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ABSTRACT

Effects of Early Childhood Climate on Cognitive Development and Home Environment*

Climate change poses a significant threat to the development of young children, but its impacts are not well known because of data and methodological limitations. Using a unique panel study in disadvantaged rural communities, we find that exposures to low temperatures undermine subsequent cognitive development before age 5, and reduce caregiver-child interactions and material investments. Results do not support income, health and temporary disruption in cognitive performance as potential channels. By undermining children's home environment, climate change may widen socioeconomic inequalities across households by their capacity to adapt, which is severely limited among disadvantaged households.

JEL Classification: I14, I18, J13, P25

Keywords: early childhood, cognitive skills, home environment, temperature, climate change, China

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1 Introduction

Temperature changes have increased in frequency and variability around the world because of climate change (Bathiany et al., 2018; Schär et al., 2004). They may have far-reaching consequences on the welfare of society through their impact on children's development during early childhood, a critical period of human development that predict long-term life outcomes (Heckman and Mosso, 2014). Children are physiologically limited in their ability to withstand changes in external environment, making them highly vulnerable to the effects of temperature variations (Currie and Deschênes, 2016). Further, children must rely on their caregivers to provide for their home environment (Philipsborn and Chan, 2018). However, some families, such as those in low-income rural areas, are unable to respond effectively to climate change effects. Further, these effects may erode their capacity to adapt, widening socioeconomic inequalities across families and communities (Geruso and Spears, 2018; Mertz et al., 2009).

Our understanding of the effects of temperature change is thus incomplete, given the lack of evidence on the effects on children's early childhood skills development and home environment. Previous studies have not investigated how temperature affects early childhood cognitive development although it is predictive of a wide range of long-run outcomes (Heckman and Mosso, 2014). In addition, it remains unknown how temperature changes affect comprehensive measures of early childhood home environment, including caregiver-child interactions and material investments, which protect children from climate changes and promote their development. The literature on the effects of temperature changes on children is limited to a narrow range of birth and health outcomes (Ogasawara and Yumitori, 2019; Sanchez, 2018).

In this study, we investigate the impacts of exposure to ambient temperature changes in early childhood, covering *in utero* period and the first 5 years after birth.[1] We study how temperature

[1] We focus on "ambient" temperature variability. We do not consider extreme weather events such as hurricanes, floods, droughts, and blizzards, which can impact children in a myriad of ways including destruction of property. In addition, we investigate the effects of both high and low temperatures rather than restricting our attention to temperature variations in any one direction.

changes impact early childhood cognitive skills, caregivers' behaviors, and material home environment, filling crucial gaps in our understanding of the effects of climate change and children's human capital development. Joint analysis of the temperature effects on cognitive skills and home environments sheds light on how well households with children can adapt to temperature changes and generates implications for effective policy responses.

Our study is set in rural China, characterized by high rates of poverty and developmental delay among infants (Yue et al., 2017; Wang et al., 2019; Johnstone et al., 2021), poor home environment and limited access to local amenities (Geruso and Spears, 2018; Mertz et al., 2009). The impacts of temperature changes in this area are likely to be significant on children's development and the caregivers' burden in responding to these changes. Our results are therefore highly relevant in understanding the situation of disadvantaged households in rural areas around the world.

We use longitudinal data following households from 4 to 54 months after childbirth, covering 100 rural villages in the northwest region of China. The villages were selected to capture the experience of the caregivers and the children in disadvantaged rural households. The data set contains rich measures of children's birth outcomes, cognitive developmental measures, and home environment measures including caregiver-child interactions and material investments. The survey and data collection were administered by trained staffs rather than relying on self reports to maintain measurement quality and minimize attrition. The Bayley Scales of Infant and Toddler Development and Wechsler Preschool and Primary Scale of Intelligence are used because they are standard measures for the age range of children in our sample (Bayley, 2006; Wechsler, 2012). These variables are analyzed jointly with daily temperature variation at the village level.

As a consequence, we capture the effects of temperatures that deviate from "the normal" level for which villagers would have already adapted. We achieve this by comparing the outcomes of children within the same village born in the same month across different birth years, fully exploiting the panel dimension of the data following multiple cohorts of children in different villages. Our effects are therefore based on temperature variations that the villagers could not plausibly anticipate.

Further, we separately identify the effects of an additional day of exposure to high and low daily temperatures at any time from up to 3 years before birth to 5 years after birth. We also identify the temperature effects on skills measured years after temperature exposure and the skills measured on the day of temperature exposure.

We show that exposures to cold temperature undermine subsequent early childhood cognitive skills development measured before age 5. The effects of exposures at age 1 are significant on cognitive skills measured at ages 2–5. There is no immediate effect of temperature exposures, suggesting that temporary disruption of children's performance because of poor weather is unlikely to be an important explanation for our results. The effects of exposure to high temperature are negative but not significantly different from zero.

Examining temperature effects on home environment, we find that caregivers reduce cognitively stimulating interactions with their children and material investments at home when they are exposed to cold temperatures. These results are surprising, given that parents are known to compensate for children's disadvantages (Restrepo, 2016; Yi et al., 2015; Fan and Porter, 2020). We do not find evidence that temperatures affect farm income, household asset, children's health, or a variety of other potential channels that could shape children's cognitive skills and home environments.

We contribute to understanding how climate change affects human development. First, we fill a gap in the literature by providing evidence on temperature effects on human capital development in early childhood. Our results connect the negative effects of climate change found on birth outcomes and adult outcomes such as education and income. The results also imply that ambient temperature is an input of cognitive skills development in early childhood, an important predictor of long-term outcomes of children (Heckman and Mosso, 2014).

Second, our results highlight how climate change may widen socioeconomic inequalities by damaging those already vulnerable. Our study focuses on disadvantaged households with young children in rural China. Parents in this setting may lack access to basic amenities at home and in the community to adapt to the effects of even modest temperature exposures studied in this paper. With early childhood shocks to skills and disinvestment in home environment, the children in these households would require even more investment to catch up to their better-off peers. Such difficulties are likely to be observed among children in other vulnerable communities affected by climate change.

Finally, our paper presents the first evidence on the effects of temperature variations on comprehensive measures of home environment. By showing that caregivers inadequately respond to temperature changes, we emphasize the need for assistance beyond that available at home. The caregivers may lack understanding of children's needs or face resource constraints that prevent them from providing sufficient care to their children (Cunha et al., 2020; Dizon-Ross, 2019; Garg et al., 2020). Given that caregivers at home interact closely with the children, targeting policy responses to the home environment would be effective in countering the effects of climate change on children's development. Programs that help children in part by investing in the early childhood home environment are shown to be highly effective in improving children's short- and long-run outcomes (Elango et al., 2016).

2 Literature review

Our study most directly contributes to the literature on the effects of temperature changes in early childhood on childhood and adolescent outcomes. There is no evidence on temperature effects on outcomes in early childhood, between birth and age 5 (Table 1). Children's development during this "critical period" in human development predicts a wide range of long-term outcomes including education, earnings, and health (Heckman and Mosso, 2014). Evidence on late childhood outcomes shows that exposure to low temperature in early childhood negatively affects height, cognitive skills, and noncognitive skills measured in primary school period (Ogasawara and Yumitori, 2019; Sanchez, 2018). As for adolescent outcomes, exposure to high temperature between pregnancy and age 5 leads to less schooling in ages 12 to 16 (Randell and Gray, 2019) and worse academic outcomes among the second and eighth graders (Barron et al., 2018).

There is a relatively large literature regarding temperature effects on birth outcomes. *In utero* exposure to high temperature increases the chance of pregnancy loss and infant mortality (Banerjee and Maharaj, 2020; Hajdu and Hajdu, 2022; Geruso and Spears, 2018). An infant's height and weight decrease in response to pregnant mother's exposure to low and high temperatures (Andalón et al., 2016; Chen et al., 2020; Davenport et al., 2020; Deschênes et al., 2009; Le and Nguyen, 2021; Molina and Saldarriaga, 2017).

Studies also report long-run consequences of exposure to temperature changes in early childhood. Exposure to high temperature in the prenatal period and before age 1 negatively impacts outcomes in adulthood such as earnings (Isen et al., 2017), education, cognitive skills, and height (Agüero, 2014; Hu and Li, 2019). Findings by Wilde et al. (2017) are unusual in showing *positive* effects of *in utero* exposure to temperature variability on long-run outcomes. They argue that fetal mortality selection likely drives the results.

Although temperature change can impact caregivers' behaviors and household expenditures that constitute children's home environment, the literature is silent on its impact on comprehensive measures of home environments that shape children's human capital development (Table 1). Instead, the literature shows that temperature can affect limited aspects of home environments. Variations in ambient temperature can reduce caregivers' time allocated to childcare (Garg et al., 2020) or undermine their physical and mental health (Hua et al., 2022; Yang et al., 2021). Caregivers may experience difficulty carrying out cognitively demanding tasks in uncomfortable temperatures (Graff Zivin et al., 2018; Park, 2022). To the extent that cognitively stimulating interactions with children requires caregivers' active engagement, temperature changes can directly undermine caregiver-child interactions.

3 Data

3.1 Early Childhood Data

Our early childhood data set consists of a survey of households that began in 2015 in 100 villages across 20 counties in rural areas of the Qinba Mountain Area in northwest China. This area is known for its high poverty rate, low social and economic development, and weak industrial base (Tian et al., 2018; Wu et al., 2020).

The survey followed a multistage cluster sampling design to select children in the age range of 4–29 months at the household level. First, we selected townships (*xiang zhen*, the administrative division layer between the county level and the village level) that are typical rural areas. We excluded townships that housed the county center (*xian cheng*) because such townships tend to be wealthier and more urban. We also excluded townships that did not have any villages with 800 or more registered households. After these restrictions were applied, 100 townships were selected from 20 counties. Second, we randomly selected one village from each township to be included in the survey. If a village had fewer than five children in the eligible age range, we randomly selected another village in the same township to ensure that at least five eligible children were included in the survey from each township.[2]

Ethical approval for this study was granted by the Stanford University Institutional Review Board (IRB) (Protocol ID 35921). All subjects gave written informed consent in accordance with the Declaration of Helsinki. The survey was administered by the Center for Experimental Economics in Education of Shaanxi Normal University.

We use the cognitive scale from the third edition of the BSID (*Bayley-III*; Bayley, 2006) to measure the cognitive performance as the key outcome of interest for children under 42 months old. For those 42 months old or more, we use Wechsler Preschool and Primary Scale of Intelligence (WPPSI; Wechsler, 2012), a measure of general intellectual ability and cognitive functioning for

[2]The survey was conducted as a part of center-based early childhood parenting intervention. For half of the townships, two parenting trainers provided weekly parenting training at local daycare centers (Sylvia et al., 2022). We find that our results do not interact with parents' using daycare centers (Section 5.4).

children aged 2.5 to 7.25 years. We normalize these scores to be mean zero and standard deviation one within child's age in months and within each wave. We additionally create a binary indicator that equals one if the score is below one standard deviation relative to the whole sample mean. The validity of the scale for the children in the Qinba Mountain Area is verified in Yue et al. (2019, 2021). Distribution of cognitive skill measures for each wave does not contain unusual outliers, as shown in Figure A1.

The data set also provides measures of home environment including cognitively stimulating caregiver-child interactions and material investments into the home environment. Caregiver-child interactions include cognitively stimulating activities such as reading books together, singing songs, and telling stories. The material home environment includes measures of having different kinds of toys or books at home. These are commonly used measures of investment in children's human capital in studies of child development in China and elsewhere (Johnstone et al., 2021).

Measures of socio-demographic characteristics for children and households include the child's gender, number of siblings, primary caregiver's age and education level, primary caregiver's relationship with the child, and whether the family received Minimum Living Standard Guarantee Payments from the government (a poverty indicator and a form of government welfare for the families with very low income throughout the country). The age of the child is obtained from the birth certificate. The primary caregiver is defined as the individual identified in the survey as the most responsible for the child's care, often the child's mother or grandmother.

3.2 Climate Data

Temperature data are obtained from the National Meteorological Information Center of China. The data set includes daily average, maximum, and minimum temperatures, sunlight duration, and precipitation levels. We extract humidity data from the Geospatial Data Cloud and use the space-time random forest approach (Wei et al., 2019) to identify spatial concentrations of fine particulate matter with diameter less than 2.5 micrometers ($PM_{2.5}$), a standard measure of air pollution (Li et al., 2019). To control for physical geography characteristics, we measure the enhanced vegetation index from Earth Science Data Systems (ESDS) Program built by the National Aeronautics and Space Administration (NASA). All information in raster data is converted to village-level variables using the ArcGIS algorithm.

3.3 Summary Statistics

We use three waves of surveys conducted between 2015 and 2019, covering children born in 2013 to 2016.[3] The survey was continuously conducted during this time period, so that the next survey has already started for some households even as the previous round of survey was being conducted in other households. There was also overlap in the age distribution across surveys. The baseline wave (wave 0) approximately spanned ages 0 and 2, wave 1 spanned ages 1.5 and 3.5, and wave 2 spanned ages 2.5 and 4.5 (Figure 1, Figure A2). The retention rate is 81.69% at the end of wave 2 (Table 2). We examine the sensitivity of our main results to attrition in Section 5.4.

The first panel of Table 2 shows that about half of the children are female and half of the children are first-born. Only 20% of the mothers finished high school, indicating low socioeconomic status of the households in the sample. Caregivers tend to increase material investments ("toys and books") over child's age, as shown in the second panel.

The last panel shows the climate variables we use. The heating degree days (HDD) variable measures low temperatures in an area. It was originally designed to measure the heating needs of a building (Vaughn, 2005). For a base degree of 18.33°C,[4] HDD for the past 1 day would be 8.33 if the average temperature for that date was 10°C. If the average temperature was 10°C for each of the past 10 days, then HDD for those ten days would be 83.3. A higher value of HDD indicates greater exposure to low temperatures. Cooling degree days are similarly defined to measure high temperature. HDD is zero for temperatures above the base value. Figure 2 shows that days with low temperatures with a daily average below 5°C are more common than days with high temperatures

[3]Earlier waves of this survey data are used in Fatima et al. (2022), Sylvia et al. (2022), Wang et al. (2022), Yue et al. (2019), and Yue et al. (2021), before the third wave of survey became available for research.

[4]This is 65°F, a commonly used base to calculate degree days in the climate literature because it represents comfortable daily average temperature for most people (Albouy et al., 2016; Vaughn, 2005).

with a daily average above 30°C in the sampling area. The upper-left subfigure in Figure A3 shows the distribution of HDD, showing no major outliers.

Summary statistics on precipitation, sunshine, and air pollution are shown in the last panel of Table 2 and in Figure A3. Values of average weather variables in the sampling area are within the range of other provinces in China in 2016, showing that overall weather in sampling area was not unusual compared to that in the rest of China during the study period (National Bureau of Statistics of China, 2017). Precipitation in the sampling area was lower than in Chongqing (in the western region of China), which had annual precipitation of 1348.0 millimeters but greater than in Beijing (669.1 millimeters). Annual sunshine hours were 1228.4 in Chongqing and 2502.1 in Beijing. The mean air pollution in the sampling area was lighter than the Chinese national average of 42.0 $\mu g/m^3$ (Zhang et al., 2019).

4 Empirical Strategy

Our empirical models are motivated by the conceptual framework presented in the Section B of the Appendix. We estimate the following equation, using HDD variable as the measure of temperature exposure:

$$Y_i = \alpha + \sum_c \gamma_c \sum_{d \in C_i} \max\{18.33 - T_d, 0\} + x_i'\beta + \lambda_{\text{village-year}} + \varepsilon_i, \tag{1}$$

where Y_i is the outcome of interest measured in wave 2. The term $\max\{18.33 - T_d, 0\}$ is HDD for day d with the base temperature at $18.33°C$ $(65°F)$.

$c \in \{[-2,-1), [-1,0), [0,1), [1,2)\}$ denotes the period in years relative to birth (at 0), or "age," during which the child is exposed to temperature changes. We choose whole-year windows to isolate the temperature effects from the seasonality or birth-cohort effects. C_i is the set of days that belong to the exposure period c for child i. Then $\sum_{d \in C_i} \max\{18.33 - T_d, 0\}$ is HDD for the time period C_i. We consider only 2 years before and after birth in the baseline specification because the youngest subject in wave 2 is about 2.5 years old, so that 2-year window applies to the entire sample. We also estimate alternative specifications with longer exposure windows as robustness checks. The coefficient of interest is γ_c, the effect on Y_i of a unit change in HDD during period c.

x_i is a vector of baseline characteristics that includes the children's gender, age, indicators for month of birth, the number of siblings interacted with birth order, indicators for mother's education levels (no education, primary school, middle school, high school, associate degree, bachelor's degree and above), indicators for mother's age at delivery, household asset score at wave 0,[5] indicators for owning heating devices at home,[6] sunlight duration, precipitation and $PM_{2.5}$ in each exposure period. We account for the effects of interview timing and interviewer identity by including fixed effects for the year-by-month, day-of-week of the survey, and examiner of the cognitive tests.

To account for within-village correlation due to historical weather, cultural, and economic factors and their time trends, we include village-by-year fixed effects, $\lambda_{\text{village-year}}$. These fixed effects ensure that our estimation is based on deviations from village averages rather than on spatial differences in climate. The error term ε_i is clustered at the village level.

Our identification is therefore based on comparing the outcomes of children within the same village, the same birth month, and the same survey year and month, but across different birth years. Fixed effects interacting village and survey year account for village-level characteristics and survey-year effects specific to each village. Birth-month fixed effects account for seasonal effects. Identifying variations in temperature come from those that deviate from what villagers might anticipate from season-of-year and experiences specific to each village.

Identification requires that unobserved factors that promote cognitive skills are uncorrelated with temperature variations, conditional on observable baseline characteristics and fixed effects. This assumption would be violated if, for example, the timing of the survey or household characteristics, perhaps through household location choice, are associated with both cognitive skill de-

[5] To capture household wealth, we construct a household asset score using polychoric principal component analysis on variables corresponding to the availability of 10 assets: tap water, toilet, water heater, washing machine, computer, internet, refrigerator, air conditioner, motorcycle/scooter, and car. This score is measured only at wave 0.

[6] We include four indicator variables for the type of heating system that relies on: (1) natural gas, electricity or central heating; (2) burning coal with a smoke pipe; (3) burning coal without a smoke pipe; or (4) burning firewood. These indicators are measured at the second follow up, the last wave in the study.

velopment and weather. It would also be violated if some households migrate out of the sampling area in response temperature variations, leading to selective attrition. We test for these possibilities but do not reject the identification assumption (Section 5.4).

The temperature exposures may have different effects on the cognitive skills outcomes at different ages of the child. This would be the case if temperature changes undermine the cognitive skills development process, which undergoes a rapid and complex developmental changes in early childhood (Zeanah et al., 1997). We therefore allow the effects of temperature exposure at a given time to differ for outcomes measured at different ages of children. The equation is:

$$Y_{i,(\text{age})} = \alpha_{(\text{age})} + \sum_{c} \gamma_{c,(\text{age})} \sum_{d \in C_i} \max\{18.33 - T_d, 0\}$$
$$+ x'_{i,(\text{age})}\beta_{(\text{age})} + \lambda_{\text{village-year, (age)}} + \varepsilon_{i,(\text{age})}. \tag{2}$$

γ_c identifies the effect of temperature exposure on outcomes realized at child's age c. We estimate equation (2) using locally weighted regression. For each observation i, we estimate a weighted OLS on the localized subsample around i with a tri-cube weight function that gives more weights to data points j that are closer to observation i in terms of age (Cleveland, 1979). The weights are defined as $w_j = \{1 - (\frac{|x_j - x_i|}{1.0001 \max\{x_{i+} - x_i, x_i - x_{i-}\}})^3\}^3$, where $[i_- = \max\{1, i-k\}, i_+ = \min\{i+k, N\}]$ is the index set of observations with a positive weight. Let $k = (N \times bw - 0.5)/2$, N be the number of observations, and $bw \in (0,1]$ be the bandwidth. We set bandwidth as $bw = 0.5$ for the main analysis but also use alternative bandwidth values of 0.25 and 0.75 as robustness checks (Section 5.4).

We also estimate age-varying temperature effects using subsample analysis. We do this by estimating equation (1) within each subsample. We consider four subsamples, each including observations whose outcome variables are realized in one of the following age ranges: $[0,2]$, $[1,3]$, $[2,4]$, $[3,5]$.

Alternatively, temperature changes may undermine the children's performance at cognitive tasks without directly affecting their human capital development, implying that the effects of exposure to temperature changes would be observed immediately. The literature is silent on whether young children are affected by temperature in performing cognitive tasks such as responding to cognitive skills measures. Further, no study to our knowledge simultaneously examined the immediate and delayed effects of early childhood exposure to ambient temperature variations. The literature shows evidence of the disruptive effects of high temperature on cognitively demanding tasks among adolescents and adults (e.g., Graff Zivin et al., 2018).

To examine whether short-run and contemporaneous temperature effects exist for early childhood outcomes, we follow Graff Zivin et al. (2018) and estimate the panel regression model as:

$$Y_{it} = \alpha + \sum_p \sum_b \gamma_{pb} \sum_{d \in P_{it}} \mathbb{1}(T_d \in \mathrm{BIN}_b) + x_{it}'\beta + \lambda_{\text{village-year}} + \nu_i + \rho_t + \varepsilon_{it}. \tag{3}$$

$b \in \{\{T_d | T_d \leq 0\}, (0,5], (5,10], (10,15], (15,20], (25,30], (30,\infty)\}$ indicates temperature ranges, or bins. $\mathbb{1}(T_d \in \mathrm{BIN}_b)$ is an indicator variable that equals one if T_d, the daily average temperature on day d, falls within temperature bin b. $p \in \{\text{day of survey}, \text{past week}, \text{past month}, \text{past year}\}$ is the window of temperature exposure relative to the time of survey. The subscript $t \in \{0,1,2\}$ denotes the wave of survey. ν_i captures individual fixed effects and ρ_t the wave-of-survey fixed effects. The parameter of interest is γ_{pb}, the effects of temperature exposure in period p on outcomes at t. x_{it} is a set of time-varying control variables including sunlight duration, precipitation, and $PM_{2.5}$ in each exposure window. ε_{it} is the idiosyncratic error term clustered at the village level.

Finally, we estimate temperature effects with a model that relaxes the restrictions in the model for the main results. Equation (1) used for the main results restricts the HDD effects to be linear in parameters and the high temperature exposures to have zero effect on outcomes. We relax these restrictions by estimating the effect of being exposed to different ranges of temperatures for outcomes at wave 2. The equation is:

$$Y_i = \alpha + \sum_c \sum_b \gamma_{cb} \sum_{d \in C_i} \mathbb{1}(T_d \in \mathrm{BIN}_b) + x_i'\beta + \lambda_{\text{village-year}} + \varepsilon_i. \tag{4}$$

We choose $(15,20]$ as the omitted reference category because it contains $18.33°C$ $(65°F)$, the base for the HDD variable in equation (1).[7] x_i' includes the same set of control variables as in equation (1). The coefficient of interest, γ_{cb}, is interpreted as the effect of being exposed to another day of a temperature in bin b during period c, *replacing* a day of exposure to a temperature in the range of $(15, 20]$.

5 Results

5.1 Main Results

Our main results based on equation (1) show that exposures to low temperature during the year leading up to birth, covering the *in utero* period, and early childhood period, have negative effects on cognitive skills measured at ages 2 to 5 (Table 3). The effects are greater for exposures during the first year after birth than for those during the year before birth and during the second year after birth. Later, we show that exposures to high temperatures do not significantly impact cognitive skills in wave 2 in our sample (Table 4 and Figure 3).

Results in Figure 3 show that the negative effects of cold temperature exposures are concentrated on daily average temperatures below 5°C (based on equation (4)). Consistent with the restrictions in equation (1) for the main results, exposures to temperatures higher than 15°C do not impact cognitive skills of children (also see Table 4) and the magnitude of the negative effects increases approximately linearly as the temperature decreases. Subfigures in the upper-left corner of Figure 3 show the effects of temperature exposures 2 years before birth, serving as placebo tests. These results are robust to using smaller temperature bins (Figure A4).

