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Effects of temperature exposures on early childhood cognitive development and home environment[☆]

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ABSTRACT

Daily exposure to suboptimal temperature with inadequate protection can undermine children's development, but evidence is limited in the range of temperature and the set of developmental outcomes. Using a unique panel study in disadvantaged rural communities, we find that children's exposures to low temperature undermine cognitive development during early childhood. In addition, caregiver–child interactions and material investments are lower for households exposed to low temperature, highlighting their limited capacity to adapt and the potential for persistent effects on children's long-term outcomes through home environment. Our findings show the need to account for a broad range of temperature variations when promoting children's development, and propose home environment as a novel policy channel to counter the negative temperature effects on children.

1. Introduction

Relatively mild shocks in early childhood can have substantial negative consequences throughout one's life. In examining the life cycle process of human capital development, including the in utero period ("the fetal origins hypothesis") and early childhood ("the critical period"), studies show that the earlier the shocks occur, the more difficult it is to compensate for their impacts later in life (Almond et al., 2018; Heckman and Mosso, 2014). It is therefore imperative to identify negative shocks in early childhood and understand their mechanisms to improve individual and social well-being in the long term. A wide range of early childhood shocks, such as those on maternal health and household income, were investigated with respect to their effects on children's development (Almond et al., 2018). These studies highlighted the role of home environment[2] in promoting children's human capital

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1 Wu and Yang contributed equally to this work.

2 Home environment is a comprehensive concept that includes all environments at home that shape children's development such as materials at home and children's interactions with others in the household such as parents (Caldwell and Bradley, 1979; Heckman and Mosso, 2014).

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development and shaping long-run life outcomes, leading to the popularity of programs targeting early childhood learning and parenting improvement at home to reduce the outcome gap of children by household socioeconomic status (Heckman et al., 2013; Elango et al., 2016).

An important source of early childhood shock is temperature variation. Children's temperature regulation systems are not fully developed, so that their physical development can be directly affected at temperature levels that are relatively harmless to adults (Granés et al., 2024; Graff Zivin and Shrader, 2016). Uncomfortable temperature can also discourage children's exploration of environment and self-learning (Gibson, 1988; Koepp et al., 2023). Further, temperature exposure can undermine parents' cognitive performance and behavioral capacity needed for parent–child interactions that are critical for children's cognitive development (Cook and Heyes, 2020; Heckman and Mosso, 2014). Finally, especially for rural low-income households, indoor heating or cooling may not be sufficient to protect children from the effects of outside climate, even after accounting for government support. Given that young children depend on adult caregivers for a protective indoor environment, parents and the home environment they provide can be important channels in which exposure to suboptimal temperature undermines children's development, in addition to commonly studied channels such as household income and physical health.

In this study, we estimate the effects of high and low temperature exposures on children's cognitive development and early childhood home environment, adding a new understanding of how temperature can pose risks to children's development and suggesting effective responses to these risks. The setting is characterized by moderate temperature ranges in a low-income rural environment where even indoor environments are not necessarily shielded from outside temperature.

Our contributions are twofold. First, we show effects of exposure to low temperature on children's development. Although negative effects of low temperature on children's cognitive development can be expected from their effects on adults (Cook and Heyes, 2020) and children's vulnerable physiology, studies rarely investigated this possibility on children's developmental outcomes. Instead, many studies of the effects of temperature exposure on children show negative effects of high temperature, often based on high-temperature or humid regions (Geruso and Spears, 2018), exposing a gap in knowledge about the effects of temperature on children. An important exception is Cohen and Dechezleprêtre (2022) who show that even mildly cold weather can increase infant mortality.

Second, we show effects of suboptimal temperature exposure on parental investment as measured by home environment. There is no statistical evidence in the literature showing that temperature variations can impact caregiver–child interactions that are critical components of home environment, despite anecdotal evidence that suboptimal temperature can impact caregivers and their childcare behaviors as much as it can impact children (Malmquist et al., 2021). Finding temperature effects on home environment including caregiver–child interactions suggests that early childhood exposures to suboptimal temperature can impact children's long-run life outcomes through a human capital development channel. Further, evidence-based programs developed to improve early childhood home environments with significant and cost-effective results (Elango et al., 2016) would be useful in countering negative temperature effects as well.

In this study, we use a longitudinal dataset following households from 4 to 54 months after childbirth, covering 100 rural villages in the northwest region of China. The impacts of temperature changes in this area are likely to be significant because rural China is known for poor home environment, high rate of poverty and developmental delay among infants, and limited availability of local amenities (Geruso and Spears, 2018; Mertz et al., 2009; Wang et al., 2019). The villages were selected to capture the experience of the caregivers and the children in disadvantaged rural households. The dataset contains rich measures of children's birth outcomes, cognitive developmental measures appropriate for the age range of children (Bayley, 2006; Wechsler, 2012), and home environment measures including caregiver–child interactions and material investments (Caldwell and Bradley, 1979). The survey and data collection were administered by trained staff rather than relying on self-reports to maintain measurement quality and minimize attrition. We analyze these variables jointly with daily temperature variation at the village level. We investigate the effects of both high and low temperature rather than restrict our attention to temperature variations in any one direction. We conduct robustness analysis to ensure that our analysis withstands potential concerns regarding the quality of measuring cognitive skills of very young children.

