1: Change in Hourly Temperature Exposure for Children (0-14)



Notes: A. Cumulative Density Curve. B. Probability Density Curve. C. Percentage Point Deviation from 2020 to 1990.

Figure 2: Proportion of Children Experiencing Heat Stress by Proportion of Hours Across Different UTCI Thresholds

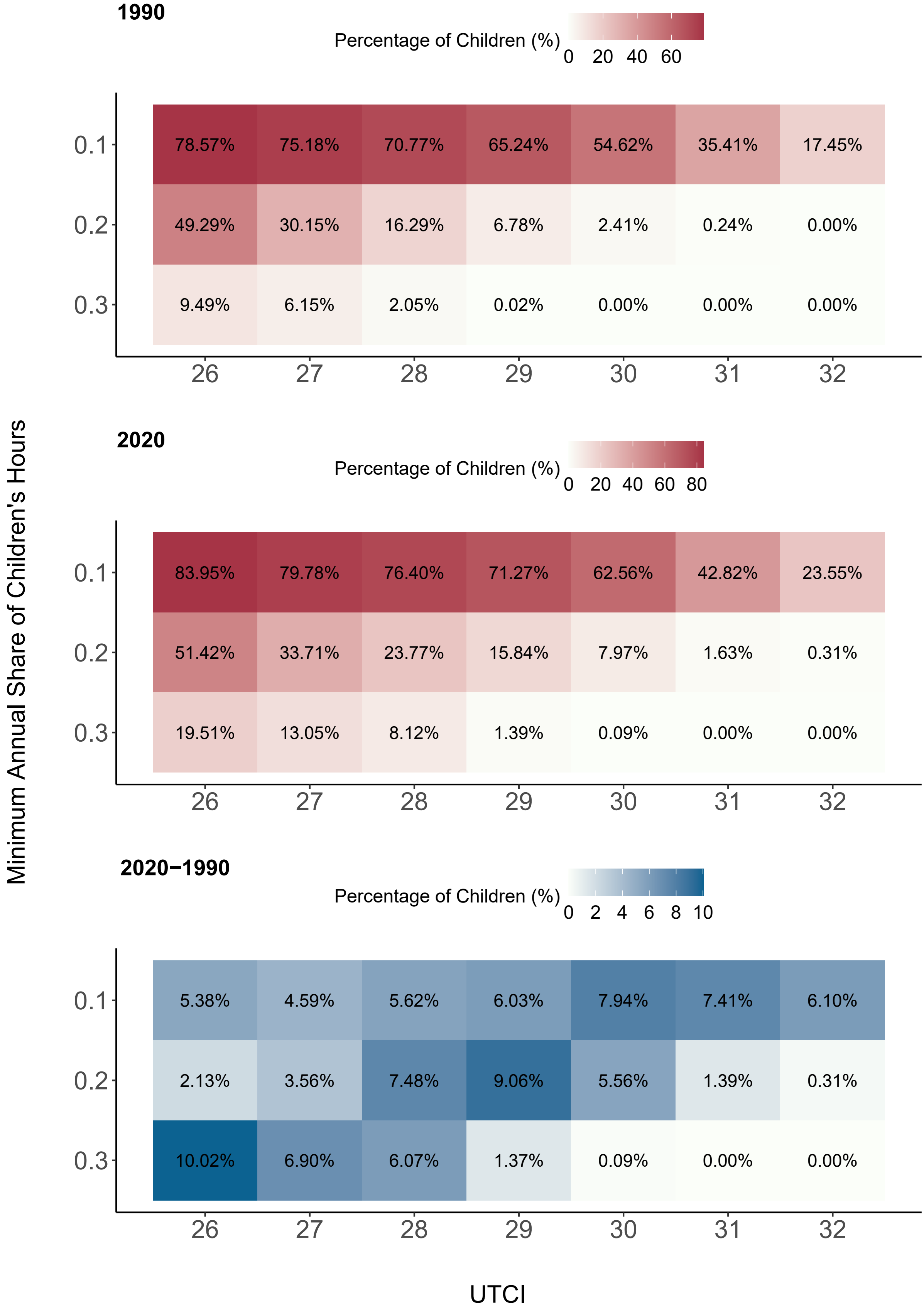
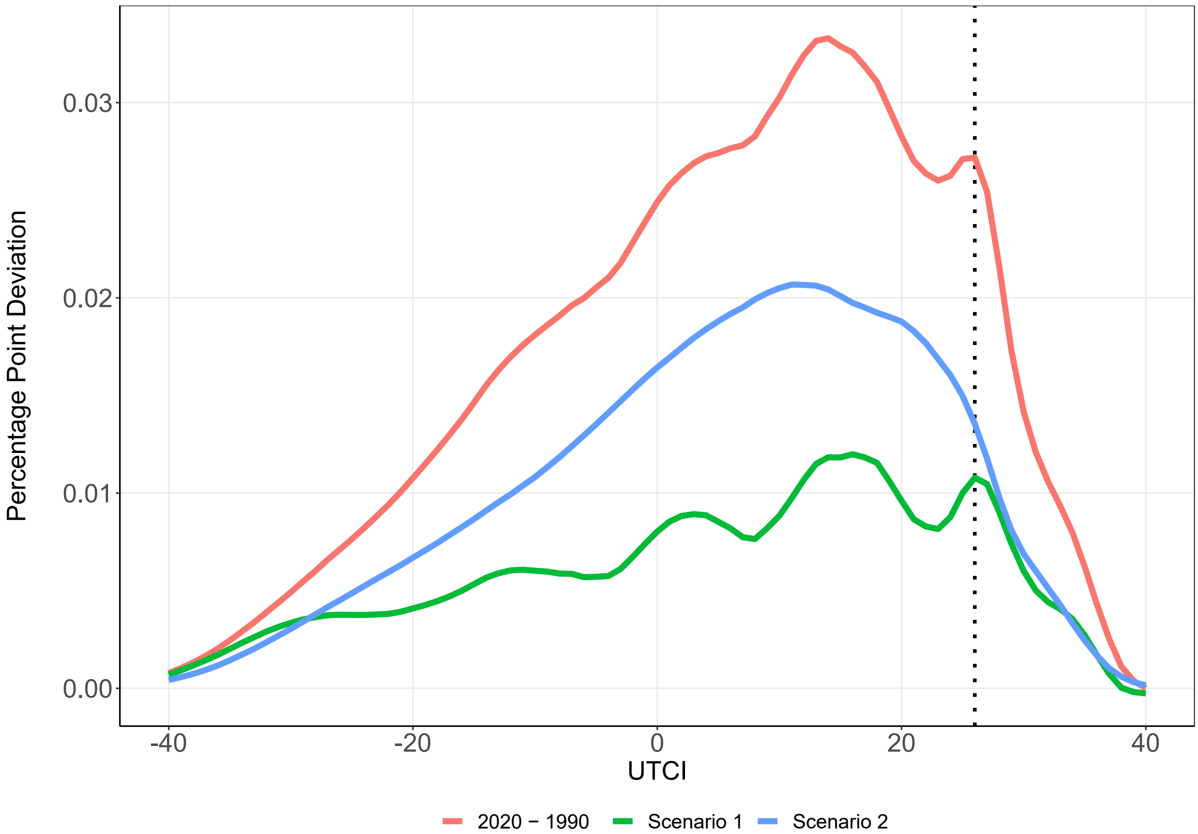
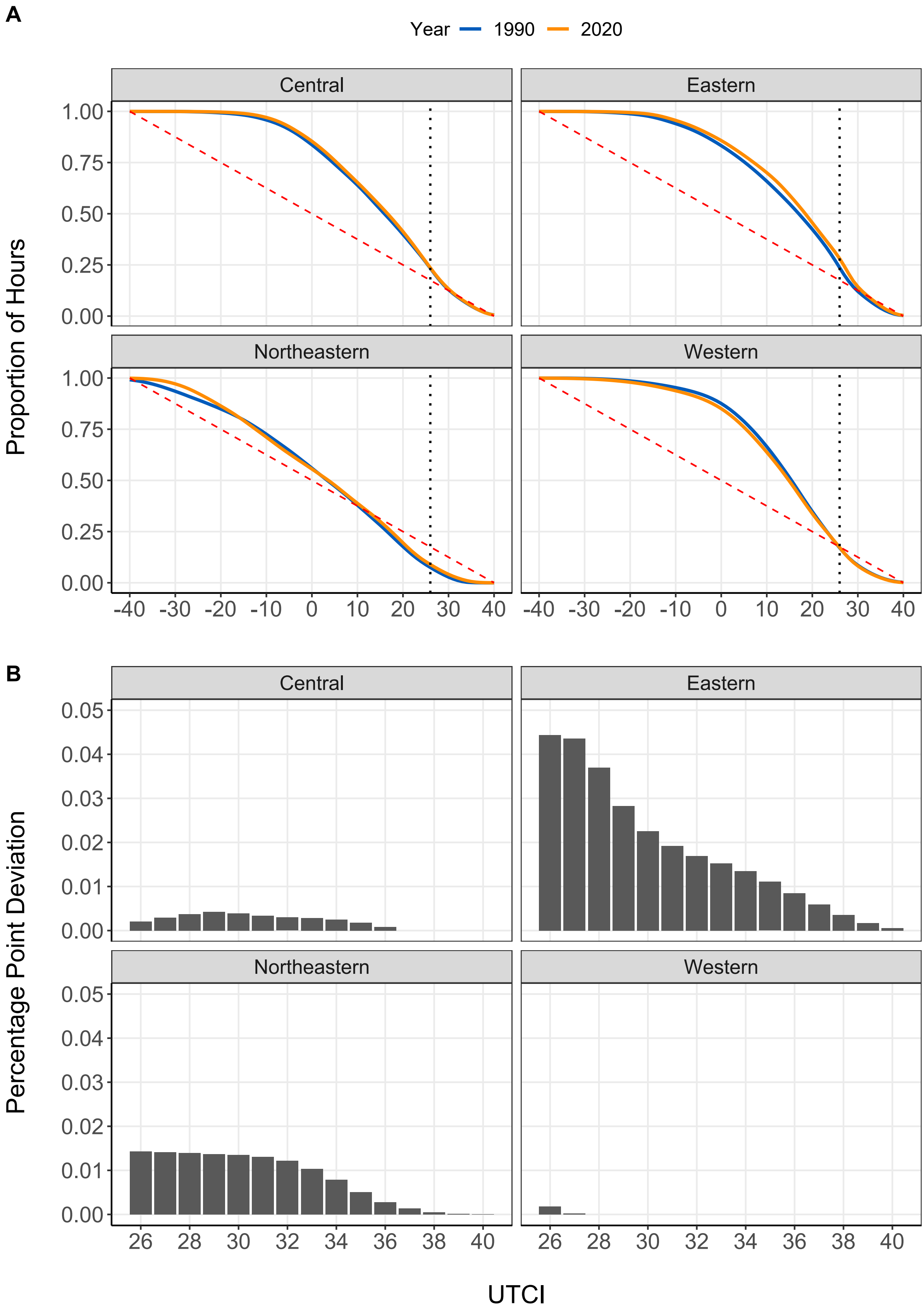