Our main results imply that mild temperature variations can have a sizable impact on cognitive development in early childhood. A 1°C decrease in the daily average temperature for 10 days during the first year of a child's life is predicted to lower the child's cognitive skill at wave 2

[7] The choice of reference category does not affect the relative values of temperature effects among different temperature bins. To examine the sensitivity of results to different widths of bins, we alternatively use three-degree bins ranging between -3 and 30°C (Section 5.4).

by 0.0862 in standard deviation unit (Column 5 of Table 3). This is similar in magnitude to the effects of a conditional cash transfer program, with transfers approximately 15% of the per capita expenditure each year, on early childhood cognitive skills among a sample of children in Nicaragua (Macours et al., 2012). Alternatively, the implied effect of a change in HDD by 60, or about 2 months of exposure to days colder by 1°C, is comparable to the effect of intensive early childhood intervention programs on cognitive skill outcomes of children in disadvantaged households in the US (Chaparro et al., 2020; Heckman et al., 2013).[8]

Heterogeneity of effects by baseline characteristics are shown in Table 5. The effects are greater for the children living in high altitude areas and those born between September and February, who spend the first few months after birth in winter. Greater negative effects in high altitude areas may be due to lower temperatures or because of a generally higher rate of poverty in high-altitude areas in China (Olivia et al., 2011). The negative effects are greater for boys, consistent with the relative vulnerabilities of male children compared to female children in the literature (Elango et al., 2016). We do not find significant differences in effects by household asset scores at baseline, potentially because the sample consists of mostly disadvantaged households. We do not find evidence of heterogeneity by caregivers' knowledge in parenting at the baseline[9] and by the availability of heating devices at home.

[8] Chaparro et al. (2020) showed that an intensive early childhood intervention called the Infant Health and Development Program, which provided intensive childcare for 2 years until children were 36-months old, improved children's Stanford-Binet IQ scores by 9.5 points at age 36-months. The normed standard deviation is 15 for this IQ score, implying that the effect is equivalent to about 73 days of exposure to colder days during the first year of child's life. Heckman et al. (2013) showed that the Perry Preschool Program, which also provided intensive childcare for 2 years between ages 3 and 5, improved children's cognitive skills outcomes at age 8 by 0.57 in standard deviation unit. This is equivalent to about 66 days of exposure.

[9] The parenting knowledge variable is based on the major factor of 10 variables on caregiver's attitudes and awareness of the importance about several positive parenting behaviors including talking to the child, playing with the child, and reading books with the child.

5.2 Immediate and Delayed Effects of Temperature Exposure

We use locally weighted regression based on equation (2) to examine whether temperature effects depend on the children's age at which cognitive skills are measured. We find that effects of temperature exposures in the first 2 years of life are large and significant on cognitive skills measured at ages 3 and 4 (Figure 4). The effects of age-3 exposure is insignificant for age-3 outcomes but starts to show on age-4 outcomes (Figure A5). We do not find effects on outcomes at age 1 under any specification. Also, the effects of temperature exposures before birth are not significant on outcomes at any age. Subsample analyses shown in Table A1 replicate these results. These results suggest that the effects of temperature exposure emerge not immediately but with a delay of at least a year.

We further confirm that the immediate effects of temperature exposures are insignificant. Results in Figure 5, based on equation (3), show insignificant effects of temperature exposures on the day of the survey, for the 7 days before survey, and for the 30 days before survey. The effects are observed only for the temperature exposures during the 365 days before the survey date, suggesting that the temperature exposure effects are unlikely to be explained by temporary disruptions on children's performances in cognitively demanding tasks.

5.3 Effects of Temperature Exposures on Home Environments

In this section, we examine whether temperature exposures affect the home environment, as measured by caregiver-child interactions and material investments in the home environment. These are key determinants of children's cognitive skills development and predict long-term outcomes (Heckman and Mosso, 2014). As explained in Section B in the Appendix, temperature exposures may directly interfere with caregivers' ability to engage with their children or provide for material investments, subject to household income and caregivers' abilities, knowledge, and beliefs about children's development processes.[10]

[10]The data set does not contain information on household income and caregivers' abilities, knowledge, and beliefs that are needed to identify the contributions of each of these factors on children's development.

Table 6, based on the panel regression model of equation (3), shows that in response to low temperature exposures, caregivers *reduce* investments on children as measured by home environment. Both caregiver-child interactions ("activities") and material investments into home environment ("books and toys") are reduced. The negative effects are significant on material investment for temperature exposures as measured by HDD (equation (3)) and on activities for exposures of temperatures below 10°C (equation (4), Figure 6). These findings imply that temperature changes in early childhood may have persistent, long-term effects through childhood home environment. Also, home environment may be channels underlying observed effects on early childhood cognitive skills.

Analysis of temperature exposure effects on each item of activities shows that the effects are concentrated on subscales related to "playing outdoors" and "telling stories" (Table A2, Figure A6 and Figure A7). These are physically and cognitively demanding tasks that may be more easily affected by temperature changes than other activities in the measure. Reduction in material investments is spread out across different items.

Finally, we investigate temperature effects on children's screen time, which are known to be associated with caregiver characteristics and home environment (Duch et al., 2013). We find that screen time is not affected by temperature exposures (Figure A8).

Heterogeneity analysis in Table A3 shows that the negative effects on home environments are greater among those with more household assets at the baseline. Reductions in activities are greater for households in high-altitude areas while reductions in materials are higher among those in low-altitude areas. These are possibly related to the negative association between household socioeconomic status and high altitude of residence in China (Olivia et al., 2011). Reductions in activities are greater for boys. There is no other noticeable differences by subgroups.

5.4 Robustness

5.4.1 Accounting for Attrition

Systematic attrition can introduce bias to estimates based on panel data analysis without adjustment. In Table A4, we use linear regression to examine potential sources of attrition, which is relatively modest at 18.31%. We do not find significant association between baseline characteristics and attrition probabilities except for the effects from the number of siblings of children. Based on predicted sample retention probabilities from this model, we estimate equation (1) with inverse probability weights. Our main results are robust to adjusting for attrition (Table A5).

5.4.2 Test of Assumptions

A key assumption for the identification of temperature effects is that temperature is exogenously determined with respect to family and child characteristics. This can be violated if the choice of survey timing is correlated with baseline characteristics that also affect child outcomes. We examine the association between baseline characteristics and the day of the survey and find that the survey date is likely not determined in favor of one household over another (Table A6).

The identification assumption can also be violated because of endogenous migration, either across or out of villages, in response to ambient temperature variation. Table A7 shows that none of the baseline characteristics is associated with HDD in each year of a child's life. We further find no association between children's temperature exposures and parental migration decisions, separately by the mother and the father (Table A8).

5.4.3 Other Robustness Checks

We first examine the robustness of main results in Section 5.1 to alternative sets of control variables. The main results in Table 3 first show that the results are robust to removing various control variables. The results of exposure to different ranges of temperature, based on equation (4), are also robust to different sets of controls we examine, as shown in the Appendix (see Figures A9, A10, A11, A12, A13, and A14).

We further account for temperature exposures other than those measured by HDD. We control for high temperature exposures as measured by CDD, the average range of temperature variation in each day (daily maximum minus daily minimum), and the average of its squares. We consider the temperature variation range because daily fluctuations may put more strain on the children and the household in adapting to temperature changes. The main results based on equation (1) are robust to adding these controls (Table 4).

Temperature effects may be confounded by adaptive behaviors of caregivers at home beyond those measured in our study. We examine this possibility and find that our results are robust to controlling for the characteristics of the primary caregiver at home and of caregivers' visits to local daycare centers. We also show the results of not controlling for the availability of heating devices at home. Although temperature exposures and the presence of heating appliances at home are not significantly correlated in the sample, heating appliances variables are measured at the second wave rather than at the baseline, making them inappropriate controls. The results are robust to these controls (Table A9).

We used 18.33°C to define HDD thus far, a standard practice in the literature. The estimates may be sensitive to this choice if, for example, the effects are concentrated in a limited range of temperatures rather than continuously spread throughout cold temperatures. We use different values to define HDD and find consistent results (Table A10).

We examine the sensitivity of results to model specification by examining the effects of temperature exposures up to 3 years before and after birth, moving beyond the main results model that considered only 2 years before and after birth. We confirm that the outcomes 3 years before birth pass the placebo test and that the effect of first-year exposure is still observed at 3 years after birth (Table A11). The magnitudes of effects are smaller for exposures nearer to the time of measurement.

We used the standard bandwidth length of 0.5 for the locally weighted regression (equation (2)) that estimates the effects of temperature exposure on children's cognitive skills measured at different ages. We show that these results are robust to the choice of bandwidth lengths by repeating the analysis with 0.25 and 0.75 as bandwidth lengths, respectively (Figure A15 and Figure A16).

We consider alternative ways to define the dependent variable, including percentile measure, indicator variable for cognitive delay, and the raw score of the Bayley scale (Table A12). We find that the coefficient signs and magnitudes are consistent and the effects of exposures during the first and second years after birth are significant throughout different specifications. Effects of *in utero* exposures are marginally significant and sometimes insignificant.

We examine the temperature exposure effects on the language skills of the children (Table A13, Figures A17 and A18). Language skills are different from cognitive skills as they may reflect "crystallized intelligence" to a greater extent than cognitive ability measures that are thought to be closer to pure reasoning abilities (Almlund et al., 2011). The item response rate is also much lower for these variables, limiting the statistical power. The coefficient signs and magnitudes are nonetheless consistent throughout, and the effects of first- and second-year exposures are significant except for the expressive language scale.

Finally, we account for the possibility that the "extreme" temperatures, even within the range of ambient temperature variations, may have affected children's cognitive development. Instead of daily average temperatures as the variable of interest, we alternatively use daily maximum and daily minimum temperatures to estimate the effects of temperature exposure (Figure A19). The results from daily maximum temperatures are consistent in sign but weaker in significance. The results from daily minimum temperatures closely follow our main results. We conclude that low temperatures within the day primarily generated our results.

5.5 Alternative Channels

Climate change literature suggests that temperature exposure can impact children's outcomes through household income by reducing crop harvest or livestock among farming households (Garg et al., 2020; Groppo and Kraehnert, 2016; Shively et al., 2015) or by shifting parents' time allocation away from farm work (Huang et al., 2020). We are unable to check for this channel directly because we do not have information on household income, occupation of parents, or involvement in agriculture. Instead, we searched news media looking for mentions of unusual weather in the sampling area. On 6–7 April, 2018, severe cold currents in northwestern China caused frost damage to fruit crops such as apples in Shaanxi province (Gilleski, 2018; Inouye, 2018; Wang, 2018). Because the effect of this weather shock on household income may occur with delay, we tested its importance by replacing the temperature data in March and April of 2018 with the corresponding values in 2010, 2011, and 2012. Table A14 shows that our results are robust to this manipulation, confirming that the effects are not driven by the cold spell in April 2018.

We also examine whether children's dietary intake is affected by temperature. Reduced income may have persuaded parents to reduce the cost of foods provided to the children. Figure A20 and Table A15 show that exposure to low temperatures in the previous year increases provisions of rice and beans but reduces dairy, meat, eggs, vitamin supplements, and fruits. The parents are also less likely to provide four or more different kinds of foods to children. While this pattern is consistent with temperature's having negative impacts on household income, none of the estimates is significantly different from zero. It is therefore difficult to claim these results as evidence of income channel.

We examine the effects of exposures to other climate variables including precipitation, sunlight, and air pollution during early childhood period. Light increase in rainfall can increase agricultural yield and household income (Beuermann and Pecha, 2020; Yamashita and Trinh, 2022). Sunlight and air pollution can undermine health of the children and the parents (Brunekreef and Holgate, 2002; Moan et al., 2008). As Table A16 shows, however, none of the effects of these other climate variables is significant in our sample.

The exposures to low temperatures may directly affect children's health (Bunyavanich et al., 2003; Burke et al., 2018; Philipsborn and Chan, 2018). Children are biologically sensitive, physiologically immature, and limited in their capacity to adapt to external threats compared to adults. Therefore, large variations in ambient temperature can directly impact the physical development of the fetus or the infant (Molina and Saldarriaga, 2017). Figure A21 shows that the number of sick days during the 2 weeks prior to the interview is not affected by temperature exposures.

Temperature variation may make it stressful for the child to explore indoor or outdoor local environments, hindering cognitive development. Outside activities of children with or without caregivers can be discouraged by bad weather (e.g., Hesketh et al., 2017). Indoor activities would be similarly affected without appropriate heating or cooling appliances, but we are not able to find studies focusing on the impact of weather on children's indoor activities.

Therefore, as discussed in Section B, our conceptual framework and the empirical models do not distinguish temperature exposures indoors or outdoors. If, for example, good caregivers systematically responded to low temperatures by taking their children to the warmer indoors, our estimates may be confounded by the characteristics of caregivers who neglect to take their children inside. However, the effects of temperature exposure are not large or significant on measures of home environment focused on outdoors activities, as shown in Figure A6 and Table A2. Further, inadequate heating facilities at home in rural low-income communities would have limited the relative benefits of indoor activities.

6 Conclusion

We investigate the effects of exposures to ambient temperatures on subsequent cognitive skills development home environment in early childhood. We overcome data limitation in the prior literature with unique panel data in rural China with detailed information on children's cognitive skills, caregiver-child interactions, and material investments in home environments, merged with daily climate data for each village. Our study bridges the two strands of literature temperature exposure effects: the literature on the birth outcomes and the literature on long-term outcomes such as education and income (Table 1).

We find that exposures to low temperatures have negative effects on children's cognitive development in early childhood. The effects are not significant immediately but are significant least a year after initial exposure. These results suggest that low temperature exposures lower outcomes by undermining children's development process rather than by temporarily disrupting children's performance at cognitively demanding tasks. Effects of exposure to high temperature are negative but small and insignificant.

Further, we find that when exposed to low temperatures, caregivers *reduce* investments into the home environment as measured by interactions with children and material home environment. These decreases in investments may channel temperature effects on developmental outcomes in early childhood and even on long-term outcomes such as education and income. We examine but do not find evidence of alternative channels such as household income or children's health.

These findings fill the gap in our knowledge about human costs of climate change and the determinants of human capital development among children. They suggest that the costs of climate change are greater and more persistent than previously known, and are likely to be heavier among disadvantaged households similar to those in rural Chinese communities in our sample. Through its negative impact on home environment, climate change can undermine the adaptive capacities of vulnerable households and communities, further widening socioeconomic inequalities across generations.

Our results imply that policies targeting families with disadvantaged home environment can be effective in mitigating the damages of temperature variations on children's development. Caregivers in our sample were not able to provide the children with sufficient protection from temperature effects. It is well known that investing in early childhood skills generates high returns over the life cycle of children, and that caregivers at home are "first responders" to children's needs (Elango et al., 2016). Further, climate change is expected to increase both the frequency and intensity of temperature variations (Bathiany et al., 2018; Schär et al., 2004). Therefore, helping the caregivers in disadvantaged households to protect their children from the effects of temperature may lead to significant long-term gains in human capital development and social welfare.

References

Agüero, J. (2014). Long-Term Effect of Climate Change on Health: Evidence from Heat Waves in Mexico. IDB Working Paper IDB-WP-481.

Alberto, I. C., Y. Jiao, and X. Zhang (2021). Too hot or too cold to study? the effect of temperature on student time allocation. *Economics of Education Review 84*, 102152.

Albouy, D., W. Graf, R. Kellogg, and H. Wolff (2016). Climate Amenities, Climate Change, and American Quality of Life. *Journal of the Association of Environmental and Resource Economists 3*(1), 205–246.

Almlund, M., A. L. Duckworth, J. Heckman, and T. Kautz (2011). Personality psychology and economics. In *Handbook of the Economics of Education*, Volume 4, pp. 1–181. Elsevier.

Andalón, M., J. P. Azevedo, C. Rodríguez-Castelán, V. Sanfelice, and D. Valderrama-González (2016). Weather shocks and health at birth in colombia. *World Development 82*, 69–82.

Banerjee, R. and R. Maharaj (2020). Heat, infant mortality, and adaptation: Evidence from india. *Journal of Development Economics 143*, 102378.

Barron, M. et al. (2018). In-utero weather shocks and learning outcomes. Peruvian Economic Association Working Paper 137.

Bathiany, S., V. Dakos, M. Scheffer, and T. M. Lenton (2018). Climate models predict increasing temperature variability in poor countries. *Science Advances 4*(5), eaar5809.

Bayley, N. (2006). *Bayley scales of infant and toddler development, third edition: Technical manual*. San Antonion, TX: Hartcourt Assessment.

Beuermann, D. W. and C. J. Pecha (2020). The effects of weather shocks on early childhood development: Evidence from 25 years of tropical storms in Jamaica. *Economics & Human Biology 37*, 100851.

Brunekreef, B. and S. T. Holgate (2002). Air pollution and health. *The lancet 360*(9341), 1233–1242.

Bunyavanich, S., C. P. Landrigan, A. J. McMichael, and P. R. Epstein (2003). The impact of climate change on child health. *Ambulatory Pediatrics 3*(1), 44–52.

Burke, S. E., A. V. Sanson, and J. Van Hoorn (2018). The psychological effects of climate change on children. *Current psychiatry reports 20*(5), 1–8.

Chaparro, J., A. Sojourner, and M. J. Wiswall (2020). Early childhood care and cognitive development. Technical Report w26813, National Bureau of Economic Research.

Chen, X., C. M. Tan, X. Zhang, and X. Zhang (2020). The effects of prenatal exposure to temperature extremes on birth outcomes: the case of China. *Journal of Population Economics 33*(4), 1263–1302.

Cleveland, W. S. (1979). Robust locally weighted regression and smoothing scatterplots. *Journal of the American statistical association 74*(368), 829–836.

Cunha, F., I. Elo, and J. Culhane (2020). Maternal subjective expectations about the technology of skill formation predict investments in children one year later. *Journal of Econometrics*.

Currie, J. and O. Deschênes (2016). Children and Climate Change: Introducing the Issue. *The Future of Children*, 3–9.

Davenport, F., A. Dorélien, and K. Grace (2020). Investigating the linkages between pregnancy outcomes and climate in sub-Saharan Africa. *Population and Environment 41*(4), 397–421.

Deschênes, O., M. Greenstone, and J. Guryan (2009). Climate change and birth weight. *American Economic Review 99*(2), 211–17.

Dizon-Ross, R. (2019). Parents' beliefs about their children's academic ability: Implications for educational investments. *American Economic Review 109*(8), 2728–65.

Duch, H., E. M. Fisher, I. Ensari, and A. Harrington (2013). Screen time use in children under 3 years old: a systematic review of correlates. *International Journal of Behavioral Nutrition and Physical Activity 10*, 1–10.

Elango, S., J. L. García, J. J. Heckman, and A. Hojman (2016). Early Childhood Education. In R. A. Moffitt (Ed.), *Economics of Means-Tested Transfer Programs in the United States, Volume II*, pp. 235–298. University of Chicago Press.

Fan, W. and C. Porter (2020). Reinforcement or compensation? parental responses to children's revealed human capital levels. *Journal of Population Economics 33*(1), 233–270.

Fatima, H., S. Zhao, A. Yue, S. Li, and Y. Shi (2022). Parental discipline and early childhood development in rural china. *Sustainability 14*(4), 1988.

Garg, T., M. Gibson, and F. Sun (2020). Extreme temperatures and time use in China. *Journal of Economic Behavior & Organization 180*, 309–324.

Garg, T., M. Jagnani, and V. Taraz (2020). Temperature and human capital in India. *Journal of the Association of Environmental and Resource Economists 7*(6), 1113–1150.

Geruso, M. and D. Spears (2018). Heat, humidity, and infant mortality in the developing world. NBER Working Paper 24870, National Bureau of Economic Research.

Gilleski, S. (2018). Stone fruit annual. Global Agricultural Information Network Report CH 18037, USDA Foreign Agricultural Service.

Graff Zivin, J., S. M. Hsiang, and M. Neidell (2018). Temperature and human capital in the short and long run. *Journal of the Association of Environmental and Resource Economists 5*(1), 77–105.

Groppo, V. and K. Kraehnert (2016). Extreme weather events and child height: Evidence from Mongolia. *World Development 86*, 59–78.

Hajdu, T. and G. Hajdu (2022). Climate change and the mortality of the unborn. *Journal of Environmental Economics and Management*, 102771.

Heckman, J., R. Pinto, and P. Savelyev (2013). Understanding the mechanisms through which an influential early childhood program boosted adult outcomes. *American Economic Review 103*(6), 2052–86.

Heckman, J. J. and S. Mosso (2014). The economics of human development and social mobility. *Annual Review of Economics 6*(1), 689–733.

Hesketh, K. R., R. Lakshman, and E. M. van Sluijs (2017). Barriers and facilitators to young children's physical activity and sedentary behaviour: a systematic review and synthesis of qualitative literature. *Obesity Reviews 18*(9), 987–1017.

Hu, Z. and T. Li (2019). Too hot to handle: The effects of high temperatures during pregnancy on adult welfare outcomes. *Journal of Environmental Economics and Management 94*, 236–253.

Hua, Y., Y. Qiu, and X. Tan (2022). The effects of temperature on mental health: evidence from China. *Journal of Population Economics*.

Huang, K., H. Zhao, J. Huang, J. Wang, and C. Findlay (2020). The impact of climate change on the labor allocation: Empirical evidence from China. *Journal of Environmental Economics and Management 104*, 102376.

Inouye, A. (2018). Fresh deciduous fruit annual. Global Agricultural Information Network Report CH 18074, USDA Foreign Agricultural Service.

Isen, A., M. Rossin-Slater, and R. Walker (2017). Relationship between season of birth, temperature exposure, and later life wellbeing. *Proceedings of the National Academy of Sciences 114*(51), 13447–13452.

Johnstone, H., Y. Yang, H. Xue, and S. Rozelle (2021). Infant cognitive development and stimulating parenting practices in rural China. *International Journal of Environmental Research and Public Health 18*(10), 5277.

Le, K. and M. Nguyen (2021). The impacts of temperature shocks on birth weight in Vietnam. *Population and Development Review 47*(4), 1025–1047.

Li, X., L. Jin, and H. Kan (2019). Air pollution: a global problem needs local fixes.

Macours, K., N. Schady, and R. Vakis (2012). Cash transfers, behavioral changes, and cognitive development in early childhood: evidence from a randomized experiment. *American Economic Journal: Applied Economics 4*(2), 247–73.

Mertz, O., K. Halsnæs, J. E. Olesen, and K. Rasmussen (2009). Adaptation to Climate Change in Developing Countries. *Environmental management 43*, 743–752.

Moan, J., A. C. Porojnicu, A. Dahlback, and R. B. Setlow (2008). Addressing the health benefits and risks, involving vitamin d or skin cancer, of increased sun exposure. *Proceedings of the National Academy of Sciences 105*(2), 668–673.

Molina, O. and V. Saldarriaga (2017). The perils of climate change: *In utero* exposure to temperature variability and birth outcomes in the Andean region. *Economics & Human Biology 24*, 111–124.

National Bureau of Statistics of China (2017). China statistical yearbook 2017.

Ogasawara, K. and M. Yumitori (2019). Early-life exposure to weather shocks and child height: Evidence from industrializing japan. *SSM-Population Health 7*, 100317.

Olivia, S., J. Gibson, S. Rozelle, J. Huang, and X. Deng (2011). Mapping poverty in rural china: how much does the environment matter? *Environment and Development Economics 16*(2), 129–153.

Park, R. J. (2022). Hot temperature and high-stakes performance. *Journal of Human Resources 57*(2), 400–434.

Park, R. J., J. Goodman, M. Hurwitz, and J. Smith (2020). Heat and learning. *American Economic Journal: Economic Policy 12*(2), 306–39.

Philipsborn, R. P. and K. Chan (2018). Climate change and global child health. *Pediatrics 141*(6).

Randell, H. and C. Gray (2019). Climate change and educational attainment in the global tropics. *Proceedings of the National Academy of Sciences 116*(18), 8840–8845.

Restrepo, B. J. (2016). Parental investment responses to a low birth weight outcome: who compensates and who reinforces? *Journal of Population Economics 29*(4), 969–989.

Sanchez, A. (2018). Early-life Exposure to Weather Shocks and Human Capital Accumulation: Evidence from the Peruvian Highlands. Young Lives Working Paper 178.

Schär, C., P. L. Vidale, D. Lüthi, C. Frei, C. Häberli, M. A. Liniger, and C. Appenzeller (2004). The role of increasing temperature variability in european summer heatwaves. *Nature 427*(6972), 332–336.

Shively, G., C. Sununtnasuk, and M. Brown (2015). Environmental variability and child growth in nepal. *Health & Place 35*, 37–51.

Sylvia, S., R. Luo, J. Zhong, S.-E. Dill, A. Medina, and S. Rozelle (2022). Passive versus active service delivery: Comparing the effects of two parenting interventions on early cognitive development in rural China. *World Development 149*, 105686.

Tian, Y., Z. Wang, J. Zhao, X. Jiang, and R. Guo (2018). A geographical analysis of the poverty causes in China's contiguous destitute areas. *Sustainability 10*(6), 1895.