Our identification relies on differences in cumulative exposure to temperature during the first few years before and after children's birth. We account for the season (month) of birth and the village of birth in our estimation, meaning that our estimates are not based on comparing the outcomes of children across different villages or seasons of birth. Our empirical design captures the effects of temperature that deviate from the "normal" level so that the villagers would not have anticipated these changes or be ready for them. Further, we separately identify the effects of temperature exposures for the 12-month intervals before and after birth and the effects of "contemporaneous" exposures around the time children's outcomes were measured.

We show that exposure to low temperature, near 0 °C, undermines subsequent cognitive skills development measured in early childhood. The effects of exposure during the first 12 months after birth are negative and significant on cognitive skills at ages 2–5. The impacts for exposure from 13 to 24 months of age are negative and significant but smaller in magnitude. There is no immediate effect of temperature exposures for periods shorter than a year, consistent with the explanation that exposure to suboptimal temperature disrupts human capital development process over time. The effects of exposure to high temperature are negative but not significantly different from zero, potentially because days of low temperature are relatively more common than days of high temperature in the study area.

Examining temperature effects on home environment, we find less cognitively stimulating interactions with children and their caregivers and less material investments at households exposed to low temperature. The evidence does not support the idea that parents can adapt to the environment to compensate adequately for the negative effects of low temperature exposure on their children (Almond and Mazumder, 2013; Yi et al., 2015). We also look for temperature effects on air pollution, household income, household assets, children's health, and parental migration, but do not find evidence that they can explain the effects of temperature on children's outcomes. Our evidence is inconclusive on whether indoor air pollution explains the negative effects of low temperature exposures.

Our study presents the first evidence on the negative effects of low temperature exposures on both early childhood cognitive development and home environment. The setting is in a low-income rural region in a large developing country located in a temperate region. The findings imply that policy responses to temperature changes should account for low temperature as well as high temperature that are more often associated with the negative effects of climate. Further, given negative effects on home environment, one way to help low-income households in rural areas may be by improving home environment using evidence-based programs that directly target caregivers at home (Elango et al., 2016).

2. Temperature and human capital development

Temperature variation can impact children's development directly through physical development. Infants are exposed to the risk of low and high body temperature (hypothermia and hyperthermia, respectively), which are associated with poor brain and body development (Chandra and Baumgart, 2005; Waldron and MacKinnon, 2007). The human central nervous system is vulnerable to environmental stress such as temperature variations that affect long-term neurocognitive development (Jones et al., 2011). Such risks are greater among children whose temperature regulation system is not fully developed compared to that of adults (Graff Zivin and Shrader, 2016).[3] Further, uncomfortable temperature variation can discourage children's exploration of the environment, an important part of the learning process in early childhood (Gibson, 1988).

More generally, the literature shows that cognitive functioning suffers in uncomfortable temperature. The body reacts to cold temperature by allocating energy such as carbohydrates to temperature maintenance, which preserves the core temperature necessary for survival but reduces cognitive functioning and creates perceptual discomfort (Cheung et al., 2016; Taylor et al., 2016). Exposure to heat beyond the level the body can efficiently discard can impede brain development and learning processes (Graff Zivin and Shrader, 2016). Experimental evidence confirms that task accuracy, short-term memory, and work productivity decline when individuals are subjected to heat, typically above 25 °C, or cold stress, typically below 15 °C (Dell et al., 2014; Taylor et al., 2016). Such effects are observed outside the laboratory as well—students perform poorly on tests if the outside weather is too hot (Graff Zivin et al., 2018, 2020; Park, 2022) or too cold (Cook and Heyes, 2020; Johnston et al., 2021).

Although children's development and caregiver–child interactions can take place indoors during poor weather, studies show that outside weather can negatively affect indoor task performance even with good temperature control. Cook and Heyes (2020) show that cold weather on the day of the test lowers the test scores of college students in Canada even though tests are taken inside well-heated buildings. They argue that individual adaptation is a likely channel by showing that the effects are greater for those less used to cold weather.[4] Johnston et al. (2021) also show negative effects of cold weather on test scores of adolescent students in Australia. Authors suggest that the results can be explained by lack of adaptation to low temperature by Australians who are accustomed to typically warm Australian weather. Heyes and Saberian (2019) show that outside heat can influence US judges to make more severe court case decisions made indoors with good climate control by affecting their mood and risk appetite. Park et al. (2020) show that cumulative exposure to heat undermines students' learning and lowers test scores taken years later, with some mitigation provided by air conditioning in schools.

Such negative effects may be worse in the low-income rural setting, the focus of this study. First, almost half of energy consumption by rural Chinese households consists of burning firewood, which provides inadequate space heating for the inhabitants (Ma et al., 2021; Niu et al., 2010). Burning coal is the next popular method, followed by using electricity, which is not always favored because rural electrification remains incomplete in many areas (Ding et al., 2018; Ma et al., 2021). Second, government subsidy supports the adoption of air conditioner to boost demand for local home appliances, but the subsidy has limited impact on domestic consumption (Ji et al., 2019). For low-income households, the rate of air conditioner adoption remains below that of other household appliances such as television sets and refrigerators (Auffhammer and Wolfram, 2014; Li et al., 2019b).[5]

Our study is distinguished from other works on the effects of temperature variations by focusing on how children depend on adults' care for survival, adaptation, and development. Temperature can indirectly disrupt children's development by reducing caregivers' time allocated to childcare (Garg et al., 2020a) or undermining their physical and mental health (Hua et al., 2022; Yang et al., 2021). Caregivers exposed to uncomfortable temperature may experience difficulty carrying out cognitively demanding tasks (Graff Zivin et al., 2018; Park, 2022) such as stimulating children's learning in caregiver–child interactions.