Figure 3: Counterfactual Decomposition Analyses



Notes: For all lines, the baseline reference is the children's share of total hour above certain threshold in 1990. The red line represents the percentage difference between children's shares of total hour above certain UTCI threshold and the baseline; In the first counterfactual decomposition, we use children population distribution in 2020 with the observed temperature in 1990. The blue line (Scenario 1) represents the percentage difference between the decomposition results with the baseline. In the second counterfactual decomposition, we use children population distribution in 1990 with the observed temperature in 2020. The green line (Scenario 2) represents the percentage difference between the decomposition results with the baseline.

Figure 4: Regional Differences in UTCI: Ages 0 to 14



Notes: A. Cumulative Density Curve by Regions. The vertical line indicates 26°C. B. Percentage Point Deviation from 2020 to 1990.

ONLINE APPENDIX

Rising Temperatures, Rising Risks:
A Three-Decade Analysis of Children's Heat Exposure in China
(1990-2020)

A Method—Population, Time, and Temperature Exposure

Population, Time, and Temperature Exposure 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 $\underline{t}$ and $\underline{t}+\tau$, the share of time that individuals at location l experience temperature $c_l(t)$ over threshold c^* is, $s_l\left(c^*, t, \tau\right)$:

$$s_l\left(c^*, \underline{t}, \tau\right) = \frac{1}{\tau}\int_{\underline{t}}^{\underline{t}+\tau} \mathbf{1}\{c_l(t) > c^*\}\, dt\ . \tag{1}$$

Additionally, let $P_{\underline{t}\leqslant t<\underline{t}+\tau}\left(l|m\right)$ be the share of population for socio-demographic group m in location l, among L locations in total between time $\underline{t}$ and $\underline{t}+\tau$ where: $\sum_{l=1}^{L} P_{\underline{t}\leqslant t<\underline{t}+\tau}\left(l|m\right) = 1$. Meaning that the population m at location l is experiencing exposure.

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

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

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

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

$\Delta\mathcal{S}_{m,t',t}\left(c^*, \tau\right)$ 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. $\Delta\mathcal{S}_{m,t',t}\left(c^*, \tau\right)$ shifts due to both shifts in the population distribution as well as the distribution of temperature between t and t', thus taking into account population and meteorological change.

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. Our objective here is not to provide what these thresholds should specifically be but to consider, for the first time, these two joint dimensions of risks in computing population-demographic-related exposure statistics. Specifically, let $s^*(\tau)$ be a particular share-of-time threshold within span of time τ above a specific temperature risk threshold. In our analysis, we use an $s^*(\tau)$ of 0.10; 0.20; and 0.30 as shares of time above each UTCI temperature between 26 and 32. 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:

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

By construction, $\mathcal{R}_m(c^*, s^* = 0, t, \tau) \leqslant 1$ 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: $\lim_{c^* \to \infty} \mathcal{R}_m(c^*, s^*, t, \tau) = 0$.

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

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

In our empirical application t is 1990 and, t' is 2020, τ is one calendar year, and m is children between age 0 to 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.

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 boundaries of administrative boundaries, especially across large spans of time. In our analysis, the unit of interest is m, the socio-demographic group; at times t and t', thus the geographical boundaries can shift.

Existing literature The existing literature focuses on computing location-specific temperature measurements, focused on overall averages, averages of minimums, and averages of maximums. In the context of the notations that we are using, this means computing:

A large number of papers focused on climatic changes across locations compute location-specific means between times $\underline{t}$ and $\underline{t}+\tau$, and use $E_{l,\underline{t},\tau}$ for comparison across locations:

$$E_{l,\underline{t},\tau}(c) = \frac{1}{\tau}\int_{\underline{t}}^{\underline{t}+\tau} c_l(t)\, dt \ . \tag{6}$$

Additionally, by dividing the interval of time τ into M sub-periods (e.g., days), some paper focus on analyzing the averages of minimum and maximum. Specifically, given M sub-periods, $E^{max}_{l,\underline{t},\tau,M}$ is the average of sub-period-specific maximum temperature between $\underline{t}$ and $\underline{t}+\tau$:

$$E^{max}_{l,\underline{t},\tau,M} = \sum_{m=1}^{M} \frac{1}{M} \max\left(c_l(t) \cdot \mathbb{1}\left(\underline{t} + \frac{\tau}{M}\cdot(m-1) \leqslant t < \frac{\tau}{M}\cdot(m)\right)\right) \ . \tag{7}$$

And $E^{min}_{l,\underline{t},\tau,M}$ is the average of the sub-period-specific minima:

$$E^{min}_{l,\underline{t},\tau,M} = \sum_{m=1}^{M} \frac{1}{M} \max\left(c_l(t) \cdot \mathbb{1}\left(\underline{t} + \frac{\tau}{M}\cdot(m-1) \leqslant t < \frac{\tau}{M}\cdot(m)\right)\right) \ . \tag{8}$$

Various papers in the existing scientific literature focus on comparing these statistics over time between period t and t' to study changes in climatic conditions across time for different locations.