Vaughn, D. M. (2005). Degree days. In O. J.E. (Ed.), *Encyclopedia of World Climatology. Encyclopedia of Earth Sciences Series*. Dordrecht: Springer.

Wang, B., X. Luo, A. Yue, L. Tang, and Y. Shi (2022). Family environment in rural china and the link with early childhood development. *Early Child Development and Care 192*(4), 617–630.

Wang, J. Y. (2018). *Xīběi huángtǔ gāoyuán děng guǒ qū wǎn shuāngdòng wéihài jí zāihòu huīfù cuòshī* [Damage of late frost and post-disaster recovery measures in fruit producing areas of Northwest Loess Plateau]. *Zhōngguó Guǒshù[China Fruits] 192*, 1–3.

Wang, L., W. Liang, S. Zhang, L. Jonsson, M. Li, C. Yu, Y. Sun, Q. Ma, Y. Bai, C. Abbey, et al. (2019). Are infant/toddler developmental delays a problem across rural China? *Journal of Comparative Economics 47*(2), 458–469.

Wechsler, D. (2012). *Wechsler Preschool and Primary Scale of Intelligence—Fourth Edition*. San Antonio, Texas: The Psychological Corporation.

Wei, J., W. Huang, Z. Li, W. Xue, Y. Peng, L. Sun, and M. Cribb (2019). Estimating 1-km-resolution pm2. 5 concentrations across china using the space-time random forest approach. *Remote Sensing of Environment 231*, 111221.

Wilde, J., B. H. Apouey, and T. Jung (2017). The effect of ambient temperature shocks during conception and early pregnancy on later life outcomes. *European Economic Review 97*, 87–107.

Wu, Z., G. Cheng, D. Wang, and Q. Guo (2020). Urban and Rural Space Development in Qinba Mountain Area Based on Basins. *Strategic Study of Chinese Academy of Engineering 22*(1), 56–63.

Yamashita, N. and T.-A. Trinh (2022). Effects of prenatal exposure to abnormal rainfall on cognitive development in vietnam. *Population and Environment 43*(3), 346–366.

Yang, Z., B. Yang, P. Liu, Y. Zhang, and X.-C. Yuan (2021). Impact of temperature on physical and mental health: evidence from china. *Weather, climate, and society 13*(4), 709–727.

Yi, J., J. J. Heckman, J. Zhang, and G. Conti (2015). Early health shocks, intra-household resource allocation and child outcomes. *The Economic Journal 125*(588), F347–F371.

Yue, A., Q. Jiang, B. Wang, C. Abbey, A. Medina, Y. Shi, and S. Rozelle (2019). Concurrent validity of the ages and stages questionnaire and the Bayley Scales of Infant Development III in China. *PLOS ONE 14*(9), e0221675.

Yue, A., X. Luo, M. Jia, B. Wang, Q. Gao, Y. Shi, and S. Wang (2021). Concurrent validity of the macarthur communicative development inventory, the ages and stages questionnaires and the bayley scales of infant and toddler development: A study in rural china. *Infant and Child Development 30*(3), e2219.

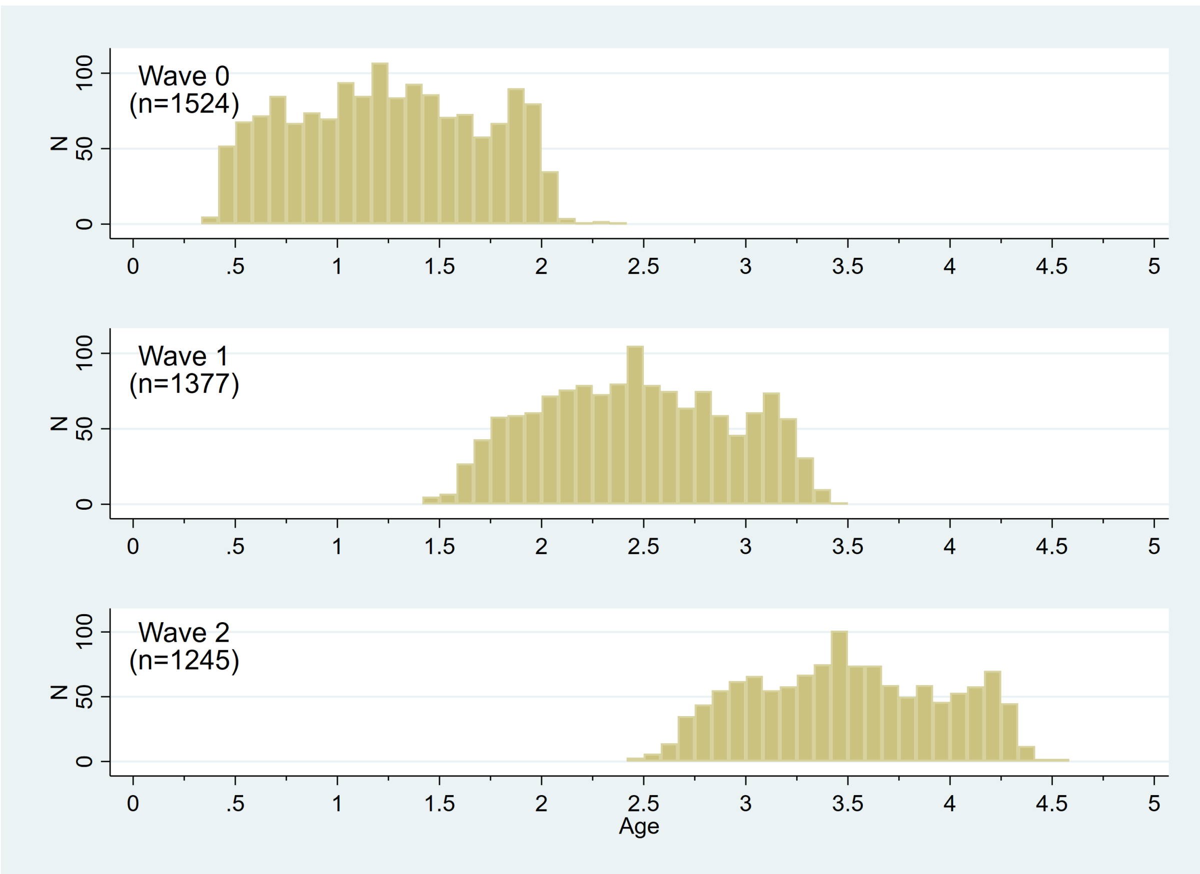
Yue, A., Y. Shi, R. Luo, J. Chen, J. Garth, J. Zhang, A. Medina, S. Kotb, and S. Rozelle (2017). China's invisible crisis: Cognitive delays among rural toddlers and the absence of modern parenting. *The China Journal 78*(1), 50–80.

Zeanah, C. H., N. W. Boris, and J. A. Larrieu (1997). Infant Development and Developmental Risk: A Review of the Past 10 Years. *Journal of the American Academy of Child & Adolescent Psychiatry 36*(2), 165–178.

Zhang, Q., Y. Zheng, D. Tong, M. Shao, S. Wang, Y. Zhang, X. Xu, J. Wang, H. He, W. Liu, et al. (2019). Drivers of improved pm2. 5 air quality in china from 2013 to 2017. *Proceedings of the National Academy of Sciences 116*(49), 24463–24469.

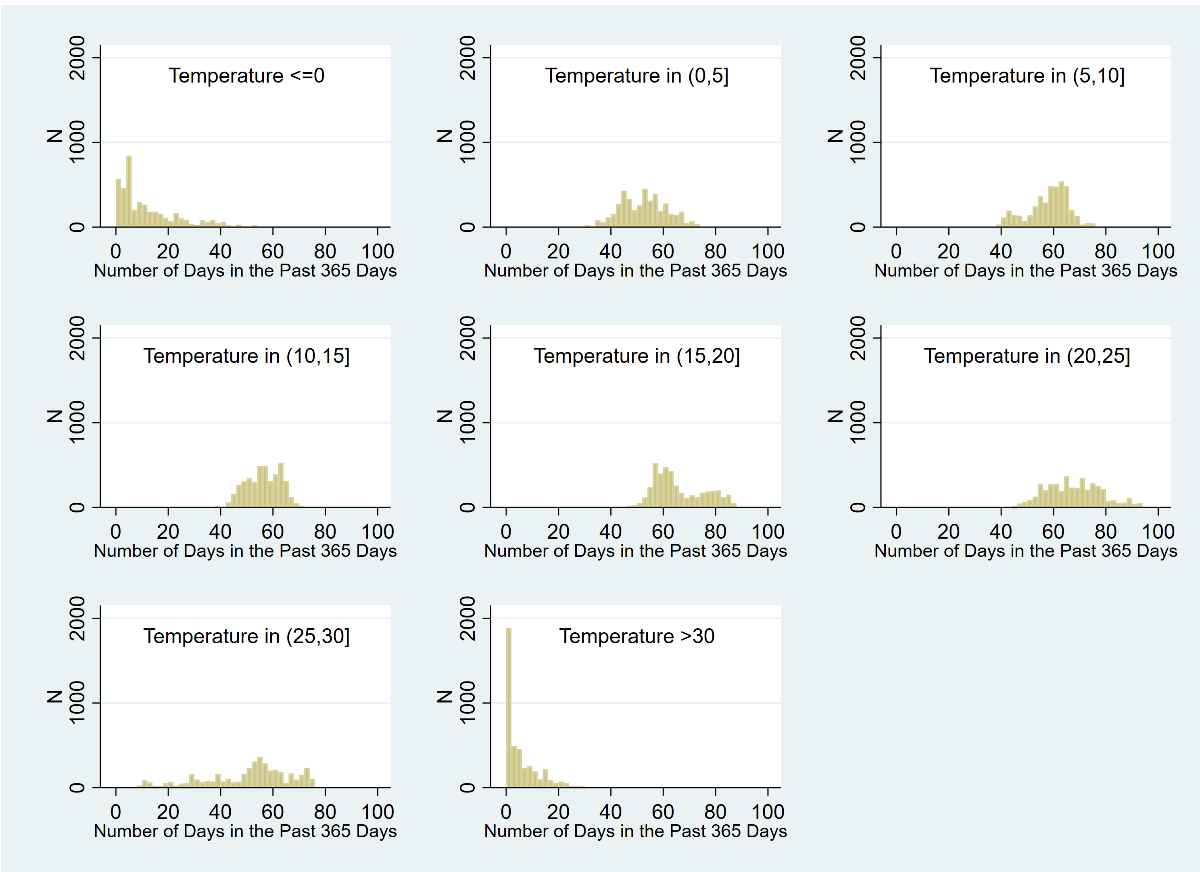
Zheng, G. and W. Bu (2018). Review of heating methods for rural houses in china. *Energies 11*(12), 3402.

Figure 1: Age Distribution in Each Wave



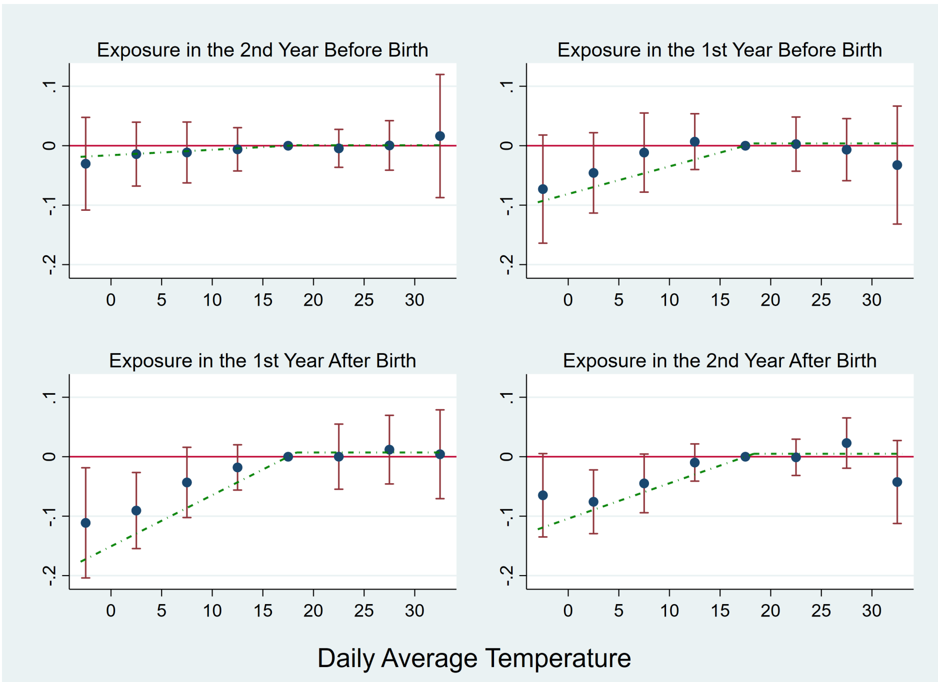
Notes: Bars represent the number of observations in each age range.

Figure 2: Temperature Distribution in Wave 2



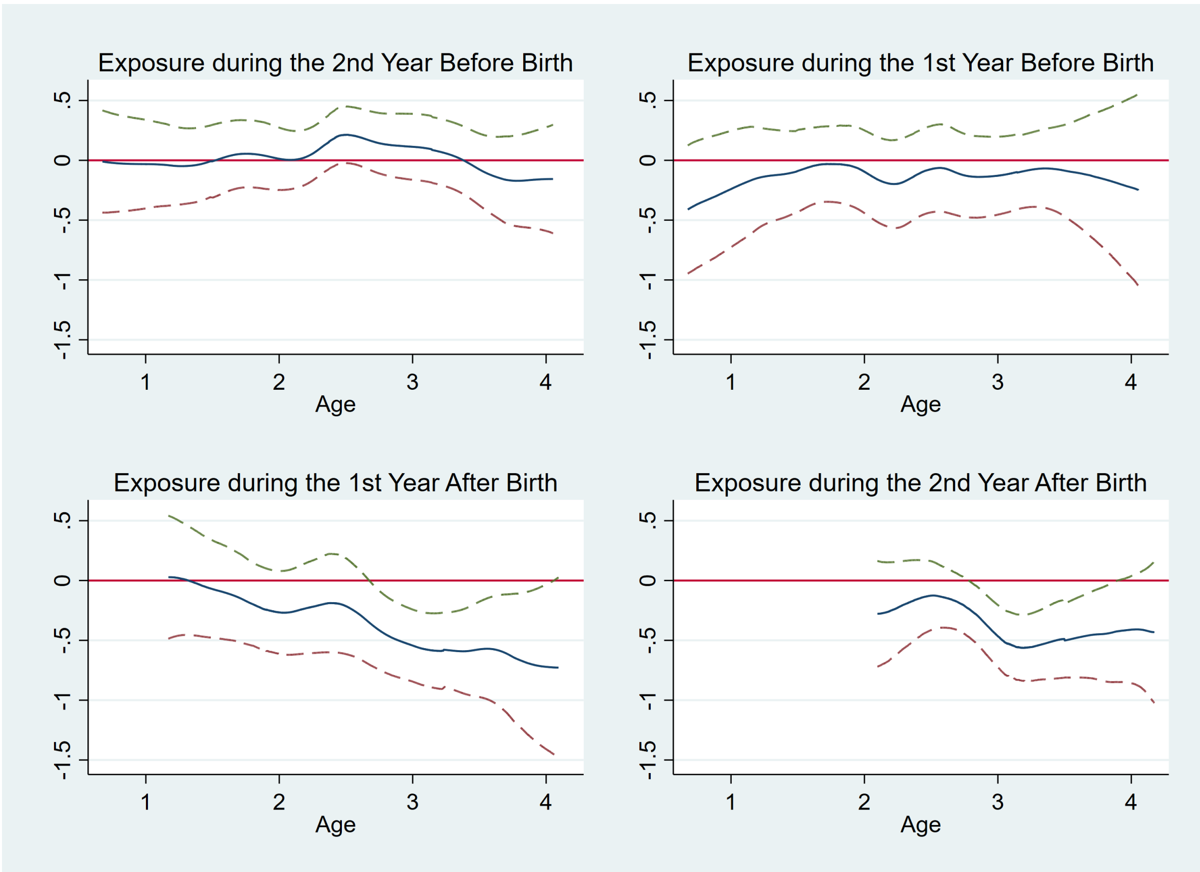
Notes: Bars represent the number of days in each temperature range during the 365 days prior to the interview date in wave 2 of the survey.

Figure 3: Effects of Ambient Temperature Exposure on Cognitive Skills in Early Childhood



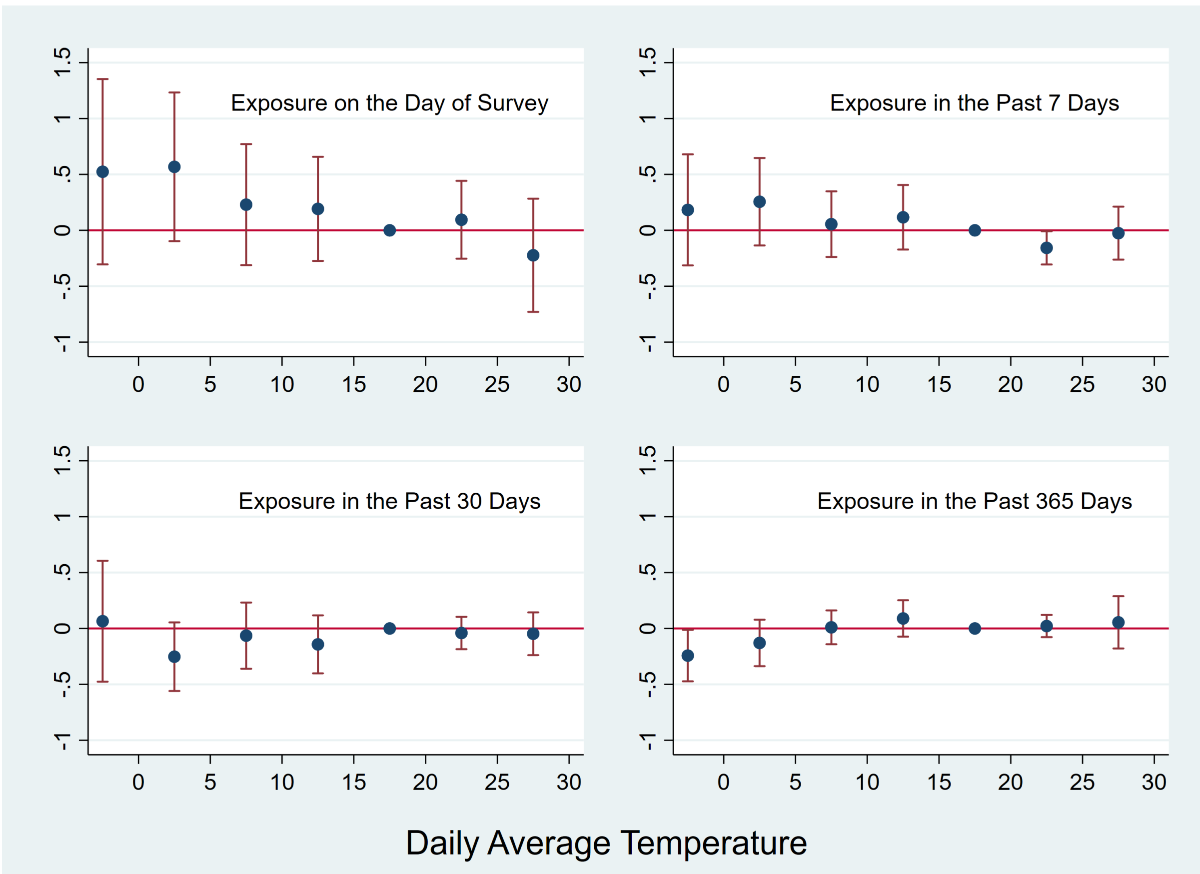
Notes: Error bars indicate 95% confidence intervals. Standard errors are clustered at the village level. Circles represent estimates based on equation (4). Dotted lines represent estimates of a linear spline model with a knot at 18.33°C and the slope on the right of the knot fixed at zero. Other control variables include: village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; children's age, gender, and the number of siblings by birth order; indicators for month of birth; indicators for mother's age at delivery; indicators for mother's six education levels; asset score at wave 0; indicators for having heating devices at home; precipitation, sunshine and $PM_{2.5}$ during each period.

Figure 4: Temperature Effects by Children's Age



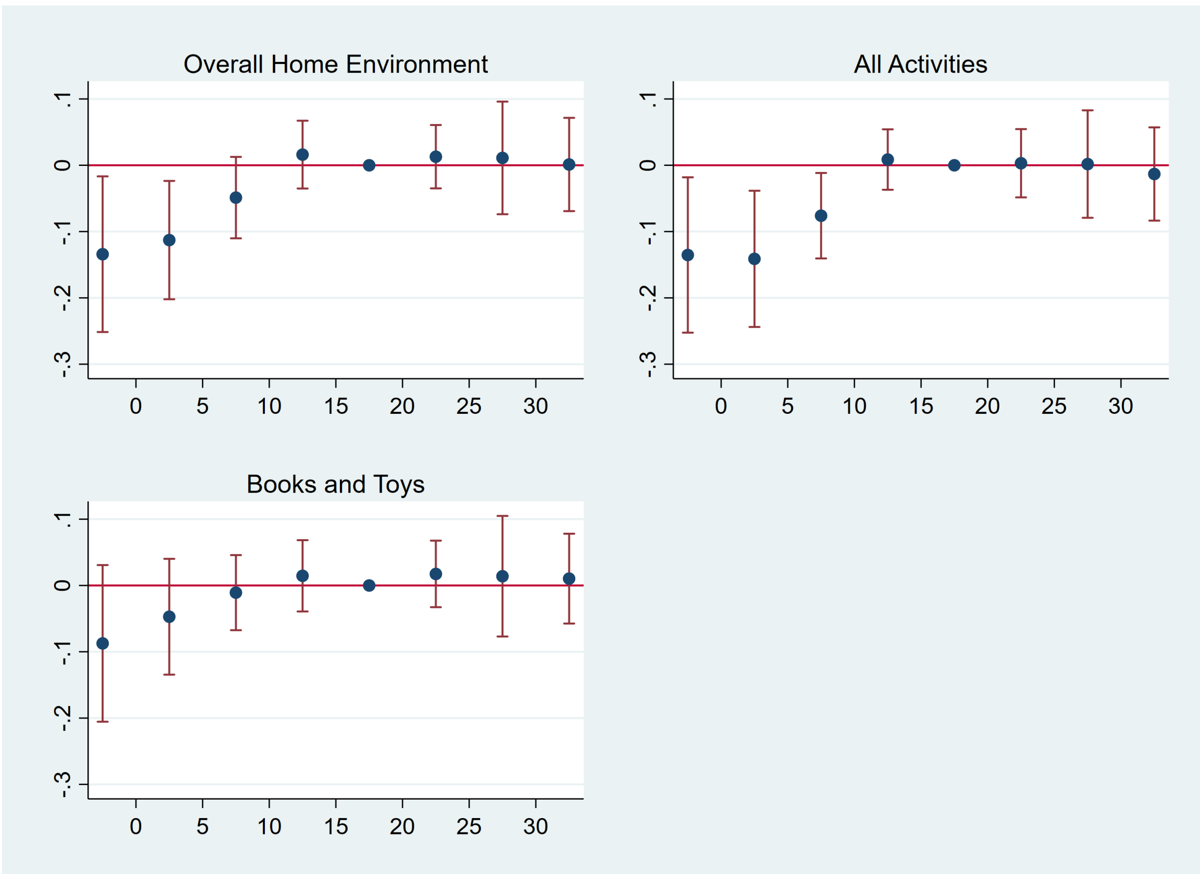
Notes: Dashed lines indicate 95% confidence intervals. Standard errors are clustered at the village level. Regressions are locally-weighted around each observation. Weights are calculated using tricube kernels with a relative bandwidth of 0.5. Y-Axis indicates the impacts of HDD/100 on cognitive scores. X-axis indicate the age in which the outcome is measured. Other control variables include: village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; children's age, gender, and the number of siblings by birth order; indicators for month of birth; indicators for mother's age at delivery; indicators for mother's six education levels; asset score at wave 0; indicators for heating devices at home; precipitation, sunshine and $PM_{2.5}$ during each period.

Figure 5: Panel Regressions of Temperature Effects on Cognitive Scores



Notes: Error bars indicate 95% confidence intervals. Standard errors are clustered at the village level. Other control variables include: child fixed effects; wave fixed effects; village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; children's age, gender, and the number of siblings by birth order; precipitation, sunshine and $PM_{2.5}$ during each period.