Upon observing negative effects on children's development, however, caregivers may choose to compensate for these disadvantages by increasing investment in children's learning (Almond and Mazumder, 2013; Yi et al., 2015). Such compensatory investments could be limited if the households are constrained in resources or do not have the necessary skills or technology (Almond and Mazumder, 2013). No authors have investigated the effects of temperature or climate on comprehensive measures of home environment that can illuminate the relative importance of these two opposing sides of caregiver responses.

[3] Although we cannot examine the physiological channel directly because of data limitations, we examine whether temperature exposures have an effect on the number of sick days in Section 8.

[4] Interestingly, cumulative exposure to cold weather prior to tests improves academic performance, likely by substituting students' leisure for indoor work. Such substitution is unlikely for children under 5 and parents in low-income households in our sample.

[5] According to the central government's announcement in 2011, subsidized appliances include television, refrigerator, mobile phone, washing machine, wall-mounted air conditioner, floor-standing air conditioner, computer, solar water heater, storage water heater, gas water heater, induction cooker, and microwave oven. Heaters are excluded from this list. See the announcement at http://www.moa.gov.cn/ztzl/lszczc/201103/t20110325_1955090.htm (in Chinese).

3. Conceptual framework

We describe a simple conceptual framework to motivate the empirical model. For child's outcome measured at age t, we describe the production of child's human capital outcome y_t as

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

in which $\tau = -1$ is the time of conception, $\tau = 0$ is the time of birth, and $\tau = 1$ is 12 months after birth. X_τ is a period-τ row vector of all potential factors that can shape children's development of skills y_t. Temperature is one such factor. As reviewed in the previous section, it can impact children directly through physiological development and by affecting their learning behaviors. It can also impact children indirectly by disrupting parents' ability to interact with their children, both outdoors and indoors, or provide for materials at home. Some of the other potential channels include air pollution, due to using dirty heating devices such as wood or coal heaters, and lower household income caused by diminished crop yields. Whereas we have detailed measures of home environments, we also have measures of air pollution, availability of different heating devices at home, children's nutrition intake, and the number of days the children were sick, which are accounted for in the empirical analyses in Section 8.

Then, letting the first element of $X_{\tau\prime}$, denoted $X_{\tau\prime,1}$, be the exposure to temperature from time $\tau\prime - 1$ to $\tau\prime$, the total effect of a change in temperature exposure $X_{\tau\prime,1}$ on the outcome at time t is:

$$\frac{dy_t}{dX_{\tau\prime,1}} = \frac{\partial f_t(.)}{\partial X_{\tau\prime,1}} + \sum_{\tau=\tau\prime}^{t}\sum_{k=2}^{K}\frac{\partial f_t(.)}{\partial X_{\tau\prime,k}}\frac{dX_{\tau\prime,k}}{dX_{\tau\prime,1}} \tag{2}$$

in which K is the length of vector X_τ. $X_{\tau\prime,2},\ldots,X_{\tau\prime,K}$ include all potential inputs other than the first input that can possibly affect the child outcome realized at time t. As represented by the second component of the right-hand side of Eq. (2), an exposure to temperature from time $\tau\prime - 1$ to $\tau\prime$ may affect the entire profile of inputs from time $\tau\prime$ to t, the time outcome is measured. Regressing children's skills at age t on temperature exposure between $\tau\prime - 1$ and $\tau\prime$ identifies the total effect $\frac{dy_t}{dX_{\tau\prime,1}}$. These inputs include both measured inputs included in the dataset and unmeasured inputs that affect the outcome but not included in the dataset. Unmeasured inputs will be represented by the error term in the empirical model.

Temperature exposure may have an instantaneous effect on cognitive skill measures. Then, letting the second element of $X_{\tau\prime}$, denoted $X_{\tau\prime,2}$, be the exposure to the temperature at the exact time point $\tau\prime$, we expect the instantaneous effect to be realized immediately: $\frac{dy_t}{dX_{\tau\prime,2}}$. Observing $\frac{dy_t}{dX_{\tau\prime,2}} = 0$ and $\frac{dy_t}{dX_{\tau\prime,1}} \neq 0$ at the same time rules out the possibility that the effects are driven by the instantaneous effects alone.

The effect of temperature exposure at a given period of time on outcomes realized at different ages is given by $\frac{dy_{t\prime}}{dX_{\tau\prime,1}}$, $t\prime \neq \tau\prime$. Persistent effects of temperature exposure $X_{\tau\prime,1}$ would be observed on outcomes measured at a time far away from $\tau\prime$.