In the social science literature, the focus has been on estimating the effects of temperature exposures $E^{mean}_{l,\underline{t},\tau}$, $E^{max}_{l,\underline{t},\tau,M}$, $E^{min}_{l,\underline{t},\tau,M}$ on outcomes related to human capacities ranging from educational attainment, health outcomes, to productivity outcomes.

Rather than using $c_l(t)$ directly, a subset of the literature in social science computes the above mentioned statistics with $c^z_l(t)$, which are based on location-specific deviations from prior trends, sometimes computed in standard deviation units, for example: $c^z_l(t) = \frac{E^{mean}_{l,t,\tau} - E^{mean}_{l,t^*,\tau^*}}{\sqrt{VAR_{l,t^*,\tau^*}}}$

B Method Data Frmaework

B.1 Extreme Temperature Definitions and Classifications

While an exact match in terms of measurement methods to the purpose and data being observed (both extreme heat and cold) is relatively difficult to find, existing literature on climate and Chinese/international society is used to inform the critical threshold measures. Being that our work attempts to observe multiple counties, across China, a measurement that controls for geographic differences is that of using a percentile approach. The historical mean daily twenty-four-hour average temperature of each specifically observed locale in a given time period is placed at the 50th percentile and points outside certain percentile markers are considered extreme heat or cold. Choosing boundaries is variable across the literature (Dadvand et al., 2011; Souch and Grimmond, 2004), the 10th and 90th percentiles and the 5th to 95th percentiles are commonly used to denote extreme cold or heat respectively (Deng et al., 2023; Meng et al., 2022; Singh et al., 2019). However, perhaps most common is using the bounds of the 1st and 99th percentile (He et al., 2016; Lin et al., 2017; Ma et al., 2019; Medina-Ramón et al., 2006; Zhao et al., 2018). Some studies show the most significant correlations of temperature to health outcomes by using the 1st and 99th percentile (Guo et al., 2013; Zhan et al., 2018).

However, it is also important to consider that this method alone allows for much context to be forgotten. For example, locales with little temperature variation may falsely appear more comparable than need be to locales with wider fluctuations of temperature throughout the year. Diurnal range difference (Maximum Mean Average Temperature at a given period of time — Minimum Mean Average Temperature at a given period of time) can be calculated to contextualize the extremity temperatures (Cai et al., 2021; Cheng et al., 2014; Wang et al., 2020; Wei et al., 2020).

B.2 Population data input specification

B.3 Specifying key files

C Data

C.1 ERA5 Data Details

ERA5, produced by the European Centre for Medium-Range Weather Forecasts (ECMWF), represents the fifth generation of atmospheric reanalyses of global climate. Covering the period from 1950 to present, it offers a high-resolution (approximately 31 km) and hourly dataset, incorporating diverse observational data. ERA5 provides various atmospheric, oceanic, and land surface parameters, serving as a comprehensive resource for climate research, monitoring, and various other applications. The dataset is publicly accessible through the Copernicus Climate Change Service's Climate Data Store (CDS).

The Universal Thermal Climate Index (UTCI) data within the ERA5 dataset offers a specialized assessment of the human-perceived environment based on atmospheric conditions. Produced by the ECMWF, this UTCI data integrates various atmospheric parameters such as temperature, humidity, wind speed, and solar radiation, to calculate apparent temperature, providing insights into human thermal comfort.

UTCI is expressed in degrees Celsius (°C), and it provides a measure of how cold or hot people might feel under prevailing environmental conditions. The index categorizes thermal stress into different classes with corresponding thresholds, which are as follows:

Extreme cold stress: UTCI below -40°C; Very strong cold stress: UTCI -40°C to -27°C; Strong cold stress: UTCI -27°C to -13°C; Moderate cold stress: UTCI -13°C to 0°C; No thermal stress: UTCI 0°C to 26°C; Moderate heat stress: UTCI 26°C to 32°C; Strong heat stress: UTCI 32°C to 38°C; Very strong heat stress: UTCI 38°C to 46°C; Extreme heat stress: UTCI above 46°C;

C.2 Population data input specification

In each census year, we determine the population distribution by dividing the population of each age and gender group in each county by the entire population in the census year. For our analysis of children exposure, we focus on the age group between 0 to 14 regardless of the gender.