Figure 6: Panel Regressions of Home Environment on Last Year's Temperature



Notes: Error bars indicate 95% confidence intervals. Standard errors are clustered at the village level. Other control variables include: child fixed effects; wave fixed effects; village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; children's age, gender, and the number of siblings by birth order; precipitation, sunshine and $PM_{2.5}$ in the past 365 days.

Table 1: Current Literature on Ambient Temperature Exposure Effects

Current Study	Outcome Window	Exposure Window	Temperature	Findings	Ref.
		Effects on Child Outcomes			
	pregnancy, birth	in utero	high	(-) infant survival	*a*
	pregnancy, birth	in utero	high, low	(-) birth height, weight	*b*
✓	ages 0–5				
	ages 6–11	early childhood	low	(-) height, cognitive skill, noncognitive skill	*c*
	ages 6–11	in utero	low	(-) schooling	*d*
	ages 12–15	in utero, early childhood	high	(-) education	*e*
	adulthood	in utero	high	(-) earnings, education, height	*f*
	adulthood	in utero, early childhood	high	(+) education, literacy	*g*
		Effects on Home Environment			
✓					
		Effects on Health			
	adulthood	adulthood	high, low	(-) physical health, mental health	*h*
	adulthood	adulthood	high	(-) mental health	*i*
		Effects on Time Use and Task Performance			
	adulthood	adulthood	high	(-) childcare time, work time	*j*
	adolescence	adolescence	high, low	(-) study time	*k*
	adolescence	adolescence	high	(-) task performance, learning	*l*

Notes: This table highlights the gap in the literature filled by the current study. [a]: Banerjee and Maharaj (2020); Hajdu and Hajdu (2022); Geruso and Spears (2018). [b]: Andalón et al. (2016); Chen et al. (2020); Deschênes et al. (2009); Davenport et al. (2020); Le and Nguyen (2021); Molina and Saldarriaga (2017). [c]: Ogasawara and Yumitori (2019); Sanchez (2018). [d]: Barron et al. (2018). [e]: Randell and Gray (2019). [f]: Agüero (2014); Hu and Li (2019); Isen et al. (2017). [g]: Wilde et al. (2017). [h]: Yang et al. (2021). [i]: Hua et al. (2022). [j]: Garg et al. (2020); Huang et al. (2020). [k]: Alberto et al. (2021). [l]: Graff Zivin et al. (2018); Park et al. (2020); Park (2022) and many others.

Table 2: Summary Statistics

	Mean (SD)		
	Wave 0 (1)	Wave 1 (2)	Wave 2 (3)
Age	1.25 (0.46)	2.47 (0.46)	3.50 (0.47)
Female	0.49 (0.50)	0.49 (0.50)	0.48 (0.50)
Any Sibling	0.51 (0.50)	0.52 (0.50)	0.53 (0.50)
First-Born	0.52 (0.50)	0.52 (0.50)	0.50 (0.50)
Mother's Age at Delivery	26.32 (4.83)	26.38 (4.81)	26.37 (4.88)
Mother Finished High School	0.21 (0.41)	0.21 (0.41)	0.20 (0.40)
Asset Index in Wave 0	-0.00 (0.85)	0.00 (0.84)	0.01 (0.85)
Cognitive Score	-0.00 (1.00)	-0.00 (1.00)	0.00 (1.00)
Home Environment Score	-0.35 (0.83)	0.14 (0.87)	0.28 (0.87)
Subscore: Toys and Books	-0.44 (0.81)	0.13 (0.78)	0.40 (0.75)
Subscore: Activities	-0.07 (0.75)	0.08 (0.81)	-0.01 (0.84)
Weather in the Past 365 Days			
Heating Degree Days ($^{\circ}C$)	2011 (280)	2054 (221)	2126 (239)
Precipitation (mm)	887 (260)	787 (188)	806 (146)
Sunshine (Hours)	1682 (243)	1684 (190)	1651 (222)
$\text{PM}_{2.5}(\mu g/m^3)$	39.9 (4.9)	37.4 (4.5)	35.3 (3.5)
Observations	1524	1377	1245

Notes: Age is defined as $\frac{1}{365.25} \times (\text{days after birth})$. Asset score measures household wealth at wave 0. Cognitive scores are normalized within each wave by each month of age. Home environment score is estimated as the major component in the factor analysis of 18 items including toys and books (music toys, drawing toys, books, block toys, rolling toys, color-and-shape toys, role-play toys) and activities (reading books, telling stories, singing songs, playing outdoors, playing with toys, naming/drawing/counting). Subscores of Home Environment Scores are similarly estimated. Heating Degree Days is the sum of HDD for each day: $HDD_c = \sum_{d \in D_c} \max\{(18.33 - x_d), 0\}$, where x_d is the average temperature for day d.

Table 3: Effects of Ambient Temperature Exposure on Cognitive Skills in Early Childhood

	Cognitive Score in Wave 2				
	(1)	(2)	(3)	(4)	(5, Baseline)
HDD/100, 2nd Year Before Birth	-0.020	0.040	0.018	-0.001	-0.091
	(0.074)	(0.086)	(0.098)	(0.160)	(0.158)
HDD/100, 1st Year Before Birth	-0.259*	-0.335*	-0.324*	-0.416†	-0.464*
	(0.115)	(0.140)	(0.149)	(0.214)	(0.214)
HDD/100, 1st Year After Birth	-0.331*	-0.515***	-0.599***	-0.668***	-0.862***
	(0.135)	(0.151)	(0.163)	(0.172)	(0.204)
HDD/100, 2nd Year After Birth	-0.303***	-0.395***	-0.371***	-0.388***	-0.595***
	(0.070)	(0.095)	(0.104)	(0.110)	(0.168)
Village-Year FE	✓	✓	✓	✓	✓
Year×Month FE, Day of Week FE, Examiner FE		✓	✓	✓	✓
Age, Gender, Siblings, Mom's Educ, Asset, Heating			✓	✓	✓
Indicators for Birth Month and Mother's Age				✓	✓
$PM_{2.5}$, Sunshine and Precipitation					✓
Observations	1245	1245	1245	1245	1245

Notes: † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in the parentheses are clustered at the village level. HDD is the sum of HDD for each day within each period c: $HDD_c = \sum_{d \in D_c} \max\{(18.33 - x_d), 0\}$, where x_d is the temperature in day d.

Table 4: Effects of Ambient Temperature Exposures with Additional Control Variables

	Cognitive Score in Wave 2			
	(1, Baseline)	(2)	(3)	(4)
HDD/100, 2nd Year Before Birth	-0.091	-0.143	-0.064	-0.051
	(0.158)	(0.158)	(0.189)	(0.179)
HDD/100, 1st Year Before Birth	-0.460*	-0.499*	-0.410†	-0.375†
	(0.213)	(0.212)	(0.229)	(0.221)
HDD/100, 1st Year After Birth	-0.861***	-0.875***	-0.839***	-0.907***
	(0.204)	(0.187)	(0.194)	(0.192)
HDD/100, 2nd Year After Birth	-0.595***	-0.574**	-0.521**	-0.581**
	(0.168)	(0.171)	(0.193)	(0.192)
CDD/100, 2nd Year Before Birth		-0.155	-0.256	-0.280
		(0.242)	(0.264)	(0.263)
CDD/100, 1st Year Before Birth		-0.076	-0.122	-0.028
		(0.225)	(0.242)	(0.242)
CDD/100, 1st Year After Birth		-0.068	-0.104	-0.175
		(0.253)	(0.273)	(0.280)
CDD/100, 2nd Year After Birth		0.158	0.203	0.191
		(0.250)	(0.256)	(0.254)
Other Baseline Controls	✓	✓	✓	✓
CDD		✓	✓	✓
Daily Temperature Range in Each Period			✓	✓
Daily Range Squared in Each Period				✓
Observations	1245	1245	1245	1245

Notes: † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in the parentheses are clustered at the village level. HDD is the sum of HDD for each day within each period c: $HDD_c = \sum_{d \in D_c} \max\{(18.33 - x_d), 0\}$, where x_d is the temperature in day d. CDD is the sum of CDD for each day within each period: $CDD_c = \sum_{d \in D_c} \max\{(x_d - 18.33), 0\}$. Daily Temperature Range in Each Period is calculated as $\frac{1}{n_c} \sum_{d \in c} \left(t_{d,max} - t_{d,min}\right)$, for the daily maximum and minimum temperatures $t_{d,max}$, $t_{d,min}$, respectively, and the number of days during c, n_c. Daily Range Squared in Each Period is calculated as $\frac{1}{n_c} \sum_{d \in c} \left(t_{d,max} - t_{d,min}\right)^2$. "Other baseline controls" include: village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; children's age, gender, and the number of siblings by birth order; indicators for month of birth; indicators for mother's age at delivery; indicators for mother's six education levels; asset score at wave 0; precipitation, sunshine and $PM_{2.5}$ during each period.

Table 5: Heterogeneous Effects by Subgroups

	Cognitive Score in Wave 2												
	Overall	Gender		Asset in Wave 0		Elevation $> 560m$		Born in Sep-Feb		Knowledge in Wave 0		Heating	
		Boy	Girl	$\geq$ Median	$<$ Median	Yes	No	Yes	No	$\geq$ Median	$<$ Median	Unclean	Clean
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
HDD/100, 2nd Year Before Birth	-0.091	0.037	-0.350	0.368	-0.324	-0.196	0.248	-0.210	-0.111	0.331	-0.385	0.315	0.529
	(0.158)	(0.199)	(0.301)	(0.235)	(0.280)	(0.276)	(0.214)	(0.316)	(0.525)	(0.259)	(0.296)	(0.402)	(0.883)
HDD/100, 1st Year Before Birth	-0.460*	-0.220	-0.534	-0.228	-0.376	-0.751†	-0.232	-0.620	0.174	0.167	-0.712†	0.017	0.002
	(0.213)	(0.312)	(0.450)	(0.377)	(0.498)	(0.394)	(0.275)	(0.398)	(0.540)	(0.357)	(0.394)	(0.565)	(1.161)
HDD/100, 1st Year After Birth	-0.861***	-0.709*	-0.587	-0.850**	-0.738	-1.126**	-0.518	-0.946*	-0.304	-0.722*	-0.871*	-0.649	-0.110
	(0.204)	(0.325)	(0.435)	(0.295)	(0.471)	(0.345)	(0.312)	(0.383)	(0.458)	(0.326)	(0.404)	(0.438)	(0.623)
HDD/100, 2nd Year After Birth	-0.595***	-0.850***	-0.377	-0.753**	-0.691*	-0.933***	-0.493†	-0.847**	-0.271	-0.535*	-0.216	-0.496	-0.505
	(0.168)	(0.249)	(0.269)	(0.234)	(0.308)	(0.230)	(0.270)	(0.305)	(0.414)	(0.234)	(0.349)	(0.315)	(0.411)
Other Baseline Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1245	645	600	627	618	613	632	672	573	620	619	434	298

Notes: † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in the parentheses are clustered at the village level. HDD is the sum of HDD for each day within each period c: $HDD_c = \sum_{d \in D_c} \max\{(18.33 - x_d), 0\}$, where x_d is the temperature in day d. "Other baseline controls" include: village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; children's age, gender, and the number of siblings by birth order; indicators for month of birth; indicators for mother's age at delivery; indicators for mother's six education levels; asset score at wave 0; precipitation, sunshine and $PM_{2.5}$ during each period.

Table 6: Panel Regressions of Home Environment on Last Year's Temperature

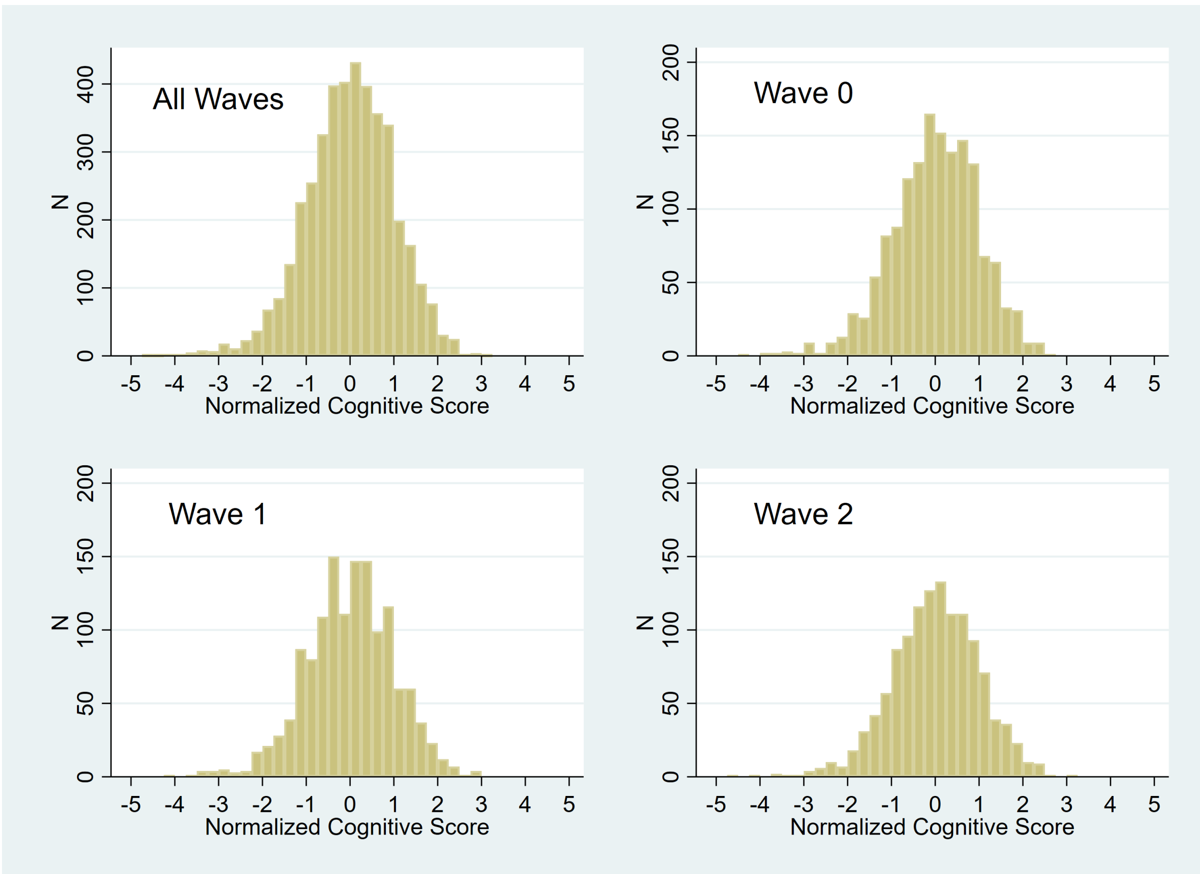
	Overall (1)	Activities (2)	Books and Toys (3)
HDD/100 in the Past 365 Days	-0.356* (0.176)	-0.295 (0.224)	-0.304† (0.172)
Village-Year FE, Individual FE, Age	✓	✓	✓
Year-Month, Day-of-Week	✓	✓	✓
Sunshine, Precipitation and $PM_{2.5}$	✓	✓	✓
Observations	4113	4120	4113

Notes: † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in the parentheses are clustered at the village level. HDD is the sum of HDD for each day within each period c: $HDD_c = \sum_{d \in D_c} \max\{(18.33 - x_d), 0\}$, where x_d is the temperature in day d.

Appendices

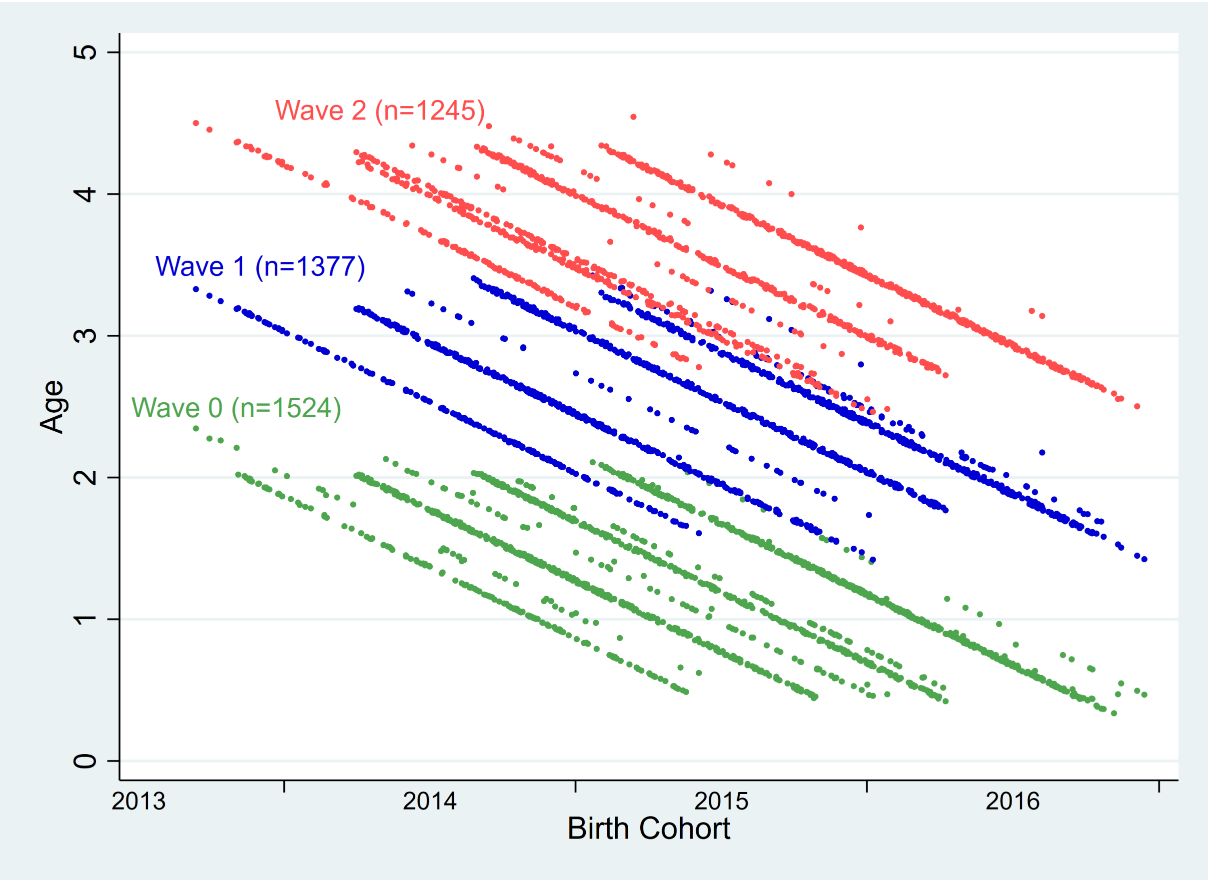
A Additional Figures and Tables

Figure A1: Distribution of Cognitive Scores in Each Wave



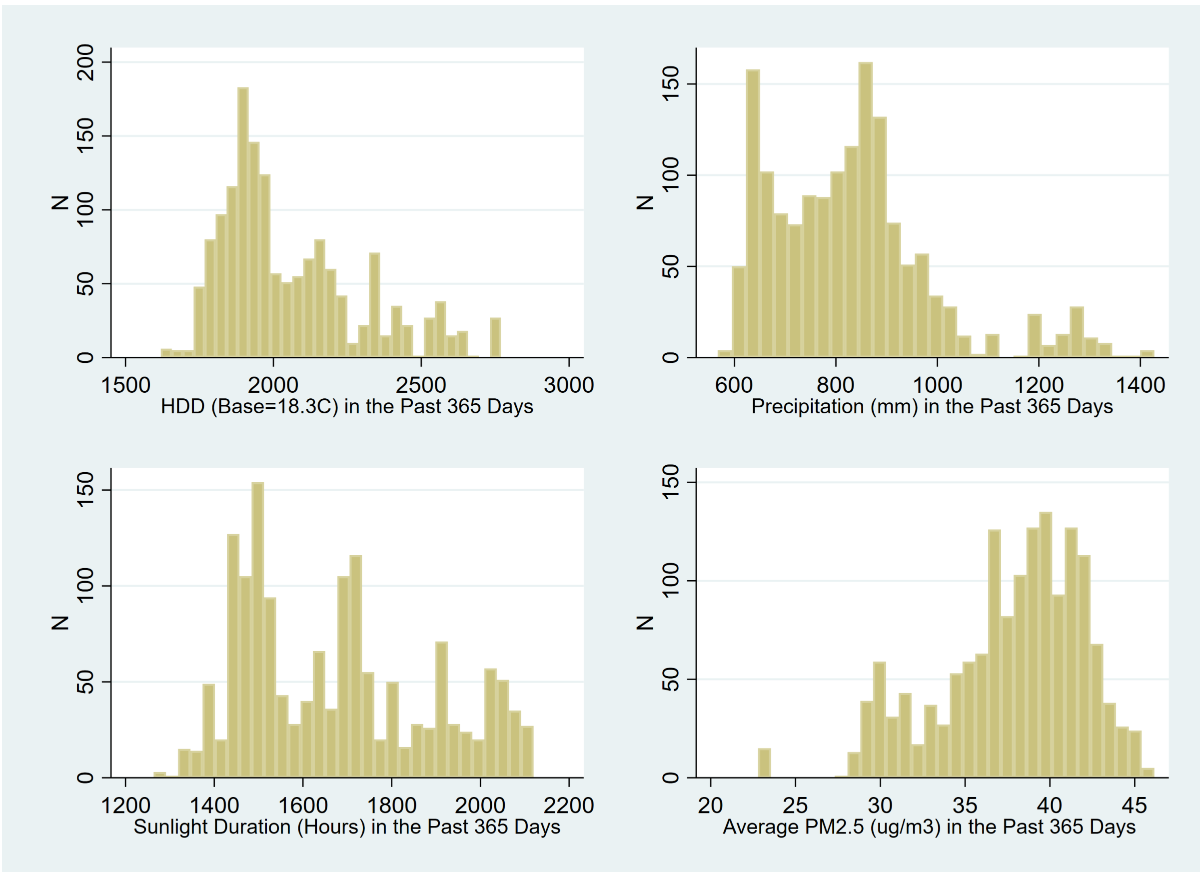
Notes: Cognitive scores are normalized within each month of age by wave.

Figure A2: Age and Birth Cohort in Each Wave



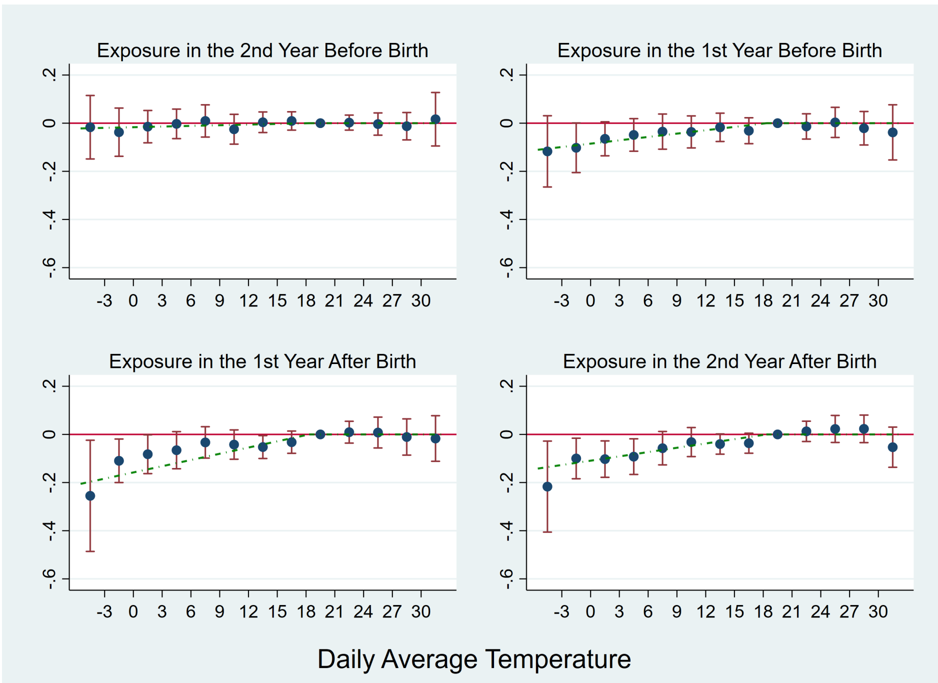
Notes: Each dot represents an observation.