One possible way in which the effects of temperature persist over time is through human capital accumulation, in which home environment is an important input. Our dataset contains measures of home environment (Caldwell and Bradley, 1979), allowing us to examine whether temperature exposure affects home environment including caregiver–child interactions and materials at home. The causal effects of home environments on children's skills are shown in a large body of literature (e.g., Heckman and Mosso, 2014), although we cannot identify their role as a mechanism in our study.

Finding temperature effects on home environment suggests that temperature exposure during early childhood may have effects on long-term outcomes, similar to how education (Elango et al., 2016), peers (Carrell et al., 2018), and shocks (Almond et al., 2018) during early childhood affect long-term outcomes such as earnings through the human capital accumulation channel.

As discussed in the previous section, changes in temperature may disrupt home environment in several ways. Let $X_{\tau\prime,3}$ be measures of home environment observed at time $\tau\prime$. On the one hand, caregivers may find it more difficult to engage with the children in uncomfortable weather. Also, temperature variation can lower household income, for example through crop harvest. These channels imply negative effects of temperature exposures on home environment. On the other hand, caregivers may attempt to compensate for observed or projected changes in children's outcomes by improving home environment (e.g., Yi et al., 2015), although low parenting knowledge or skills can limit their capacity to react (Cunha et al., 2020). If the compensating responses of caregivers dominate negative effects of temperature exposures, we expect improvement in home environments when exposed to uncomfortable temperature: $\frac{X_{\tau\prime,3}}{X_{\tau\prime,1}} > 0$. In this case, holding all else constant, we expect the negative effects of temperature exposures to fade out over time on outcomes targeted by the caregivers. If $\frac{X_{\tau\prime,3}}{X_{\tau\prime,1}} < 0$, we expect the negative effects on children's outcomes to persist or even worsen over time through home environments.

Note that caregivers' behaviors may evolve over time as children's skills develop and caregivers' own circumstances change. The effects on home environments we identify may reflect the outcomes of this dynamic evolution over the span of three years covered by the dataset in this study.

4. Data

4.1. Data collection

Our dataset 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 and selected 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 5 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.[6] Only one child from each household was included in the study.

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

The survey study enjoyed strong support from the local government in contacting and recruiting households targeted for the survey. Households participating in the study were offered a chance to receive free daycare as a part of a randomized intervention (Sylvia et al., 2021), so the households were highly supportive of the study. Once contacted, no households refused to participate.

4.2. Early childhood data

We use the cognitive scale from the third edition of the Bayley Scale of Infant Development (BSID, *Bayley-III*; Bayley, 2006) to measure cognitive performance as the key outcome of interest for children under 42 months old. For those 42 months or older, we use the Wechsler Preschool and Primary Scale of Intelligence (WPPSI; Wechsler, 2012), a measure of general intellectual ability and cognitive functioning for children 2.5 to 7.25 years of age. Both these scales are standard age-appropriate measures of children's cognitive abilities, widely used in psychological and economic research (Bayley, 2006; Wechsler, 2012). We normalize these scores so that mean is zero and standard deviation one within children 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). The distribution of cognitive skill measures for each wave does not contain unusual outliers, as shown in Figure A1. In addition, in Section 8.4, we conduct robustness analysis showing that the effects are robust to concerns about potentially low predictive validity of cognitive skill measures in very early childhood (Rasheed et al., 2023).

The dataset also provides measures of the home environment including cognitively stimulating caregiver–child interactions and material investments into the home environment (Caldwell and Bradley, 1979). 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 standard measures of caregiver-interactions and home environment widely validated and used in development psychology and economics on samples from across the world including China and the US (Cunha et al., 2010; Elardo and Bradley, 1981; Johnstone et al., 2021).

Measures of sociodemographic characteristics for children and households include the child's gender; number of siblings; and primary caregiver's age, education level, and relationship with the child. The age of the child is obtained from the birth certificate. The primary caregiver is defined as the individual identified by the survey respondent as the person most responsible for the child's care, often the child's mother or grandmother.

4.3. Climate data

Temperature data are obtained from the National Meteorological Information Center of China. The dataset includes daily average, maximum, and minimum temperature, 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 a diameter less than 2.5 micrometers ($PM_{2.5}$), a standard measure of air pollution (Li et al., 2019a).

We use the natural neighbor interpolation technique to assign weather information to specific villages. Natural neighbor interpolation uses a weighted moving average of surrounding or neighboring weather stations to calculate the interpolated values (Sibson, 1981). The interpolation was performed using the ArcGIS 10.7 spatial analysis tool.

4.4. Summary statistics

We use three waves of surveys conducted between 2015 and 2019, covering children born from 2013 to 2016.[7] The survey was continuously conducted during this time period, so that the next survey had already started for some households even as the previous round of surveys were being conducted in other households. There was also an overlap in the age distribution across surveys. The baseline wave (wave 0) approximately spanned ages 0.5 and 2, wave 1 spanned ages 1.5 and 3.5, and wave 2 spanned ages 2.5

[6] 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' use of daycare centers (Section 8).