Census 1990 We obtained 2369 geographical units at the county level nested in 31 provincial administrative region. We only include mainland China and did not include special administrative regions. Within each county, we have population data by gender and age.

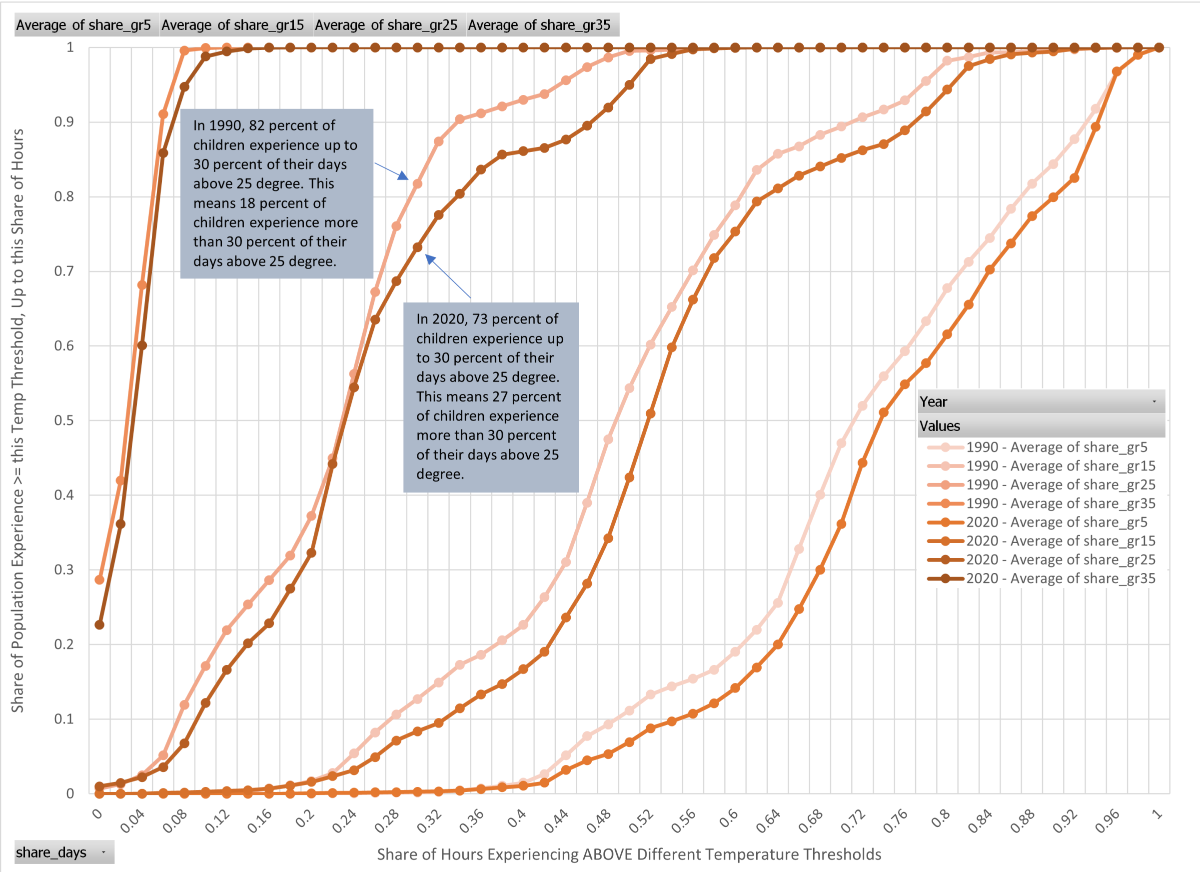
Census 2020 Tabulation on 2020 China Population Census by Count We obtained 2853 geographical units at the county level nested in 31 provincial administrative region. We only include mainland China and did not include special administrative regions. Within each county, we have population data by gender and age.