Figure A3: Distribution of Other Weather Variables in Wave 2



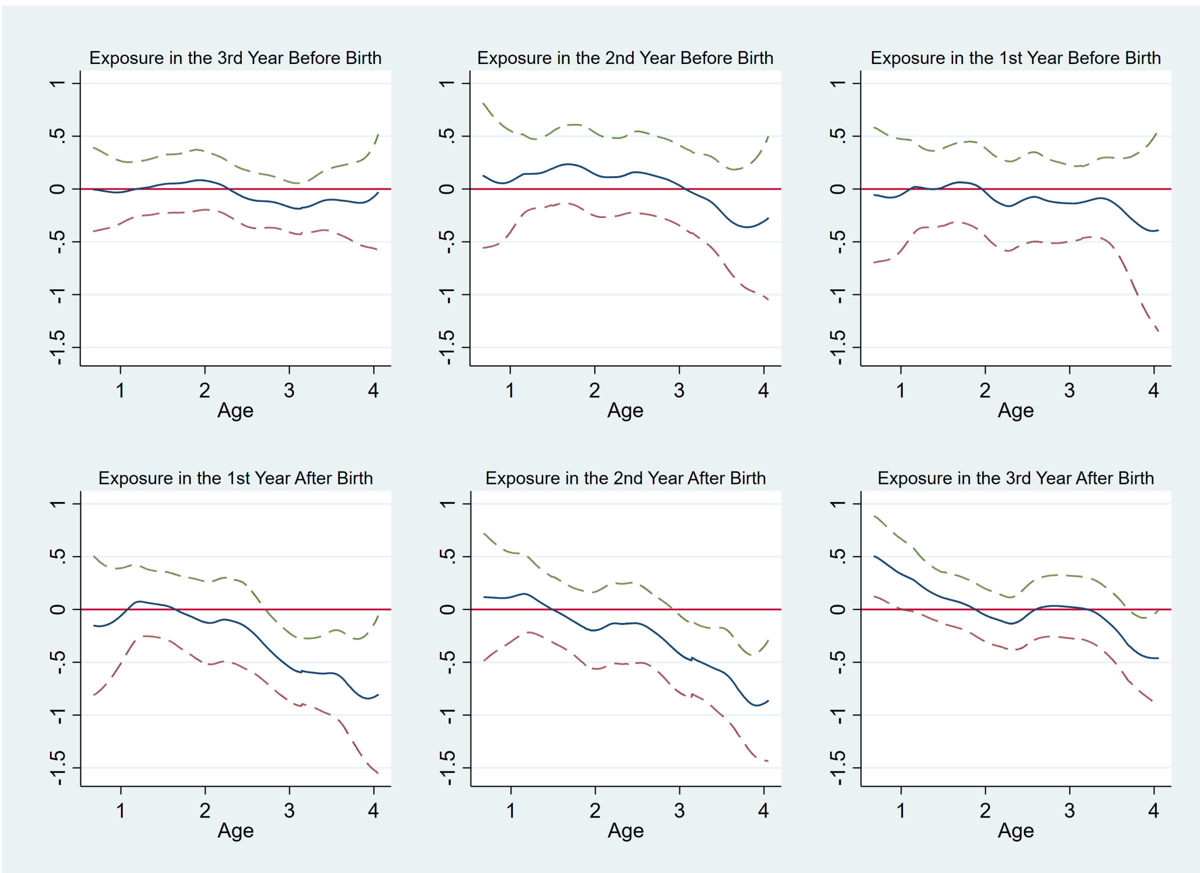
Notes: Bars represent the number of days in each range of weather variables during the 365 days prior to the interview date in wave 2 of the survey.

Figure A4: Effects of Ambient Temperature Exposure on Cognitive Skills in Early Childhood using Smaller Temperature Bins



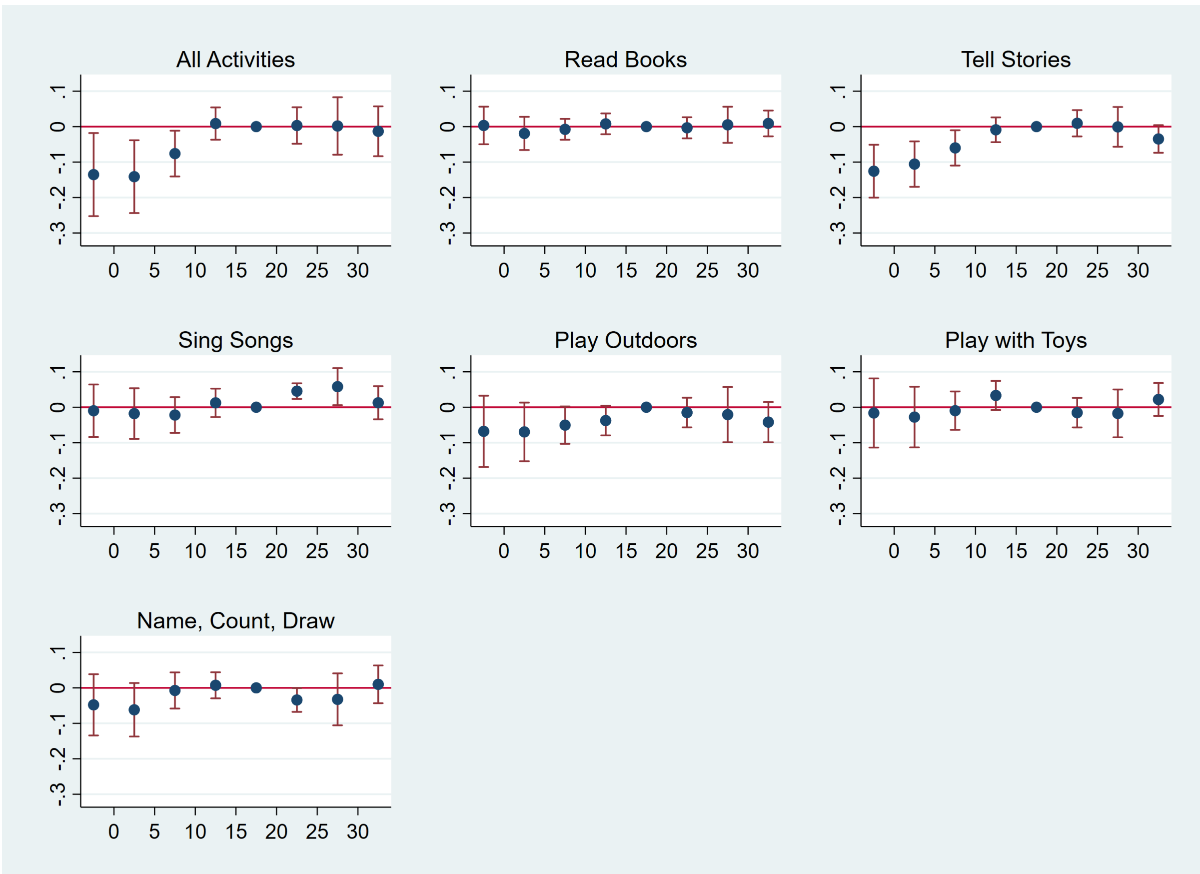
Notes: Error bars indicate 95% confidence intervals. Standard errors are clustered at the village level. Circles represent estimates based on equation (4). Dotted lines represent estimates of a linear spline model with a knot at 18.33°C and the slope on the right of the knot fixed at zero. Other control variables include: village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; children's age, gender, and the number of siblings by birth order; indicators for month of birth; indicators for mother's age at delivery; indicators for mother's six education levels; asset score at wave 0; indicators for having heating devices at home; precipitation, sunshine and $PM_{2.5}$ during each period.

Figure A5: Temperature Effects by Children's Age Covering Longer Time Period



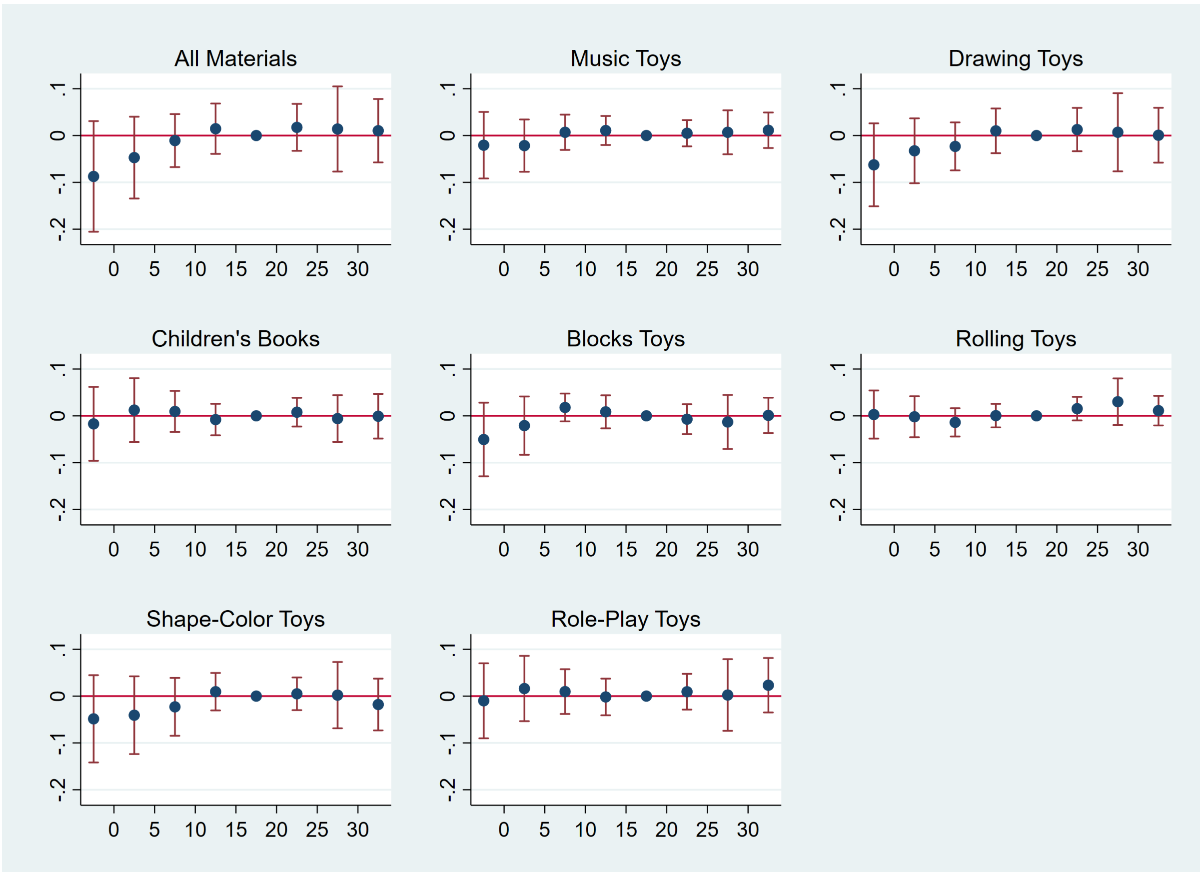
Notes: Dashed lines indicate 95% confidence intervals. Standard errors are clustered at the village level. Regressions are locally-weighted around each observation. Weights are calculated using tricube kernels with a relative bandwidth of 0.5. Y-Axis indicates the impacts of HDD/100 on cognitive scores. HDD is the sum of HDD for each day within each period: $HDD_c = \sum_{d \in D_c} \max\{(18.33 - x_d), 0\}$, where x_d is the temperature in day d. Other control variables include: village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; children's age, gender, and the number of siblings by birth order; indicators for month of birth; indicators for mother's age at delivery; indicators for mother's six education levels; asset score at wave 0; indicators for heating devices at home; precipitation, sunshine and $PM_{2.5}$ during each period.

Figure A6: Panel Regressions of Home Environment on Last Year's Temperature: Activities



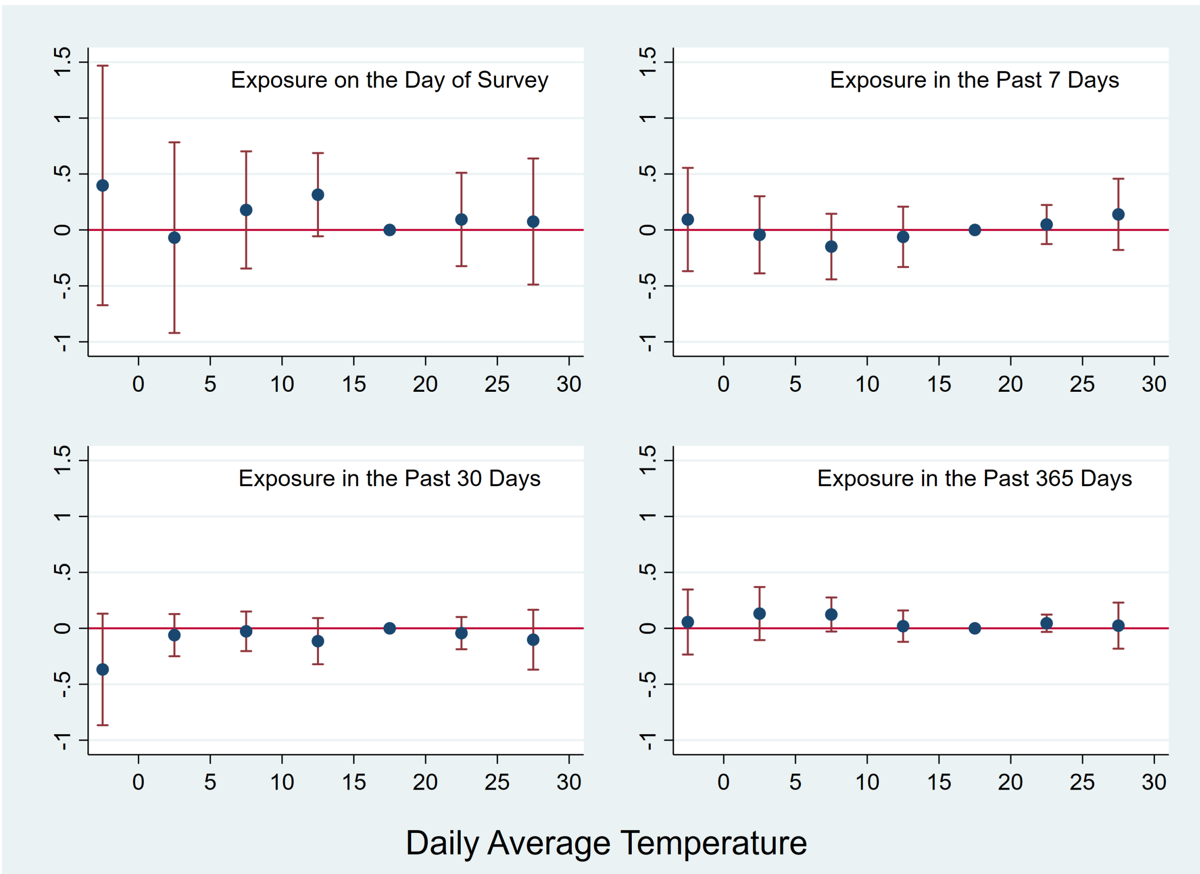
Notes: Each chart is a separate regression. Error bars indicate 95% confidence intervals. Standard errors are clustered at the village level. Coefficients indicate the association between cognitive score and one additional day of exposure to each of the following temperature categories: $\{T|T \leq 0\}$, $(0,5]$, $(5,10]$, $(10,15]$, $(15,20]$, $(25,30]$, $(30,\infty)$. Other control variables include: child fixed effects; wave fixed effects; village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; children's age, gender, and the number of siblings by birth order; precipitation, sunshine and $PM_{2.5}$ in the past 365 days.

Figure A7: Panel Regressions of Home Environment on Last Year's Temperature: Books and Toys



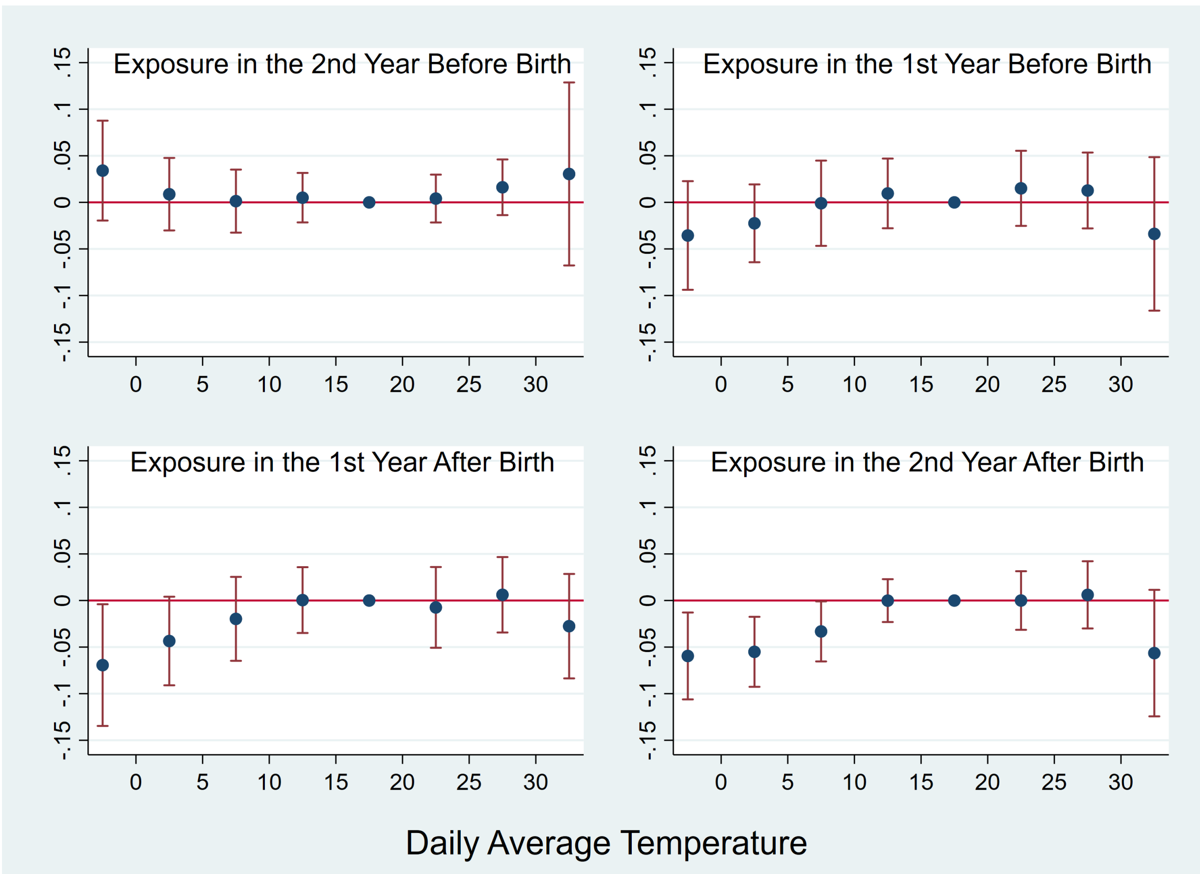
Notes: Each chart is a separate regression. Error bars indicate 95% confidence intervals. Standard errors are clustered at the village level. Coefficients indicate the association between cognitive score and one additional day of exposure to each of the following temperature categories: $\{T|T \leq 0\}$, $(0,5]$, $(5,10]$, $(10,15]$, $(15,20]$, $(25,30]$, $(30,\infty)$. Other control variables include: child fixed effects; wave fixed effects; village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; children's age, gender, and the number of siblings by birth order; precipitation, sunshine and $PM_{2.5}$ in the past 365 days.

Figure A8: Panel Regressions of Screen Time on Last Year's Temperature



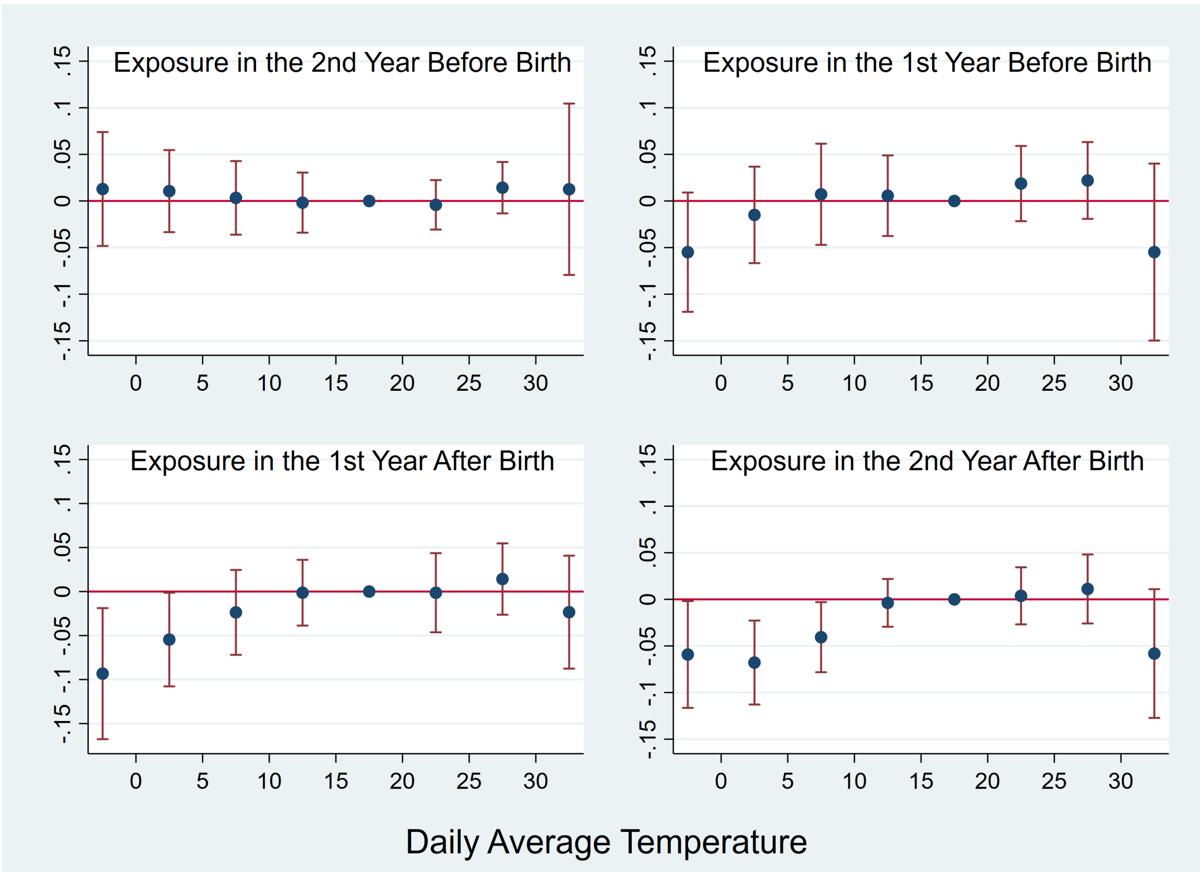
Notes: the coefficients in the four charts are from one regression. Error bars indicate 95% confidence intervals. Standard errors are clustered at the village level. Coefficients indicate the association between cognitive score and one additional day of exposure to each of the following temperature categories: $\{T|T \leq 0\}$, $(0,5]$, $(5,10]$, $(10,15]$, $(15,20]$, $(25,30]$, $(30,\infty)$. Other control variables include: child fixed effects; wave fixed effects; village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; children's age, gender, and the number of siblings by birth order; precipitation, sunshine and $PM_{2.5}$ during each period.