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

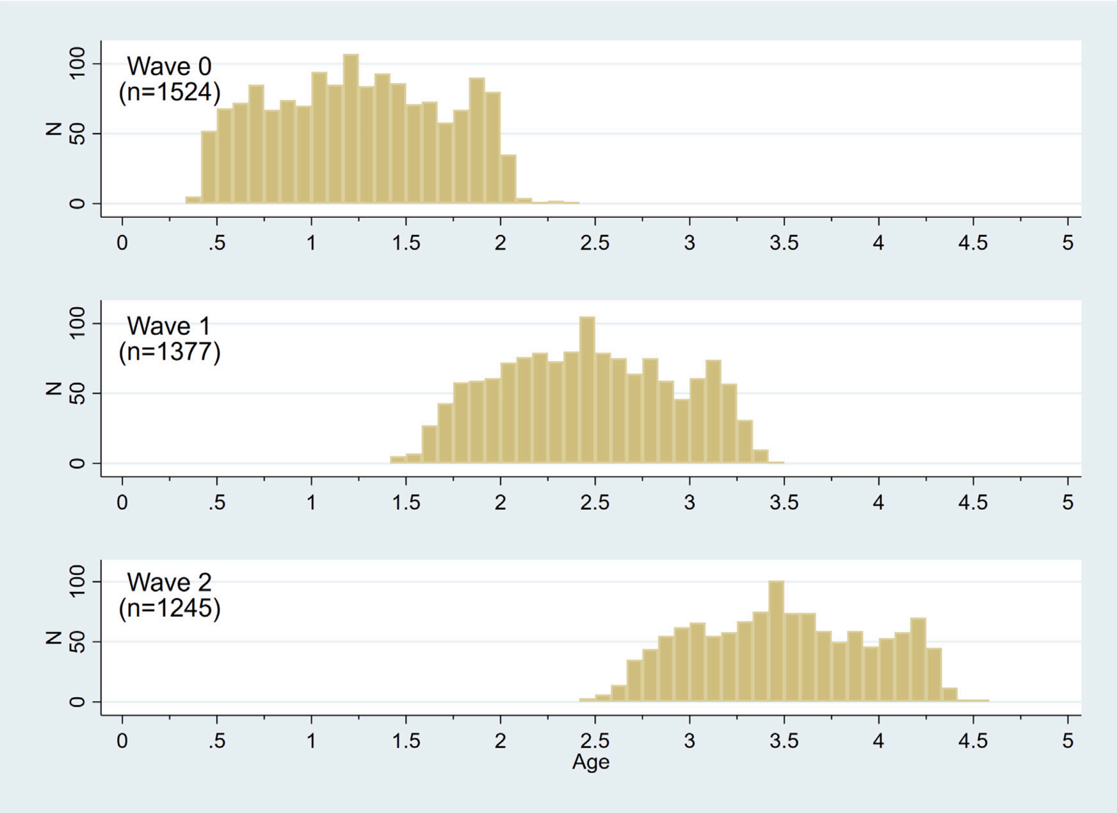

Fig. 1. Age distribution in each wave. Notes: Bars represent the number of observations in each age range.

and 4.5 (Fig. 1, Figure A2). The retention rate is 81.69% at the end of wave 2. We examine the sensitivity of our main results to attrition in Section 8. The last wave of the survey, wave 2, was collected in 2018 and 2019.

The first panel of Table 1 shows that about half of the children are female and half are first-born. Only 19.7% of the mothers finished high school, indicating low socioeconomic status of the households in the sample. The second panel shows that the cognitive score has a mean of zero because it is normalized within each wave and months of age. The home environment score is normalized within the entire sample pooling all waves together. The positive mean of the Toys and Books subscore implies that average material investment in children increased as children grew older. The activities subscore did not increase over time.

To understand more fully what the home environment measures show, we present additional information (not in the table) on the characteristics of the caregivers who provide childcare and engage in activities with the children that constitute the home environment subscore. In the wave 2 sample, out of 1,245 children, 52% are primarily cared for by the mother. Among them, 75% of the mothers said their primary activity was "watching the children", whereas the other 25% reported having some kind of work ("worker" or "farmer"). Among the 1,245 children, 40% are primarily cared for by paternal grandparents. Of these grandparents, 47% said their primary activity was "watching the children", whereas the others reported having some other activity. The remaining 8% of the 1,245 children are cared for by the father, maternal grandparents, and "others" that may include relatives, neighbors, or teachers. Overall, approximately 58% of the children are cared for by mothers or paternal grandparents who act as primary caregivers without any other work. However, given that childcare assistance from (paternal) grandparents is common in rural China (Chen et al., 2000), the primary form of childcare would be care by mothers or grandparents who focus on childcare.

The third panel of Table 1 shows the ownership of heating and cooling devices at home at the time of the wave 2 survey. More than 67% of the households in the sample own devices using natural gas or electricity heating, and 58.9% of the households own coal heaters with a ventilation pipe. Only 12.5% of the households own coal heaters without a ventilation pipe, and 30.7% own firewood stoves. As for cooling devices, 59.6% own air conditioners. It is worth noting that more than half of the households own heating devices using natural gas or electricity that cause minimal indoor air pollution, whereas less than a third of the households own firewood stove that can cause indoor air pollution.

It is worth noting that these measures are based on the availability of each type of heating device. In addition, there is no information on whether the devices are used at all, or whether they provide adequate space heating. For example, a household may own both an electric heater and a firewood stove with no information in the data on which one is used more often.