D Additional Results

D.1 Additional Inequality Results

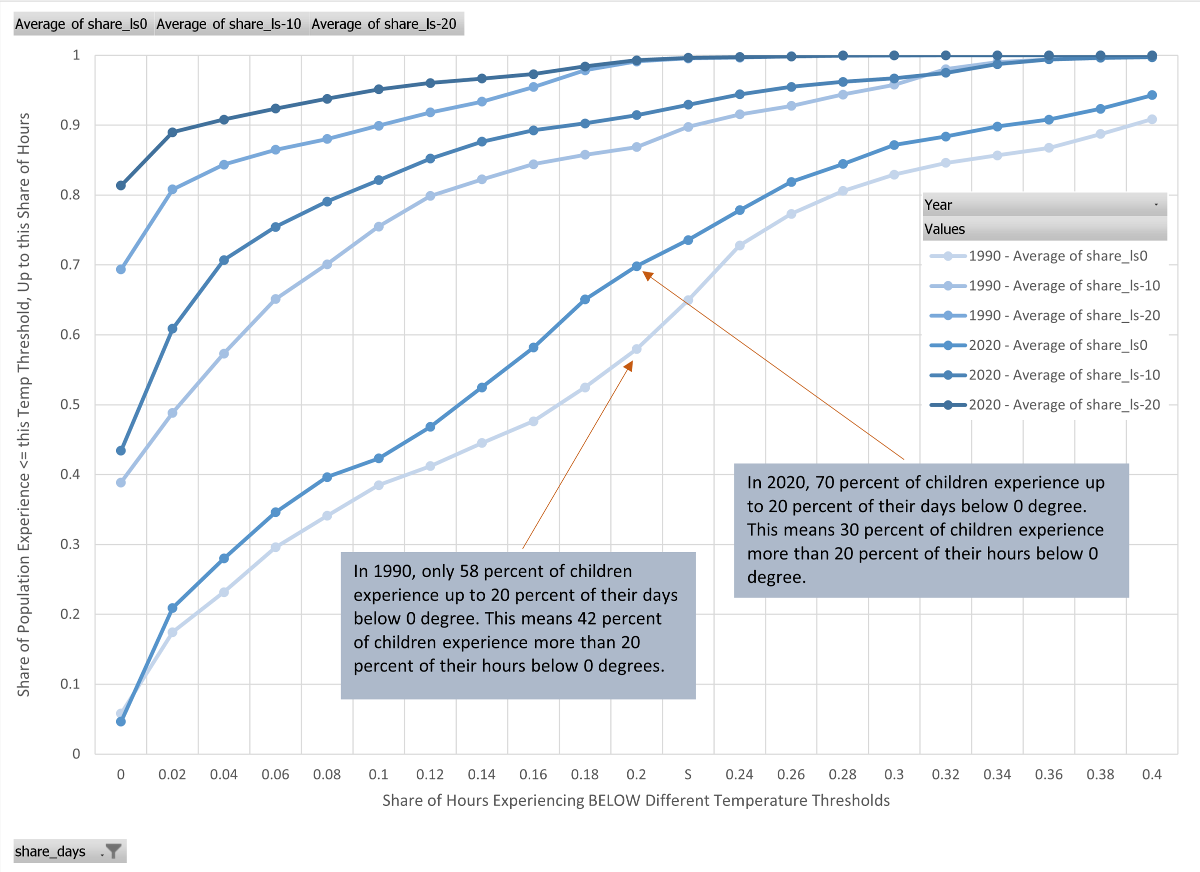
Temperature exposure risk thresholds in general are a relatively ambiguous topic. Further, for child-experienced risk thresholds, Helldén et al. (2021) and Vanos (2015) note a lack of data inputs accounting for child health and behaviors that could be used to create accurate risk thresholds. While child-oriented work such as Huang et al. (2021) does try to account for this, focusing on a case study of a children's park in the cold Xi'an, China; limited scope endangers generalizability.

Figure D.1: Hourly Heat Exposure for Children over Time



Notes: The figure above depicts the percentage of children experiencing temperatures above certain thresholds of 5, 15, 25, and 35 degrees C in the years 1990 and 2020.

Figure D.2: Hourly Cold Exposure for Children over Time



Notes: Figure B above depicts the percentage of children experiencing temperatures below certain thresholds of 0, -10, -20 degrees C in the years 1990 and 2020.