Figure A9: Temperature Effects with Alternative Control Variables (1)



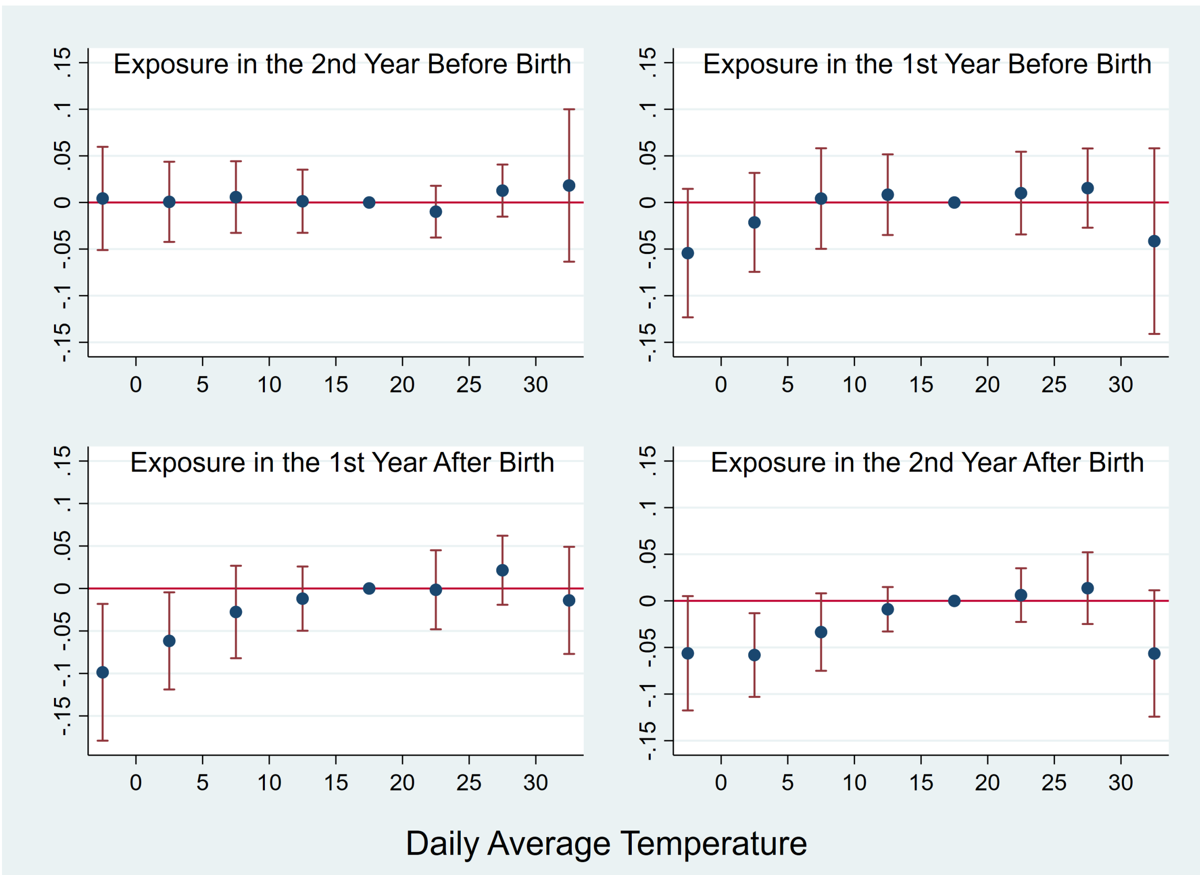
Notes: The figure shows estimates of equation (4), including village-by-year fixed effects as control variables. Error bars indicate 95% confidence intervals. Standard errors are clustered at the village level. Coefficients indicate the association between cognitive score and one additional day of exposure to each of the following temperature categories: $\{T|T \leq 0\}$, $(0,5]$, $(5,10]$, $(10,15]$, $(15,20]$, $(25,30]$, $(30,\infty)$. Control variables include village-by-year fixed effects.

Figure A10: Temperature Effects with Alternative Control Variables (2)



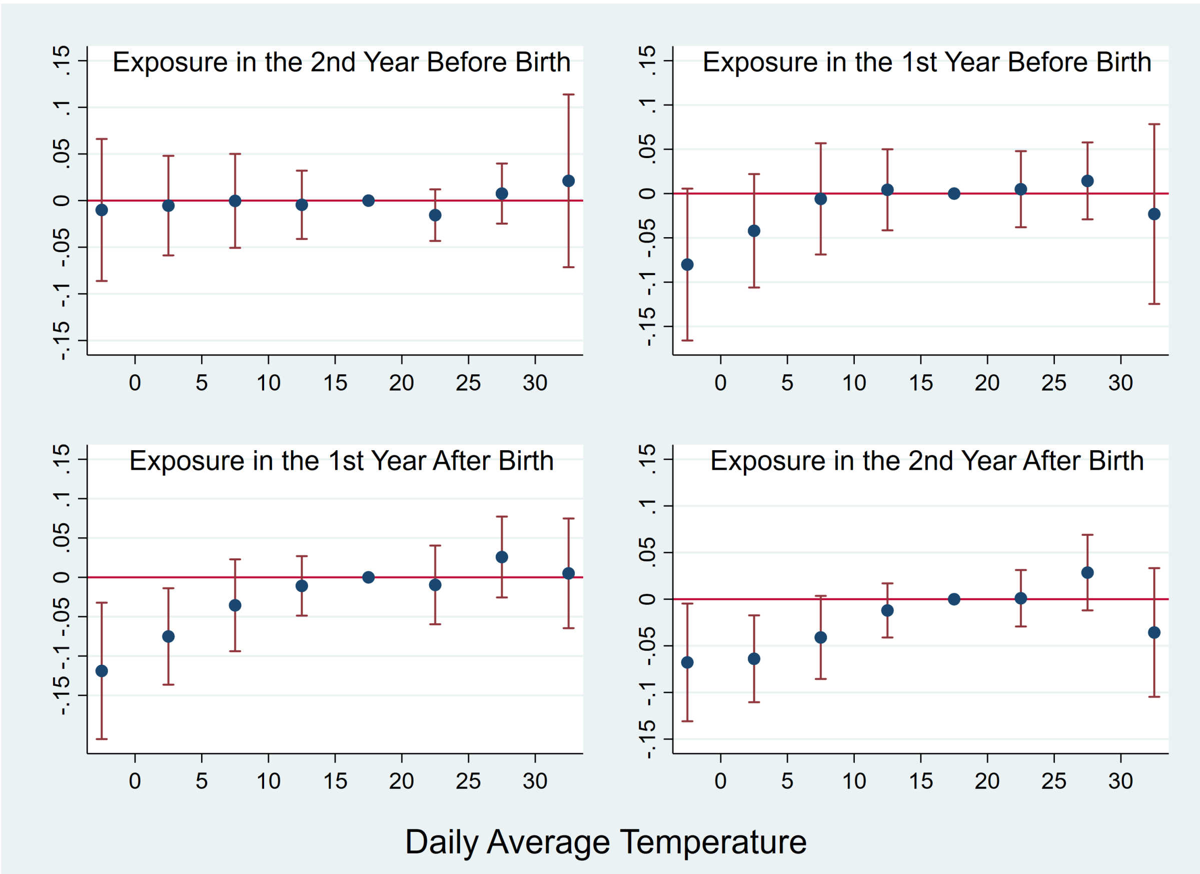
Notes: The figure shows estimates of equation (4), including (i) village-by-year fixed effects, (ii) year-by-month fixed effects, day-of-week fixed effects, and examiner fixed effects as control variables. Error bars indicate 95% confidence intervals. Standard errors are clustered at the village level. Coefficients indicate the association between cognitive score and one additional day of exposure to each of the following temperature categories: $\{T|T \leq 0\}$, $(0,5]$, $(5,10]$, $(10,15]$, $(15,20]$, $(25,30]$, $(30,\infty)$. Control variables include village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; and examiner fixed effects.

Figure A11: Temperature Effects with Alternative Control Variables (3)



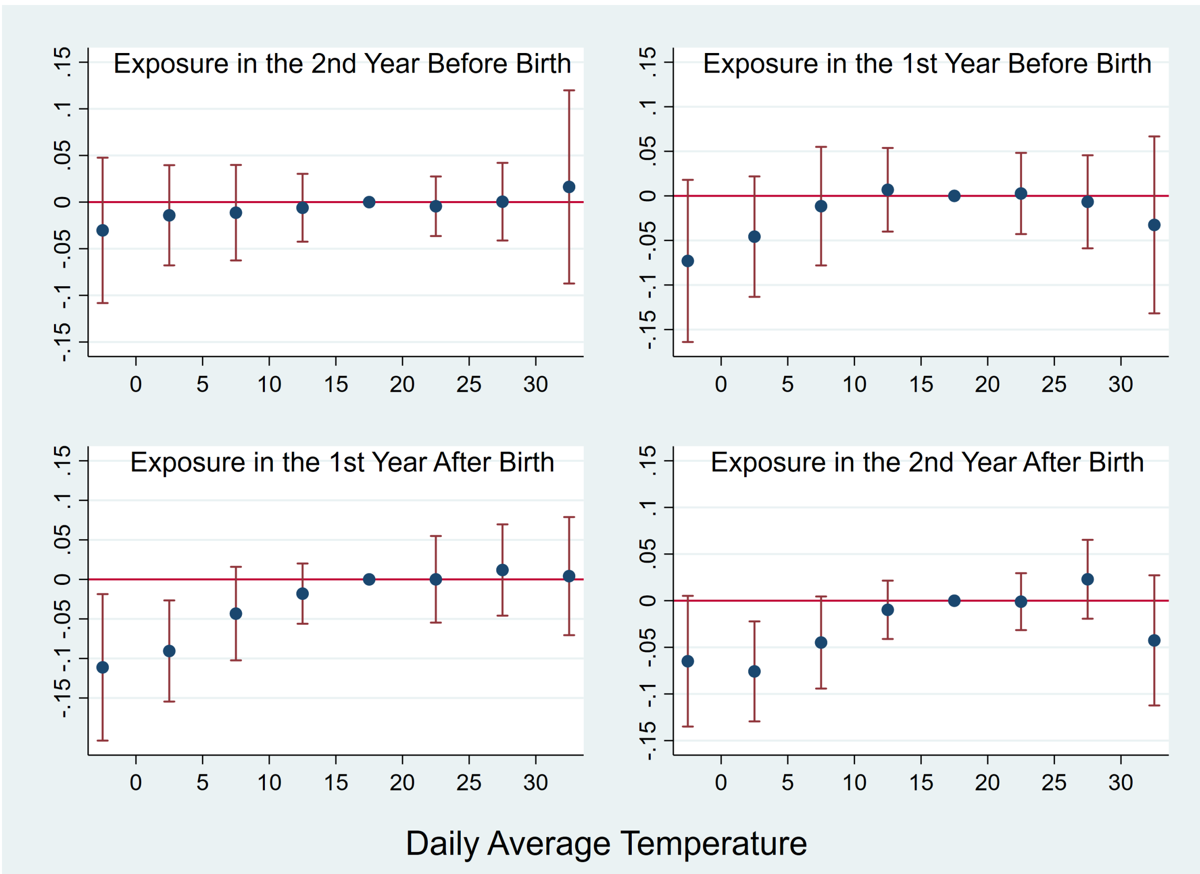
Notes: The figure shows estimates of equation (4), including (i) village-by-year fixed effects, (ii) year-by-month fixed effects, day-of-week fixed effects, examiner fixed effects, (iii) children's age, gender, sibling information, mother's education, household asset, and heating devices as control variables. Error bars indicate 95% confidence intervals. Standard errors are clustered at the village level. Coefficients indicate the association between cognitive score and one additional day of exposure to each of the following temperature categories: $\{T|T \leq 0\}$, $(0,5]$, $(5,10]$, $(10,15]$, $(15,20]$, $(25,30]$, $(30,\infty)$. Control variables include village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; children's age, gender, and the number of siblings by birth order; indicators for mother's six education levels; asset score at wave 0; and indicators for heating devices at home.

Figure A12: Temperature Effects with Alternative Control Variables (4)



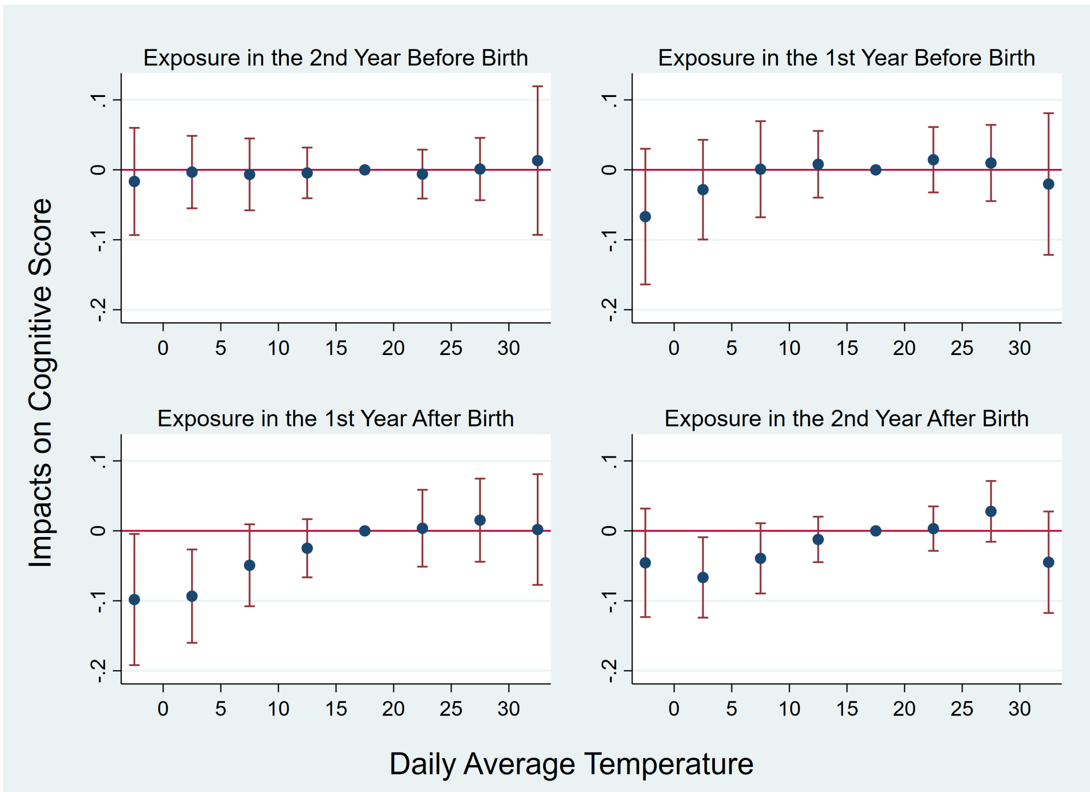
Notes: The figure shows estimates of equation (4), including (i) village-by-year fixed effects, (ii) year-by-month fixed effects, day-of-week fixed effects, examiner fixed effects, (iii) children's age, gender, sibling information, mother's education, household asset, heating devices, (iv) indicators for mother's age at delivery and month of childbirth as control variables. Error bars indicate 95% confidence intervals. Standard errors are clustered at the village level. Coefficients indicate the association between cognitive score and one additional day of exposure to each of the following temperature categories: $\{T|T \leq 0\}$, $(0,5]$, $(5,10]$, $(10,15]$, $(15,20]$, $(25,30]$, $(30,\infty)$. Control variables include village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; children's age, gender, and the number of siblings by birth order; indicators for mother's six education levels; asset score at wave 0; indicators for heating devices at home; indicators for month of childbirth; and indicators for mother's age at delivery.

Figure A13: Temperature Effects with Alternative Control Variables (5)



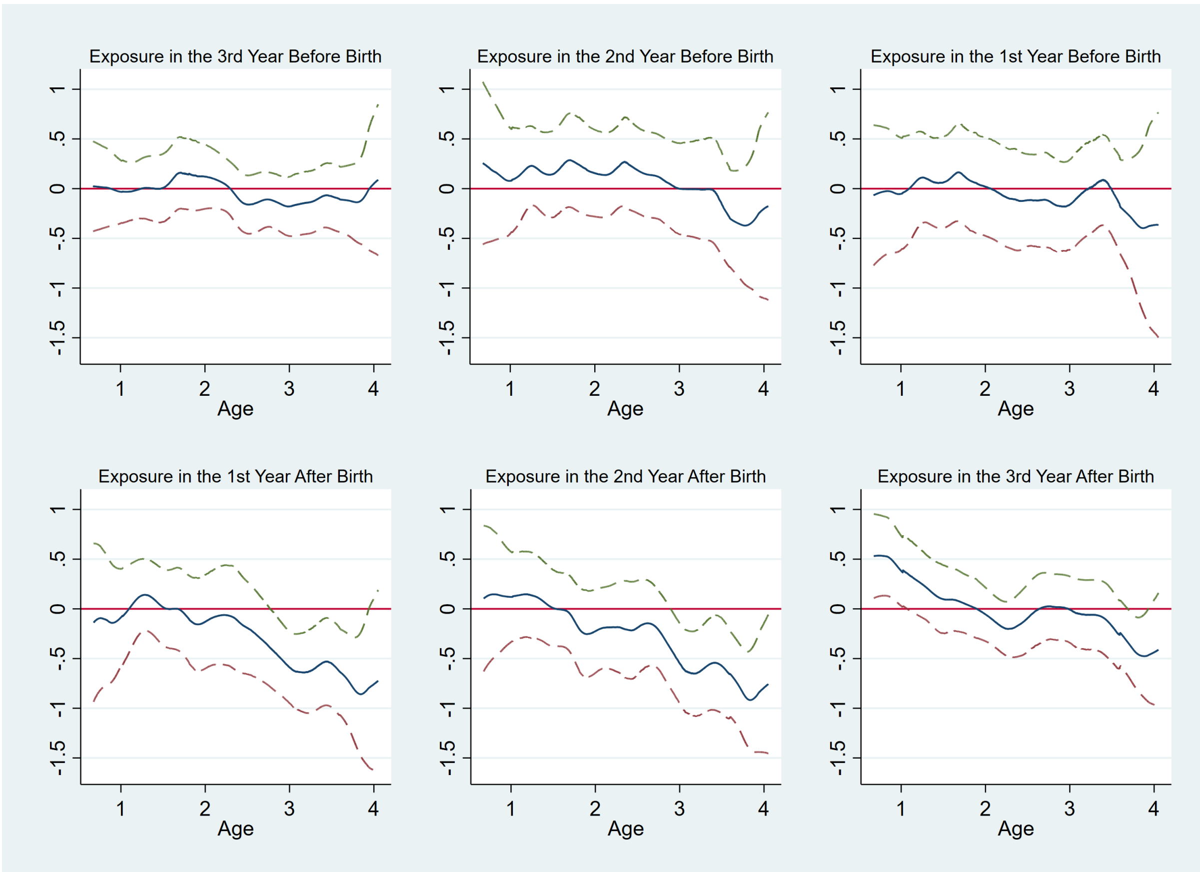
Notes: The figure shows estimates of equation (4), including (i) village-by-year fixed effects, (ii) year-by-month fixed effects, day-of-week fixed effects, examiner fixed effects, (iii) children's age, gender, sibling information, mother's education, household asset, heating devices, (iv) indicators for mother's age at delivery and month of childbirth, (v) precipitation, sunshine, and $PM_{2.5}$ as control variables. Error bars indicate 95% confidence intervals. Standard errors are clustered at the village level. Coefficients indicate the association between cognitive score and one additional day of exposure to each of the following temperature categories: $\{T|T \leq 0\}$, $(0,5]$, $(5,10]$, $(10,15]$, $(15,20]$, $(25,30]$, $(30,\infty)$. Control variables include village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; children's age, gender, and the number of siblings by birth order; indicators for month of birth; indicators for mother's age at delivery; indicators for mother's six education levels; asset score at wave 0; asset score at wave 0; indicators for heating devices at home; precipitation, sunshine and $PM_{2.5}$ during each period.

Figure A14: Temperature Effects with Alternative Control Variables (6)



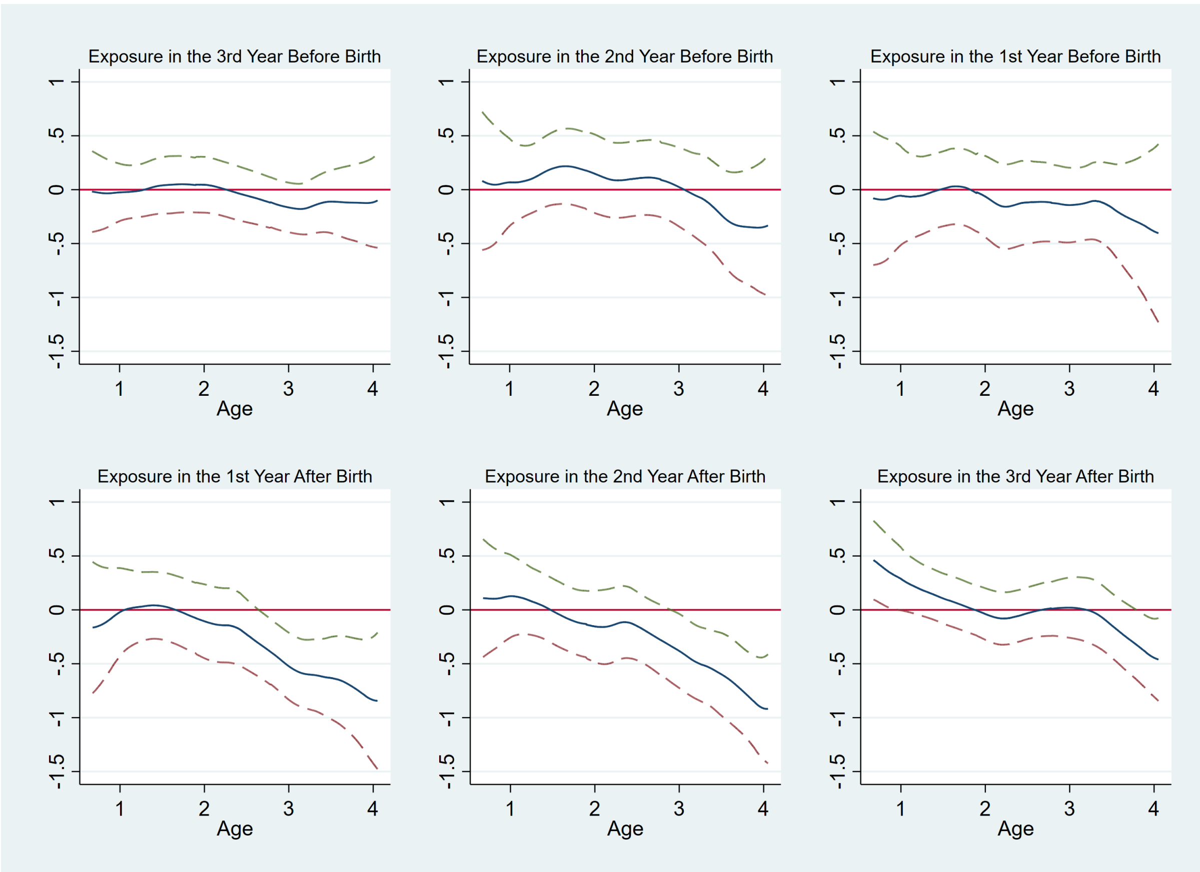
Notes: The figure shows estimates of equation (4), including (i) village-by-year fixed effects, (ii) year-by-month fixed effects, day-of-week fixed effects, examiner fixed effects, (iii) children's age, gender, sibling information, mother's education, household asset, heating devices, (iv) indicators for mother's age at delivery and month of childbirth, (v) precipitation, sunshine, and $PM_{2.5}$ as control variables. The model further includes (vi) Daily Temperature Range in Each Period and Temperature Range Squared in Each Period. Daily Temperature Range in Each Period is calculated as $\frac{1}{n_c}\sum_{d\in c}\left(t_{d,max}-t_{d,min}\right)$, for the daily maximum and minimum temperatures $t_{d,max}$, $t_{d,min}$, respectively, and the number of days during c, n_c. Daily Range Squared in Each Period is calculated as $\frac{1}{n_c}\sum_{d\in c}\left(t_{d,max}-t_{d,min}\right)^2$. Error bars indicate 95% confidence intervals. Standard errors are clustered at the village level.