We provide additional information on the distribution of heating devices across villages and years. Figure A3 in the appendix shows that types of heating devices are widely distributed across the villages without any obvious geographic pattern. Figure A4

Table 1
Summary statistics.

	Sample mean in Wave 2	Standard Deviation
Age in Years	3.502	0.469
Female	0.482	0.500
Any Sibling	0.535	0.499
First-Born	0.503	0.500
Mother's Age at Delivery	26.370	4.877
Mother Finished High School	0.197	0.398
Asset Score Measured in Wave 0	0.014	0.852
Cognitive Score	0.000	1.000
Home Environment Score	0.285	0.870
Subscore: Toys and Books	0.400	0.753
Subscore: Activities	−0.009	0.840
Heating/Cooling Devices at Home		
Heating: Natural Gas or Electricity	0.673	0.469
Heating: Coal with Ventilation Pipe	0.589	0.492
Heating: Coal without Ventilation Pipe	0.125	0.331
Heating: Firewood	0.307	0.461
Cooling: Air Conditioner	0.596	0.491
Heating Degree Days (HDD)		
Second Year Before Birth	2045	266
First Year Before Birth	2006	276
First Year After Birth	2004	274
Second Year After Birth	2026	255
Cooling Degree Days (CDD)		
Second Year Before Birth	789	139
First Year Before Birth	723	128
First Year After Birth	750	187
Second Year After Birth	810	168
Weather in the Past 365 Days		
Precipitation (mm)	806	146
Sunshine (Hours)	1651	222
$PM_{2.5}$($\mu g/m^3$)	35.3	3.5
Observations	1245	

Notes: Age is defined as $\frac{1}{365.25} \times$ (days after birth). Asset score is constructed 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 in 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 heating degree days 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. Cooling Degree Days is the sum of cooling degree days for each day within each period: $CDD_c = \sum_{d\in D_c} \max\{(x_d - 18.33), 0\}$.

shows that each type of heating device is owned across all levels of socioeconomic status measures. The proportion of households with heaters based on natural gas or electricity is higher among households with a higher education level of the mother or with higher value of asset index. Among households with college graduate mothers, less than 10% own firewood stoves or coal heaters without a ventilation pipe, potentially heavier sources of indoor air pollution compared to heating devices using electricity or natural gas (Chen et al., 2018).

The last three panels show the climate variables we use. The heating degree days (HDD) variable measures exposures to low temperature over a 12-month period 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,[8] 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 temperature. Cooling degree days (CDD) are similarly defined to measure high temperature that

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

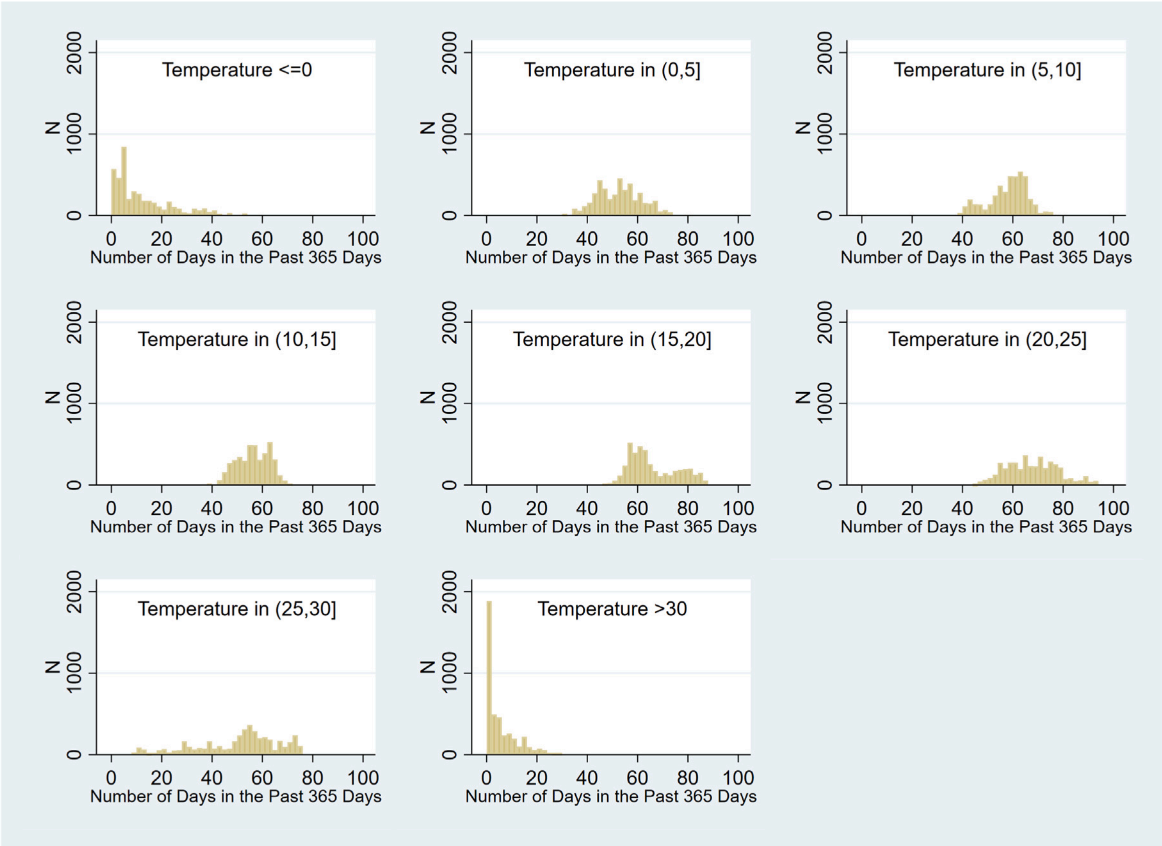

Fig. 2. Temperature distribution in Wave 2.
Notes: Bars represent the number of days in each temperature range during the 365 days prior to the interview date in wave 2 of the survey.

warrants cooling. HDD is zero for temperatures above the base value. Fig. 2 shows that days with low temperature (daily average below 5 °C) are more common than days with high temperature (daily average above 30 °C) in the sampling area. The upper-left subfigure in Figure A5 shows the distribution of HDD, showing no major outliers. Table 1 shows that HDD and CDD do not exhibit clear trends before and after the births of children.

The last panel shows average precipitation, sunshine, and ambient (outdoors) air pollution in the study area. Values of average weather variables in the sampling area were within the range of other provinces in China in 2016, showing that overall weather in the 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 China's western region), which had an annual precipitation of 1,348.0 millimeters but greater than in Beijing (669.1 millimeters). Annual sunshine hours were 1,228.4 in Chongqing and 2,502.1 in Beijing, whereas they were 1,651 in the study area. 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).

Variation in HDD across villages and over time is critical for the estimation of the empirical model. Figure A6 shows the raw distribution of HDD, showing its variation across villages and over the years (2014, 2015, 2016, 2017). Variation across villages is easily observed. There is also some variation over the years, with possible serial correlation. Table A1 more clearly shows the change in HDD and other climate-related variables over the years. Average HDD in the sample increased from 2,011 in the initial wave to 2,126 in the last wave, whereas air pollution measure (based on $PM_{2.5}$) decreased from 39.9 to 35.3, all below the national average of 42.0 $\mu g/m^3$ (Zhang et al., 2019). Precipitation and sunshine exposure do not have clear temporal patterns. Overall, weather in the sampling area shows changes over time but is not unusual compared to that in the rest of China during the study period (National Bureau of Statistics of China, 2017).

Figure A7 shows the variation in HDD by a child's birth month, a relevant variation for the estimation of empirical models, showing that the distribution differs by birth month in the median and the percentiles. Figure A8 shows the variation in HDD by the birth month, after accounting for village means. Because the empirical model includes fixed effects at the village level, this is an even more relevant distribution for the estimation. We see that, except for the second year before birth, HDD is more dispersed among those born in winter months (December–March) than those born in summer months.

5. Identification and empirical strategy

Studies show negative effects of high temperature exposures on children (e.g., Deschênes et al., 2009). One of our contributions is identifying the effects of low temperature exposures, which is relatively unknown. Therefore, we begin our analysis using a nonparametric regression model that flexibly identifies the effects across a wide range of temperature. The equation is:

$$\begin{aligned} Y_i &= \alpha + \sum_{a\in A}\sum_{b\in B}\gamma_{ab}\sum_{d\in C_{i,a}}\mathbb{I}\left(T_d \in b\right) + x_i'\beta + \lambda_{\text{village-year}} + \epsilon_i, \\ A &= \{[-2,-1),[-1,0),[0,1),[1,2)\} \\ B &= \{(-\infty,0],(0,5],\ldots,(30,\infty)\} \\ C_{i,a} &= \{\text{dates}|\text{dates} \in a,\ a\in A\} \end{aligned} \tag{3}$$

where, for child i, Y_i is the outcome of interest measured in wave 2; a is a year of a child's life relative to the child's birthday; b is a "bin" of temperature range, with a default length of 5 °C; d is a day in a calendar year; $C_{i,a}$ is a set of dates (denoted d) contained in a 365-day period $a \in A$, which is different for each i and a because children have different birthdays; T_d is a daily average temperature on date d; and $\mathbb{I}\left(T_d \in b\right)$ is an indicator function that equals 1 if T_d falls within b and 0 otherwise. We choose the temperature range $(15,20]$ as the omitted reference category. It includes 18.33 °C (65°F), the base for the HDD variable in Eq. (4). We show in Section 8 that the results are not sensitive to using bins with different widths by estimating the model with 3 °C-long bins ranging between −3 and 30 °C.

We define each period and the HDD variable based on a 12-month interval because this method is the best way to account for strong seasonality given our sample size. Accounting for seasonality with HDD defined for a shorter time period requires controlling for the beginning date of each HDD variable interacted with the village of birth, putting severe strain on our study's statistical power.

In the baseline specification, the period of a child's life covered by set A is 2 years before and after birth. We made this choice because the youngest subject in wave 2 is about 2.5 years old. Therefore, for all observations in the sample, all outcomes in the 2-year window from birth to age 2 are observed. We expand the time period to 3 years before and after birth in Section 8.