Figure A15: Temperature Effects on Cognitive Skills by Children's Age Covering Longer Time Period: Bandwidth = 0.25



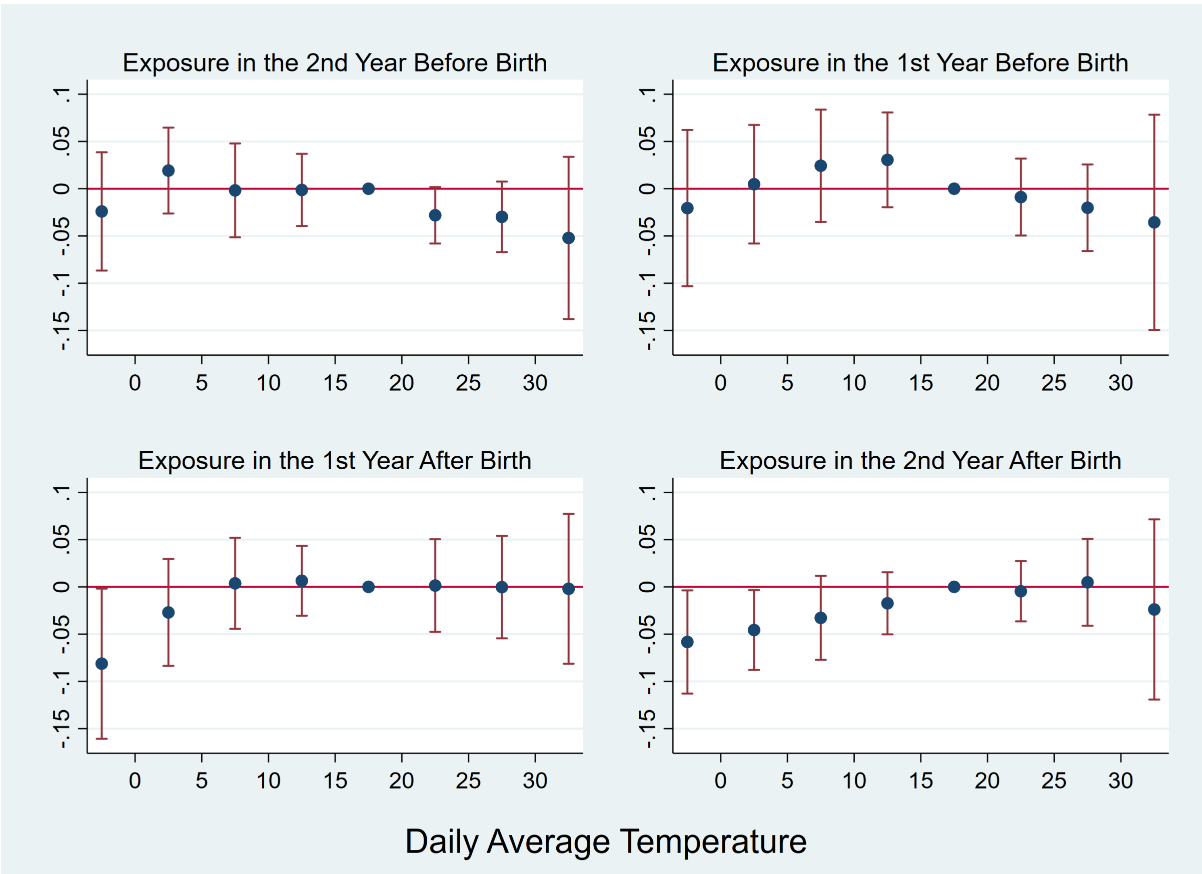
Notes: Dashed lines indicate 95% confidence intervals. Standard errors are clustered at the village level. Regressions are locally-weighted with tricube kernels around each observation. Y-Axis indicates the impacts of HDD/100 on cognitive scores. X-axis indicate the age in which the outcome is measured. HDD is the sum of HDD for each day within each period: $HDD_c = \sum_{d \in D_c} \max\{(18.33 - x_d), 0\}$, where x_d is the temperature in day d. Other control variables include: village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; children's age, gender, and the number of siblings by birth order; indicators for month of birth; indicators for mother's age at delivery; indicators for mother's six education levels; asset score at wave 0; indicators for heating devices at home; precipitation, sunshine and $PM_{2.5}$ during each period.

Figure A16: Temperature Effects on Cognitive Skills by Children's Age Covering Longer Time Period: Bandwidth = 0.75



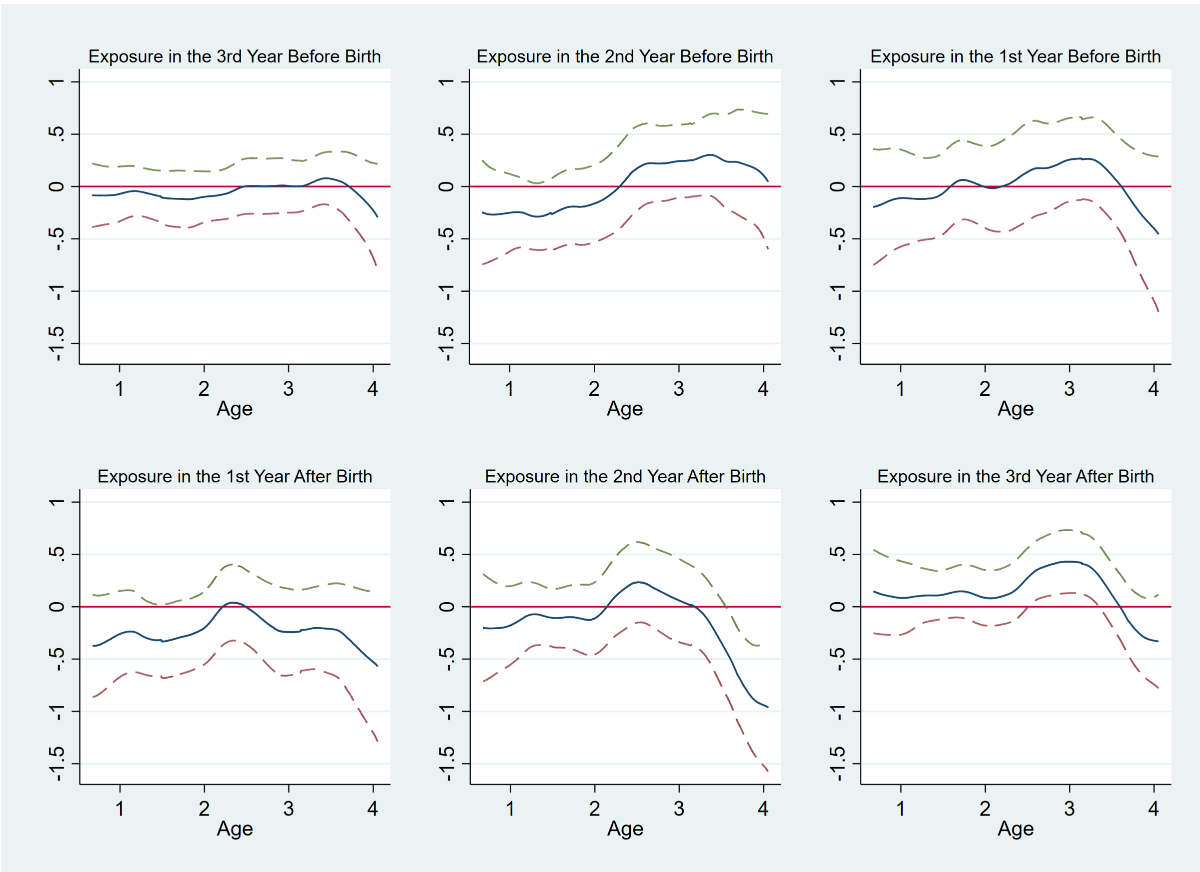
Notes: Dashed lines indicate 95% confidence intervals. Standard errors are clustered at the village level. Regressions are locally-weighted with tricube kernels around each observation. Y-Axis indicates the impacts of HDD/100 on cognitive scores. X-axis indicate the age in which the outcome is measured. HDD is the sum of HDD for each day within each period: $HDD_c = \sum_{d \in D_c} \max\{(18.33 - x_d), 0\}$, where x_d is the temperature in day d. Other control variables include: village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; children's age, gender, and the number of siblings by birth order; indicators for month of birth; indicators for mother's age at delivery; indicators for mother's six education levels; asset score at wave 0; indicators for heating devices at home; precipitation, sunshine and $PM_{2.5}$ during each period.

Figure A17: Effects of Ambient Temperature on Language Skills in Early Childhood



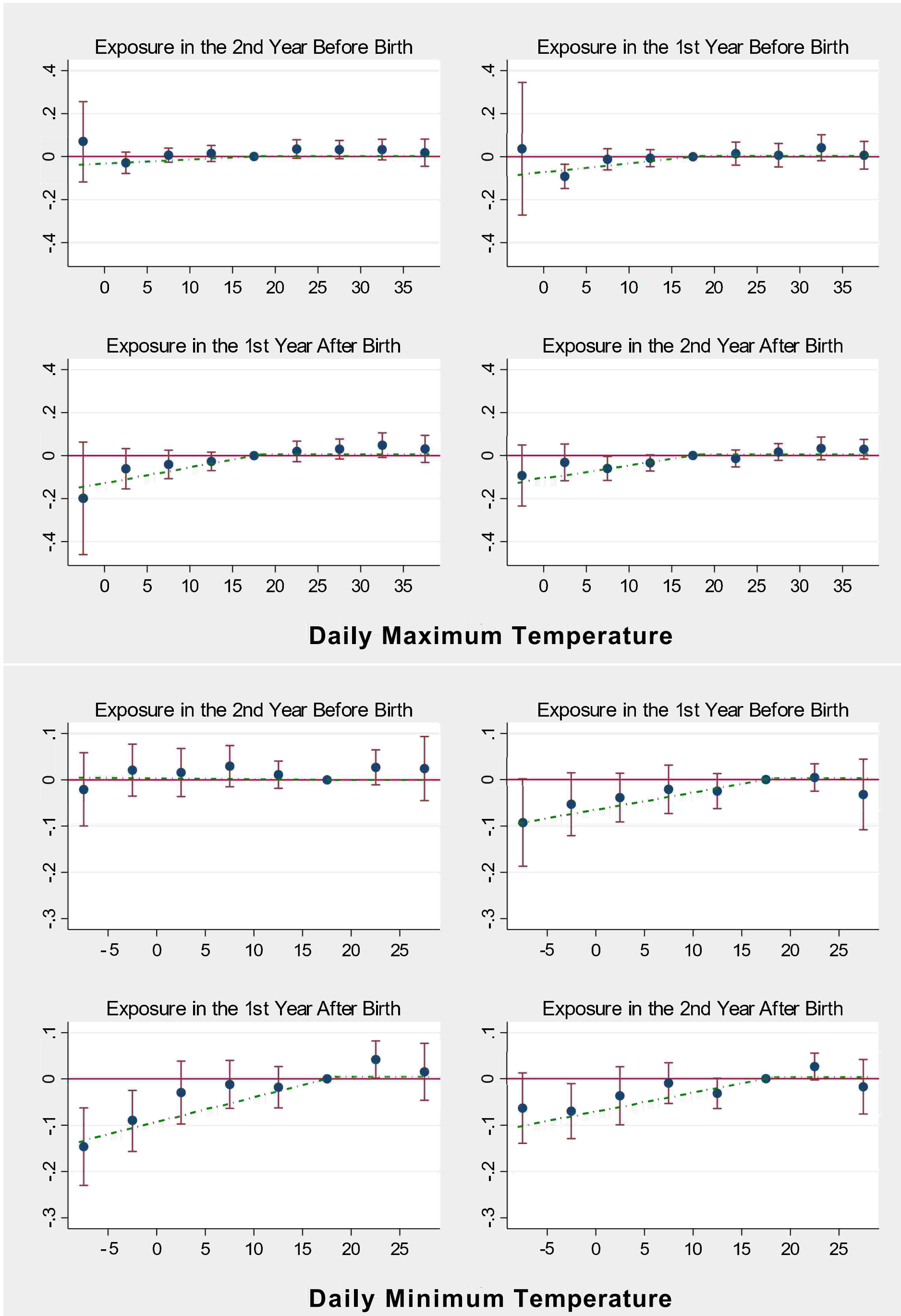
Notes: Error bars indicate 95% confidence intervals. Standard errors are clustered at the village level. Coefficients indicate the association between language score and one additional day of exposure to each of the following temperature categories: $\{T|T \leq 0\}$, $(0,5]$, $(5,10]$, $(10,15]$, $(15,20]$, $(25,30]$, $(30,\infty)$. Other control variables include: village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; children's age, gender, and the number of siblings by birth order; indicators for month of birth; indicators for mother's age at delivery; indicators for mother's six education levels; asset score at wave 0; indicators for heating devices at home; precipitation, sunshine and $PM_{2.5}$ during each period.

Figure A18: Temperature Effects on Language Skills by Children's Age Covering Longer Time Period



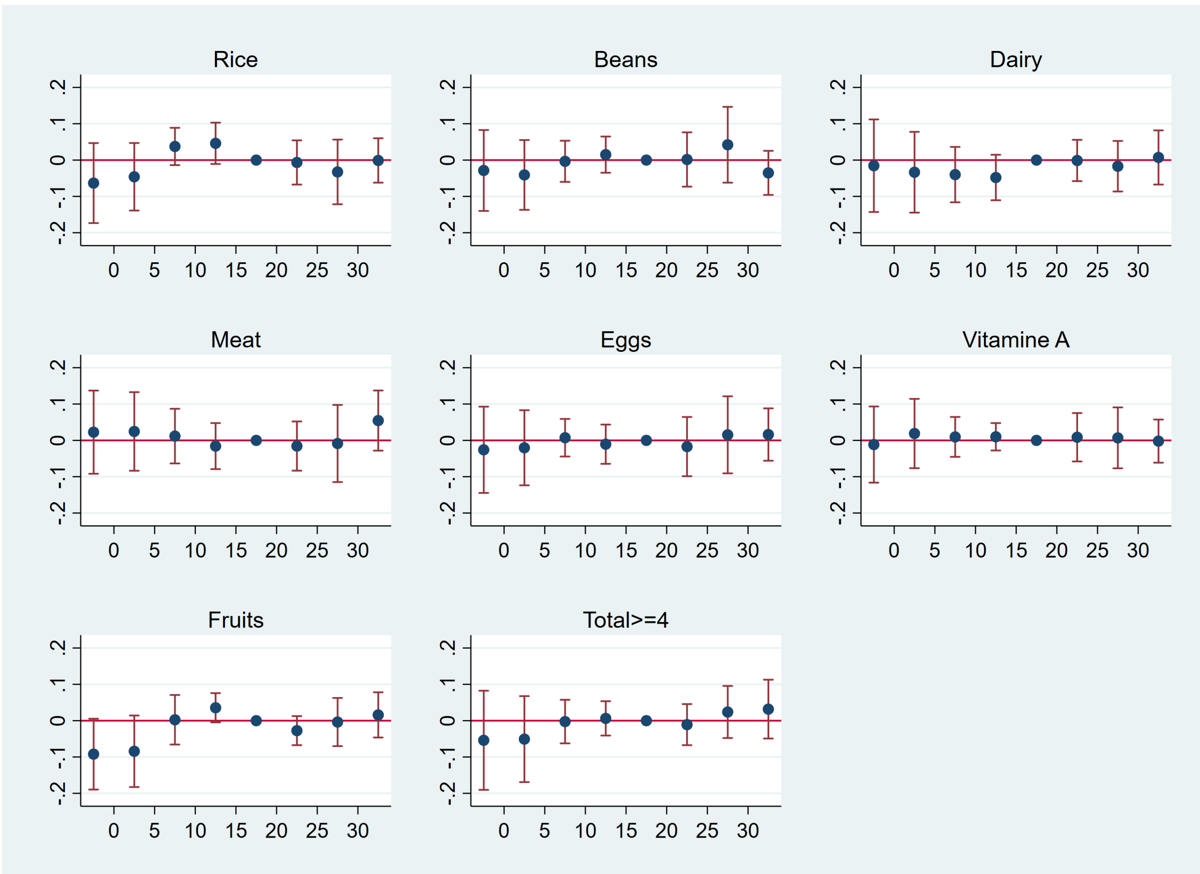
Notes: Dashed lines indicate 95% confidence intervals. Standard errors are clustered at the village level. Regressions are locally-weighted with tricube kernels and a relative bandwidth of 0.5 around each observation. Y-Axis indicates the impacts of HDD/100 on cognitive scores. X-axis indicate the age in which the outcome is measured. HDD is the sum of HDD for each day within each period: $HDD_c = \sum_{d \in D_c} \max\{(18.33 - x_d), 0\}$, where x_d is the temperature in day d. Other control variables include: village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; children's age, gender, and the number of siblings by birth order; indicators for month of birth; indicators for mother's age at delivery; indicators for mother's six education levels; asset score at wave 0; indicators for heating devices at home; precipitation, sunshine and $PM_{2.5}$ during each period.

Figure A19: Effects of Daily Maximum and Minimum Temperature on Cognitive Skills



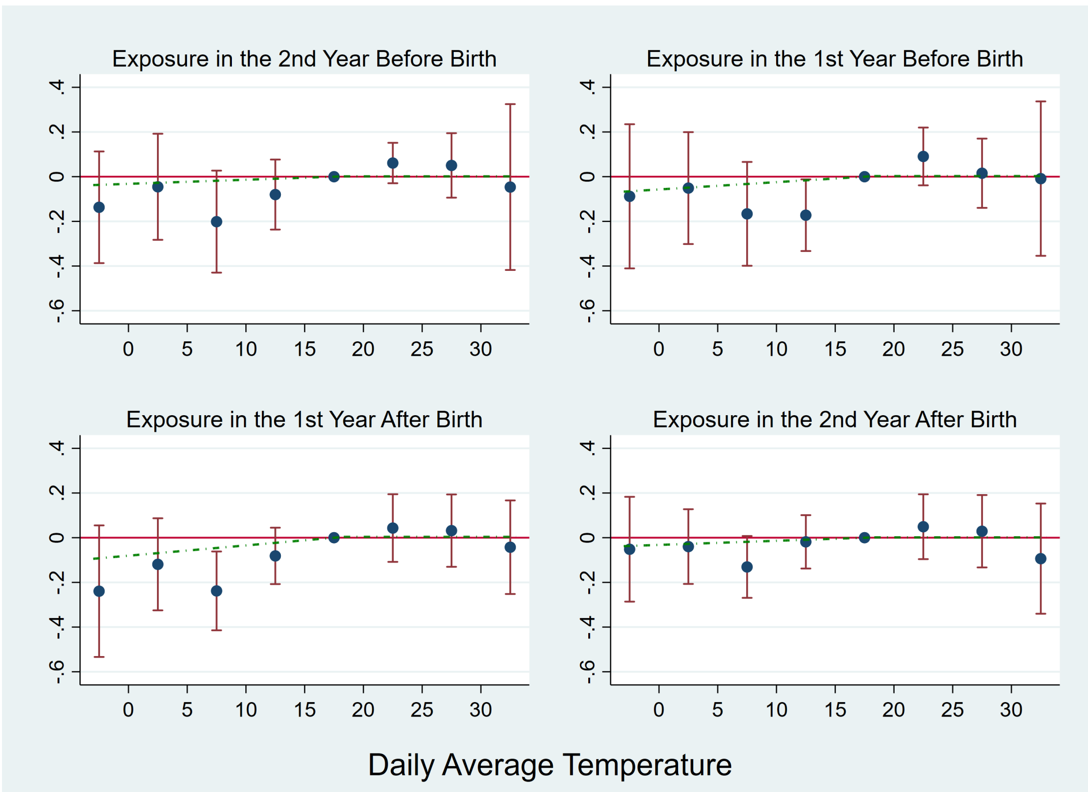
Notes: Error bars indicate 95% confidence intervals. Standard errors are clustered at the village level. Dotted lines represent estimates of a linear spline model with a knot at 18.33°C and the slope on the right of the knot fixed at zero. Other control variables include: village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; children's age, gender, and the number of siblings by birth order; indicators for month of birth; indicators for mother's age at delivery; indicators for mother's six education levels; asset score at wave 0; indicators for heating devices at home; precipitation, sunshine and $PM_{2.5}$ during each period.

Figure A20: Panel Regressions of Dietary Intake on Last Year's Temperature



Notes: Each chart is a separate regression. Error bars indicate 95% confidence intervals. Standard errors are clustered at the village level. Coefficients indicate the association between cognitive score and one additional day of exposure to each of the following temperature categories: $\{T|T \leq 0\}$, $(0,5]$, $(5,10]$, $(10,15]$, $(15,20]$, $(25,30]$, $(30,\infty)$. Other control variables include: child fixed effects; wave fixed effects; village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; children's age, gender, and the number of siblings by birth order; precipitation, sunshine and $PM_{2.5}$ during each period.

Figure A21: Effects of Daily Average Temperature on the Number of Sick Days during the Past Two Weeks



Notes: Error bars indicate 95% confidence intervals. Standard errors are clustered at the village level. Dotted lines represent estimates of a linear spline model with a knot at 18.33°C and the slope on the right of the knot fixed at zero. Other control variables include: village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; children's age, gender, and the number of siblings by birth order; indicators for month of birth; indicators for mother's age at delivery; indicators for mother's six education levels; asset score at wave 0; indicators for heating devices at home; precipitation, sunshine and $PM_{2.5}$ during each period.

Table A1: Temperature Effects by Children's Age

	Cognitive Score			
Age Restriction →	[0, 2]	[1, 3]	[2, 4]	[3, 5]
	(1)	(2)	(3)	(4)
HDD/100, 3rd Year Before Birth	-0.004	-0.012	-0.159	-0.150
	(0.113)	(0.115)	(0.108)	(0.181)
HDD/100, 2nd Year Before Birth	0.048	0.181	-0.024	-0.344
	(0.153)	(0.136)	(0.154)	(0.279)
HDD/100, 1st Year Before Birth	-0.176	-0.088	-0.121	-0.268
	(0.180)	(0.146)	(0.162)	(0.292)
HDD/100, 1st Year After Birth	-0.030	0.010	-0.441**	-0.681**
	(0.160)	(0.139)	(0.151)	(0.227)
HDD/100, 2nd Year After Birth	0.058	0.025	-0.347*	-0.809***
	(0.146)	(0.142)	(0.148)	(0.215)
HDD/100, 3rd Year After Birth	0.154	0.072	-0.066	-0.340*
	(0.110)	(0.117)	(0.122)	(0.160)
Other Baseline Controls	✓	✓	✓	✓
Observations	1740	2391	2164	1260

Notes: † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in the parentheses are clustered at the village level. HDD is the sum of HDD for each day within each period c: $HDD_c = \sum_{d \in D_c} \max\{(18.33 - x_d), 0\}$, where x_d is the temperature in day d. "Other baseline controls" include: village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; children's age and gender, and the number of siblings by birth order; indicators for month of birth; indicators for mother's age at delivery; indicators for mother's six education levels; asset score at wave 0; precipitation, sunshine and $PM_{2.5}$ during each period.

Table A2: Panel Regressions of Each Item in Home Environment on Last Year's Temperature

Panel A: Activities ($\{0,1\}$)	Read Books (1)	Tell Stories (2)	Sing Songs (3)	Play Outdoors (4)	Play with Toys (5)	Count, Name, Draw (6)
HDD/100 in the Past 365 Days	0.097 (0.140)	-0.384** (0.117)	-0.093 (0.162)	-0.171 (0.242)	0.137 (0.223)	-0.056 (0.236)
Sample Mean	0.332	0.290	0.451	0.743	0.637	0.560
Village-Year FE, Individual FE, Age	✓	✓	✓	✓	✓	✓
Year-Month, Day-of-Week	✓	✓	✓	✓	✓	✓
Sunshine, Percipitation and $PM_{2.5}$	✓	✓	✓	✓	✓	✓
Observations	4120	4120	4120	4120	4120	4120

Panel B: Toys and Books ($\{0,1\}$)	Music Toys (12)	Drawing Toys (13)	Books (14)	Blocks Toys (15)	Rolling Toys (16)	Shapes & Colors (17)	Role-Play Toys (18)
HDD/100 in the Past 365 Days	0.031 (0.146)	-0.231 (0.169)	-0.257† (0.137)	-0.072 (0.131)	-0.038 (0.094)	-0.024 (0.141)	-0.255 (0.169)
Sample Mean	0.809	0.508	0.566	0.601	0.916	0.636	0.708
Other Controls in Panel A	✓	✓	✓	✓	✓	✓	✓
Observations	4121	4119	4120	4120	4120	4114	4120

Notes: † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in the parentheses are clustered at the village level. HDD is the sum of HDD for each day within each period c: $HDD_c = \sum_{d \in D_c} \max\{(18.33 - x_d), 0\}$, where x_d is the temperature in day d.

Table A3: Temperature's Effects on Home Environment: Subgroup Heterogeneity Effects

Panel A: Overall Home Score													
	Overall	Gender		Asset in Wave 0		Elevation > 560m		Born in Sep-Feb		Knowledge in Wave 0		Heating	
		Boy	Girl	≥ Median	< Median	Yes	No	Yes	No	≥ Median	< Median	Unclean	Clean
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
HDD/100 in the Past 365 Days	-0.354*	-0.407	-0.254	-0.776***	0.083	-0.481	-0.487*	-0.435†	-0.360	-0.339	-0.373	-0.290	-0.181
	(0.176)	(0.284)	(0.356)	(0.199)	(0.308)	(0.454)	(0.233)	(0.233)	(0.455)	(0.296)	(0.432)	(0.401)	(0.408)
Village-Year FE, Individual FE, Age	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year-Month, Day-of-Week	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sunshine, Percipitation and $PM_{2.5}$	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	4113	2106	2007	2055	2057	2061	2052	2212	1901	2048	2045	1364	926
Panel B: Activities													
	Overall	Gender		Asset in Wave 0		Elevation > 560m		Born in Sep-Feb		Knowledge in Wave 0		Heating	
		Boy	Girl	≥ Median	< Median	Yes	No	Yes	No	≥ Median	< Median	Unclean	Clean
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
HDD/100 in the Past 365 Days	-0.290	-0.534†	0.139	-0.558*	0.054	-1.061*	-0.295	-0.322	-0.399	-0.340	-0.274	0.003	-0.084
	(0.224)	(0.285)	(0.354)	(0.265)	(0.288)	(0.525)	(0.285)	(0.292)	(0.508)	(0.352)	(0.377)	(0.451)	(0.451)
Other Controls in Panel A	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	4120	2108	2012	2059	2060	2063	2057	2217	1903	2050	2050	1366	928
Panel C: Toys and Books													
	Overall	Gender		Asset in Wave 0		Elevation > 560m		Born in Sep-Feb		Knowledge in Wave 0		Heating	
		Boy	Girl	≥ Median	< Median	Yes	No	Yes	No	≥ Median	< Median	Unclean	Clean
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
HDD/100 in the Past 365 Days	-0.304†	-0.203	-0.468	-0.669*	-0.004	0.138	-0.524*	-0.361	-0.274	-0.214	-0.368	-0.532	-0.189
	(0.171)	(0.293)	(0.316)	(0.273)	(0.294)	(0.482)	(0.200)	(0.265)	(0.324)	(0.298)	(0.386)	(0.353)	(0.347)
Other Controls in Panel A	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	4113	2106	2007	2055	2057	2061	2052	2212	1901	2048	2045	1364	926

Notes: † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in the parentheses are clustered at the village level. HDD is the sum of HDD for each day within each period c: $HDD_c = \sum_{d \in D_c} \max\{(18.33 - x_d), 0\}$, where x_d is the temperature in day d.

Table A4: Attrition Probabilities in Wave 2

	Dependent Variable = Attrition in Wave 2 (Mean = 0.183)			
	(1)	(2)	(3)	(4)
Cognitive Score in Wave 0	0.005	0.002	0.007	0.007
	(0.010)	(0.010)	(0.012)	(0.012)
Age in Wave 0		0.032	0.041	0.115
		(0.024)	(0.025)	(0.193)
Female		0.021	0.027	0.027
		(0.021)	(0.023)	(0.023)
Siblings in Wave 0		-0.068*	-0.067*	-0.067*
		(0.029)	(0.030)	(0.030)
Asset in Wave 0		-0.022†	-0.019	-0.018
		(0.013)	(0.014)	(0.014)
Mother: 4-Year Degree		0.128	0.142	0.128
		(0.094)	(0.099)	(0.101)
Mother: Associate Degree		0.040	0.041	0.037
		(0.053)	(0.056)	(0.056)
Mother: High School		0.026	0.021	0.020
		(0.036)	(0.034)	(0.035)
Mother: Middle School (Reference)				
Mother: Primary School		-0.009	-0.035	-0.036
		(0.030)	(0.032)	(0.033)
Mother: No Schooling		-0.031	-0.012	-0.004
		(0.072)	(0.072)	(0.073)
HDD/100, 2nd Year Before Birth				-0.035
				(0.046)
HDD/100, 1st Year Before Birth				0.023
				(0.064)
HDD/100, 1st Year After Birth				0.017
				(0.055)
HDD/100, 2nd Year After Birth				-0.032
				(0.043)
Joint F-Stat for All Educational Levels		0.6	0.9	0.8
p-Value		[0.690]	[0.481]	[0.524]
Month of Birth FE, Mother's Age Indicators		✓	✓	✓
Village-Year FE			✓	✓
Year-Month, Day-of-Week, Examiner FE			✓	✓
Sunchine, Precipitation and $PM_{2.5}$ in Each Period				✓
Observations	1524	1523	1523	1523

Notes: † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in the parentheses are clustered at the village level. HDD is the sum of HDD for each day within each period c: $HDD_c = \sum_{d \in D_c} \max\{(18.33 - x_d), 0\}$, where x_d is the temperature in day d.

Table A5: Robustness to Alternative Inverse-Probability Weights

	Cognitive Score in Wave 2		
	(1, Baseline)	(2)	(3)
HDD/100, 2nd Year Before Birth	-0.091	-0.041	-0.065
	(0.158)	(0.155)	(0.155)
HDD/100, 1st Year Before Birth	-0.464*	-0.396*	-0.437*
	(0.214)	(0.193)	(0.194)
HDD/100, 1st Year After Birth	-0.862***	-0.845***	-0.778***
	(0.204)	(0.190)	(0.197)
HDD/100, 2nd Year After Birth	-0.595***	-0.621***	-0.558**
	(0.168)	(0.161)	(0.167)
Baseline Controls and FE	✓	✓	✓
Weights Predicted by Wave-0 Child Variables		✓	✓
And by Village-Year FE			✓
Observations	1245	1245	1245

Notes: † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in the parentheses are clustered at the village level. HDD is the sum of HDD for each day within each period c: $HDD_c = \sum_{d \in D_c} \max\{(18.33 - x_d), 0\}$, where x_d is the temperature in day d.

Table A6: Randomness Check: Timing of the Survey Day for Each Child

	HDD on the Day of			
	t-2	t-1	Survey (t)	t+1
	(1)	(2)	(3)	(4)
Cognitive Score in Wave 0	0.001	-0.013	-0.022	-0.032
	(0.024)	(0.024)	(0.020)	(0.026)
Age	0.079	0.089	0.059	0.055
	(0.097)	(0.081)	(0.059)	(0.073)
Female	0.048	-0.031	-0.064	-0.043
	(0.049)	(0.046)	(0.039)	(0.054)
Siblings	0.067	0.068	0.082	-0.104
	(0.080)	(0.074)	(0.059)	(0.077)
Asset in Wave 0	-0.018	0.024	0.011	-0.040
	(0.037)	(0.034)	(0.022)	(0.038)
Mother: 4-Year Degree	-0.040	-0.059	-0.039	-0.361*
	(0.150)	(0.112)	(0.085)	(0.169)
Mother: Associate Degree	-0.061	-0.008	-0.088	-0.153
	(0.107)	(0.101)	(0.117)	(0.221)
Mother: High School	0.013	0.029	0.119†	-0.075
	(0.065)	(0.066)	(0.062)	(0.056)
Mother: Middle School (Reference)				
Mother: Primary School	-0.169	-0.001	0.004	-0.065
	(0.121)	(0.069)	(0.063)	(0.086)
Mother: No Schooling	-0.012	0.274*	0.018	0.097
	(0.107)	(0.126)	(0.092)	(0.122)
Joint F-Stat for All Educational Levels	0.6	1.1	0.9	1.4
p-Value	[0.735]	[0.367]	[0.467]	[0.221]
Month of Birth FE and Mother's Age Dummies	✓	✓	✓	✓
Village-Year FE	✓	✓	✓	✓
Year-Month, Day-of-Week, Examiner FE	✓	✓	✓	✓
Observations	1245	1245	1245	1245

Notes: † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in the parentheses are clustered at the village level. HDD is the sum of HDD for each day within each period c: $HDD_c = \sum_{d \in D_c} \max\{(18.33 - x_d), 0\}$, where x_d is the temperature in day d.

Table A7: Randomness Check: HDD in Each Period

	HDD/100			
	2nd Year Before Birth (1)	1st Year Before Birth (2)	1st Year After Birth (3)	2nd Year After Birth (4)
Mother: 4-Year Degree	-0.121	-0.102	0.053	-0.063
	(0.135)	(0.084)	(0.052)	(0.071)
Mother: Associate Degree	0.022	0.018	-0.005	0.081
	(0.062)	(0.054)	(0.040)	(0.062)
Mother: High School	-0.009	-0.030	0.038	-0.017
	(0.038)	(0.020)	(0.024)	(0.031)
Mother: Middle School (Reference)				
Mother: Primary School	0.008	0.013	-0.023	0.048
	(0.040)	(0.025)	(0.022)	(0.043)
Mother: No Schooling	-0.002	0.044	-0.091	0.126
	(0.093)	(0.050)	(0.060)	(0.124)
Joint F-Stat for All Educational Levels	0.2	1.2	1.3	1.0
p-value	[0.952]	[0.314]	[0.263]	[0.408]
Village-Year FE, Examiner FE	✓	✓	✓	✓
Year-Month, Day-of-Week of Survey	✓	✓	✓	✓
Observations	1245	1245	1245	1245

Notes: † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in the parentheses are clustered at the village level. HDD is the sum of HDD for each day within each period c: $HDD_c = \sum_{d \in D_c} \max\{(18.33 - x_d), 0\}$, where x_d is the temperature in day d.

Table A8: Association between Parents' Migration for Work and Children's Temperature Exposure

	Migration for Work in Wave 0			
	Father		Mother	
Across Border of →	County (1)	Province (2)	County (3)	Province (4)
HDD/100, 2nd Year Before Birth	0.001 (0.069)	0.013 (0.070)	0.012 (0.056)	0.014 (0.053)
HDD/100, 1st Year Before Birth	-0.102 (0.096)	-0.123 (0.088)	-0.052 (0.074)	-0.066 (0.071)
HDD/100, 1st Year After Birth	0.026 (0.101)	-0.084 (0.096)	0.058 (0.056)	0.046 (0.056)
HDD/100, 2nd Year Before Birth	-0.092 (0.059)	-0.057 (0.055)	0.057 (0.042)	0.023 (0.040)
Other Baseline Controls	✓	✓	✓	✓
Observations	1235	1235	1237	1237

Notes: † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in the parentheses are clustered at the village level. The sample is restricted to children in wave 2. Migration for work is defined as reporting a cross-county/province job location and being absent from home for at least two months in the last year. HDD is the sum of HDD for each day within each period c: $HDD_c = \sum_{d \in D_c} \max\{(18.33 - x_d), 0\}$, where x_d is the temperature in day d.

Table A9: Other Robustness Checks

	Cognitive Score in Wave 2			
	Baseline Minus Heating Indicators	Baseline	Baseline + Primary Caregiver	Baseline + Daycare Visits
	(1)	(2)	(3)	(4)
HDD/100, 2nd Year Before Birth	-0.083	-0.092	-0.092	-0.071
	(0.154)	(0.158)	(0.160)	(0.155)
HDD/100, 1st Year Before Birth	-0.428*	-0.463*	-0.470*	-0.394†
	(0.209)	(0.214)	(0.216)	(0.215)
HDD/100, 1st Year After Birth	-0.821***	-0.860***	-0.869***	-0.847***
	(0.205)	(0.204)	(0.209)	(0.205)
HDD/100, 2nd Year After Birth	-0.592***	-0.594***	-0.590***	-0.585***
	(0.169)	(0.168)	(0.169)	(0.166)
Other Baseline Controls	✓	✓	✓	✓
Observations	1245	1245	1245	1245

Notes: † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in the parentheses are clustered at the village level. HDD is the sum of HDD for each day within each period c: $HDD_c = \sum_{d \in D_c} \max\{(18.33 - x_d), 0\}$, where x_d is the temperature in day d. "Other baseline controls" include: village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; children's age, gender, and the number of siblings by birth order; indicators for month of birth; indicators for mother's age at delivery; indicators for mother's six education levels; asset score at wave 0; precipitation, sunshine and $PM_{2.5}$ during each period. Column (3) adds a set of indicators for the primary caregiver being the mother (n=651); father (n=49); paternal grandparents (n=493); maternal grandparents (n=36); and others (n=16). Column (4) adds a variable for the number of visits to teh daycare cetners as of wave 2 survey.

Table A10: Robustness to Alternative Base Temperature for HDD

	Cognitive Score in Wave 2				
Base Temp. of HDD →	$20°C$ (1)	$18.3°C$ ($65°F$) (2, Baseline)	$15°C$ (3)	$10°C$ (4)	$5°C$ (5)
HDD/100, 2nd Year Before Birth	-0.080 (0.148)	-0.091 (0.158)	-0.147 (0.170)	-0.137 (0.203)	-0.433 (0.370)
HDD/100, 1st Year Before Birth	-0.436* (0.199)	-0.464* (0.214)	-0.516* (0.227)	-0.474† (0.270)	-0.572 (0.381)
HDD/100, 1st Year After Birth	-0.787*** (0.190)	-0.862*** (0.204)	-0.951*** (0.237)	-1.100*** (0.285)	-1.477** (0.453)
HDD/100, 2nd Year After Birth	-0.565*** (0.157)	-0.595*** (0.168)	-0.626** (0.185)	-0.693*** (0.195)	-0.761* (0.292)
Other Baseline Controls	✓	✓	✓	✓	✓
Observations	1245	1245	1245	1245	1245

Notes: † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in the parentheses are clustered at the village level. HDD is the sum of HDD for each day within each period c: $HDD_c = \sum_{d \in D_c} \max\{(b - x_d), 0\}$, where b is the base temperature shown in each column head and x_d is the temperature in day d. "Other baseline controls" include: village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; children's age, gender, and the number of siblings by birth order; indicators for month of birth; indicators for mother's age at delivery; indicators for mother's six education levels; asset score at wave 0; precipitation, sunshine and $PM_{2.5}$ during each period.

Table A11: Robustness to the Number of Periods

	Cognitive Score in Wave 2			
	(1)	(2, Baseline)	(3)	(4)
HDD/100, 3rd Year Before Birth				-0.190 (0.163)
HDD/100, 2nd Year Before Birth		-0.091 (0.158)	-0.156 (0.168)	-0.319 (0.240)
HDD/100, 1st Year Before Birth	-0.405* (0.171)	-0.464* (0.214)	-0.476* (0.232)	-0.543* (0.244)
HDD/100, 1st Year After Birth	-0.740*** (0.185)	-0.862*** (0.204)	-0.864*** (0.212)	-0.908*** (0.199)
HDD/100, 2nd Year After Birth	-0.490*** (0.135)	-0.595*** (0.168)	-0.763*** (0.185)	-0.810*** (0.186)
HDD/100, 3rd Year After Birth			-0.276† (0.152)	-0.280† (0.152)
Other Baseline Controls	✓	✓	✓	✓
Observations	1245	1245	1245	1245

Notes: † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in the parentheses are clustered at the village level. HDD is the sum of HDD for each day within each period c: $HDD_c = \sum_{d \in D_c} \max\{(18.33 - x_d), 0\}$, where x_d is the temperature in day d. "Other baseline controls" include: village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; children's age, gender, and the number of siblings by birth order; indicators for month of birth; indicators for mother's age at delivery; indicators for mother's six education levels; asset score at wave 0; precipitation, sunshine and $PM_{2.5}$ during each period.

Table A12: Robustness to Alternative Cognitive Measurements

	Cognitive Score (in SD) (1)	Cognitive Percentile (0-100) (2)	Cognitive Delay {0,1} (3)	Bayley Raw Score (0-91) (4)
HDD/100, 2nd Year Before Birth	-0.091 (0.158)	-1.48 (4.61)	-0.010 (0.071)	4.05 (3.85)
HDD/100, 1st Year Before Birth	-0.464* (0.214)	-11.45* (5.23)	0.138 (0.090)	-1.25 (3.73)
HDD/100, 1st Year After Birth	-0.862*** (0.204)	-24.34*** (5.28)	0.236** (0.086)	-10.13* (4.83)
HDD/100, 2nd Year After Birth	-0.595*** (0.168)	-18.28*** (4.38)	0.182* (0.073)	-7.75† (4.14)
Other Baseline Controls	✓	✓	✓	✓
Observations	1245	1245	1245	673

Notes: † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in the parentheses are clustered at the village level. HDD is the sum of HDD for each day within each period c: $HDD_c = \sum_{d \in D_c} \max\{(18.33 - x_d), 0\}$, where x_d is the temperature in day d. "Other baseline controls" include: village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; children's age, gender, and the number of siblings by birth order; indicators for month of birth; indicators for mother's age at delivery; indicators for mother's six education levels; asset score at wave 0; precipitation, sunshine and $PM_{2.5}$ during each period. "Cognitive delay" is an indicator that equals 1 if the child's normalized cognitive skill measure is more than one standard deviation below the sample mean.

Table A13: Effects of Ambient Temperature Exposure on Language Skills in Early Childhood

	Language, Bayley and Wechsler (1)	Language, Bayley (2)	Receptive Language, Bayley (3)	Expressive Language, Bayley (4)
HDD/100, 2nd Year Before Birth	0.134 (0.134)	0.295 (0.241)	0.198 (0.250)	0.369 (0.250)
HDD/100, 1st Year Before Birth	-0.132 (0.209)	0.027 (0.364)	-0.066 (0.382)	0.026 (0.376)
HDD/100, 1st Year After Birth	-0.554** (0.208)	-0.836* (0.418)	-1.081** (0.389)	-0.446 (0.411)
HDD/100, 2nd Year After Birth	-0.504*** (0.141)	-0.549* (0.259)	-0.538* (0.259)	-0.300 (0.247)
Other Baseline Controls	✓	✓	✓	✓
Observations	1242	670	671	670

Notes: † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in the parentheses are clustered at the village level. Samples are restricted to the age range [2.5,3.5] for columns (2)-(4). HDD is the sum of HDD for each day within each period c: $HDD_c = \sum_{d \in D_c} \max\{(18.33 - x_d), 0\}$, where x_d is the temperature in day d.

Table A14: Robustness Check: Removing Weather Data around A Cold Spell in Early April 2018

	Cognitive Score in Wave 2			
Replace HDD and Weather Data in March and April in 2018 by →	No Replacement, Using Original Data (1, Baseline)	Same Period in 2010 (2)	Same Period in 2011 (3)	Same Period in 2012 (4)
HDD/100, 2nd Year Before Birth	-0.091	-0.164	-0.137	-0.139
	(0.158)	(0.154)	(0.154)	(0.153)
HDD/100, 1st Year Before Birth	-0.464*	-0.347	-0.356	-0.405†
	(0.214)	(0.221)	(0.219)	(0.222)
HDD/100, 1st Year After Birth	-0.862***	-0.712***	-0.751***	-0.818***
	(0.204)	(0.193)	(0.194)	(0.204)
HDD/100, 2nd Year After Birth	-0.595***	-0.462***	-0.531***	-0.571***
	(0.168)	(0.124)	(0.132)	(0.142)
Other Baseline Controls	✓	✓	✓	✓
Observations	1245	1245	1245	1245

Notes: † $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Standard errors in the parentheses are clustered at the village level. HDD is the sum of HDD for each day within each period c: $HDD_c = \sum_{d \in D_c} \max\{(18.33 - x_d), 0\}$, where x_d is the temperature in day d. "Other baseline controls" include: village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; children's age, gender, and the number of siblings by birth order; indicators for month of birth; indicators for mother's age at delivery; indicators for mother's six education levels; asset score at wave 0; precipitation, sunshine and $PM_{2.5}$ during each period.

Table A15: Panel Regressions of Children's Dietary Intake on Last Year's Temperature

	Rice (1)	Beans (2)	Dairy (3)	Meat (4)	Eggs (5)	Vitamine (6)	Fruits (7)	Total ≥ 4 (8)
HDD/100, Past 365 Days	0.201	0.039	-0.312	-0.287	-0.181	-0.120	-0.097	-0.356
	(0.224)	(0.231)	(0.246)	(0.194)	(0.202)	(0.190)	(0.272)	(0.223)
Sample Mean	0.549	0.355	0.681	0.490	0.436	0.755	0.779	0.661
Other Controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	3686	3684	3684	3684	3683	3685	3685	3682

Notes: † $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Standard errors in the parentheses are clustered at the village level. HDD is the sum of HDD for each day within each period c: $HDD_c = \sum_{d \in D_c} \max\{(18.33 - x_d), 0\}$, where x_d is the temperature in day d.

Table A16: Effects of Rainfall, Sunshine, and Air Pollution

	Cognitive Score in Wave 2		
	(1)	(2)	(3)
Precipitation (100 mm), 2nd Year Before Birth	-0.083	-0.087†	-0.091
	(0.052)	(0.050)	(0.070)
Precipitation (100 mm), 1st Year Before Birth	-0.004	0.017	-0.015
	(0.064)	(0.066)	(0.088)
Precipitation (100 mm), 1st Year After Birth	-0.011	0.003	0.011
	(0.059)	(0.056)	(0.077)
Precipitation (100 mm), 2nd Year After Birth	-0.006	-0.026	0.030
	(0.057)	(0.053)	(0.083)
Sunlight (100 Hours), 2nd Year Before Birth	0.011	-0.138†	-0.138
	(0.071)	(0.077)	(0.116)
Sunlight (100 Hours), 1st Year Before Birth	0.104	0.029	-0.015
	(0.109)	(0.102)	(0.127)
Sunlight (100 Hours), 1st Year After Birth	-0.116	-0.106	-0.122
	(0.130)	(0.124)	(0.129)
Sunlight (100 Hours), 2nd Year After Birth	-0.009	0.019	0.016
	(0.095)	(0.094)	(0.125)
$PM_{2.5}(\mu g/m^3)$, 2nd Year Before Birth	0.040	-0.036	-0.037
	(0.039)	(0.042)	(0.056)
$PM_{2.5}(\mu g/m^3)$, 1st Year Before Birth	0.011	0.022	-0.047
	(0.062)	(0.058)	(0.065)
$PM_{2.5}(\mu g/m^3)$, 1st Year After Birth	-0.016	-0.048	-0.051
	(0.060)	(0.061)	(0.066)
$PM_{2.5}(\mu g/m^3)$, 2nd Year After Birth	0.026	0.016	0.041
	(0.051)	(0.051)	(0.062)
Temperature Control	none	HDD	bins
Other Baseline Controls	✓	✓	✓
Observations	1245	1245	1245

Notes: † $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Standard errors in the parentheses are clustered at the village level. HDD is the sum of HDD for each day within each period c: $HDD_c = \sum_{d\in D_c} \max\{(18.33 - x_d), 0\}$, where x_d is the temperature in day d. "Other baseline controls" include: village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; children's age, gender, and the number of siblings by birth order; indicators for month of birth; indicators for mother's age at delivery; indicators for mother's six education levels; asset score at wave 0.

B Conceptual Framework

We describe a simple conceptual framework to motivate the empirical model. For child's age of outcome realization t and age of temperature exposure $\tau \leq t$, we describe the production of child's human capital outcome y_t as

$$y_t = f_t\left(\{w_\tau\}_{\tau=-1}^{t}, \{I_\tau\}_{\tau=-1}^{t}, \{X_\tau\}_{\tau=-1}^{t}\right) \tag{5}$$

in which w_τ denotes the ambient temperature the child is exposed at time (age) τ, I_τ represents caregiver-child interactions and other investments that constitute home environment, and X_τ represents all other environmental factors that affect children's skills outcomes. In this framework, we allow inputs at different ages from the conception of the child ($\tau = -1$) to age $\tau = t \geq 0$ to have independent impacts on the age-t outcomes. We adopt this framework because children at this early stage of human development can be very different in their response to external shocks or stimuli depending on the developmental stage of the child (Zeanah et al., 1997). For example, the impact of temperature variation at age 1 on outcomes at age 2 may be different from the impact at age 2 on outcomes at age 3. Conventional panel data models that impose the same relationship between the dependent variable and the independent variable regardless of timing do not account for the impacts of different developmental stages of children.

Then, the total effect of change in ambient temperature at $\tau' \leq t$ can be described as (suppressing the effects of changes in X_τ),

$$\frac{dy_t}{dw_{\tau'}} = \frac{\partial f_t(.)}{\partial w_{\tau'}} + \sum_{\tau=\tau'}^{t} \frac{\partial f_t(.)}{\partial I_\tau} \frac{dI_\tau}{dw_{\tau'}}, \tag{6}$$

which is decomposed as the direct effect of the temperature on child's cognitive skills outcomes and the indirect impact through parenting behaviors. Reduced-form regression of child's cognitive skills outcomes at age t on ambient temperature variations for all periods between prenatal period and age t identifies the total effect of temperature variations on child's cognitive skills outcomes.

Time-τ' temperature changes may impact I_τ, home environment at time $\tau \geq \tau'$, in several different ways. First, caregivers may find it more difficult to engage with the children in uncomfortable weather. Then cold or hot temperatures raise the utility cost of interacting with children, lowering I_τ. Alternatively, temperature variation can impact household income, for example through crop harvest. This channel would be highly relevant for rural villages where many households rely on agriculture for income. Finally, caregivers may respond to observed or projected changes in children's outcomes in response to temperature changes. Sufficiently altruistic parents may attempt to compensate for the negative effects of temperature variations by raising I_τ. Such changes are related not only to caregivers' parenting skills but also to their knowledge and beliefs related to children's development process, which may be highly inaccurate for low-SES parents (Cunha et al., 2020). Regression of parenting and material home environment variables on temperature variations identifies $\frac{dI_\tau}{dw_{\tau'}}$, the total effect of temperature on home environment, as a net of these different effects.

Our conceptual framework does not distinguish the effects of indoor and outdoor temperature exposures. The results should therefore be interpreted as overall temperature exposure effects, incorporating potential adjustments in outdoor activities in response to temperature changes. Given that heating facilities tend to be inadequate in rural China (Zheng and Bu, 2018), we expect that indoor activities may still be affected by cold winter temperatures.