The coefficient of interest, γ_{Ab}, is interpreted as the effect of being exposed to another day of a temperature in bin b during period A, *replacing* a day of exposure to a temperature in the range of $(15,20]$. We sum over a and b, so there are $dim(A)\times dim(B)$ many γ_{ab} estimates for each equation.

x_i is a vector of baseline characteristics that include: child's characteristics including age, gender, birth month, birth year, and the number of siblings interacted with birth order; household characteristics including mother's education level (no education, primary school, middle school, high school, associate degree, bachelor's degree and above), mother's age at delivery, household asset score in wave 0,[9] and owning heating devices at home[10]; environmental variables including sunlight duration, precipitation, and air pollution as measured by $PM_{2.5}$ in each exposure period; interview timing including fixed effects for the survey year-by-month (survey year indicators interacted with survey month indicators), survey day-of-week, and village-by-year; fixed effects for the examiner of the cognitive tests; and two dummy variables indicating whether the cognitive scale is from the BSID, WPPSI for children younger than 4 years old, or WPPSI for children aged 4 years and above. Fixed effects for the month of birth account for the effects of different orders of seasons experienced by the children, so that we compare across children who are exposed to the seasons of a year in the same order from birth. Birth month fixed effects also account for the potential endogeneity because of parents timing their births and the effects of the season of birth on infant health (Buckles and Hungerman, 2013; Lam and Miron, 1996). Village-by-year fixed effects account for within-village unobserved characteristics arising from historical weather, cultural, and economic factors, their time trends, and survey year effects specific to each village. The error term ϵ_i is clustered at the village level. Identification is therefore based on comparing the outcomes of children while accounting for sources of endogeneity from birth timing and location and a range of confounders including weather-related variables.

Given that exposures to high temperature have negligible effects on the children in our sample, as shown in Section 6, we use as our main specification a more parsimonious model that uses the HDD variable as a measure of temperature exposure[11]:

$$Y_i = \alpha + \sum_{a\in A}\gamma_a\sum_{d\in C_{i,a}}\max\{18.33 - T_d, 0\} + x_i'\beta + \lambda_{\text{village-year}} + \epsilon_i. \tag{4}$$

The same set of control variables are used for both Eq. (3) and Eq. (4).

[9] 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 in wave 0.

[10] 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 ventilation pipe; (3) burning coal without a ventilation pipe; or (4) burning firewood. These indicators are measured at the second follow-up, the last wave in the study. We include these variables even though they are measured in the second wave because it is unlikely that household ownership of heating devices changes greatly over time, and accounting for the availability of heating devices at home is critical in estimating the effects of temperature exposures. We conduct a robustness analysis in which we remove these variables from the model.

[11] The results from Eq. (3) in Section 6 shows negligible effects of high temperature exposures and linearly decreasing negative effects of low temperature exposures as temperature increases, supporting the use of the more parsimonious Eq. (4). The parsimonious model provides efficient estimates even with the limited sample size in our study.

The term $\max\{18.33 - T_d, 0\}$ is HDD for day d with the base temperature at 18.33 °C (65°F). Then $\sum_{d\in C_{i,a}} \max\{18.33 - T_d, 0\}$ is HDD for the time period $C_{i,a}$. Eq. (4) restricts the HDD effects to be linear in parameters and the high temperature exposures to have zero effect on outcomes. Although these restrictions are not rejected by the estimates based on Eq. (3), we also include the CDD variable in the model as a robustness check, where CDD is defined similarly to HDD but for high temperature above 18.33 °C. The coefficient of interest is γ_a, the effect on Y_i of a unit change in HDD during period c. This identifies the total effect of temperature on children described in Eq. (2).

For all our models, we construct temperature exposure measures as a 12-month exposure starting from each child's birthday, ensuring that children are exposed to the entire seasons of a year during each window of exposure we consider.

Even with the restrictive empirical model, there are sizable variations in temperature exposures to the children. We graphically show the distribution of temperature exposures in our sample in Figures A7 and A8 in the Appendix, showing the distribution of 12-month HDD exposed to the children in the sample for 24–13 months before birth, 12–0 months before birth, 1–12 months after birth, and 13–24 months after birth. The figures show that the variation in HDD is quite large across villages compared to within villages. But even within villages, the differences between the 25th and 75th percentile of HDD are frequently greater than 50, equivalent to a 50-day exposure to cold temperature lower by 1 °C. These variations arise from differences in temperature across years and the fact that all twelve birth months are represented in each village in the sample. Wide variations of temperature in a relatively temperate region support the external validity of our study to other places in the temperate region whose distribution of daily temperature overlaps with ours.

As explained in Section 3 on our conceptual framework, temperature exposures may have different effects on the cognitive skills outcomes depending on the age of children. This would be the case if temperature changes undermine the cognitive skills development process, which undergoes 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:

$$Y_{i,(age)} = \alpha_{(age)} + \sum_{a\in A} \gamma_{a,(age)} \sum_{d\in C_{i,a}} \max\{18.33 - T_d, 0\} + x'_{i,(\text{age})}\beta_{(\text{age})} + \lambda_{\text{village-year, (age)}} + \epsilon_{i,(\text{age})}, \tag{5}$$

where (age) is the "age", the point in time in which child i's outcome $Y_{i,(age)}$ is observed. Note that $a \in A$ is defined as in Eq. (3), so that the outcome measured at a point in time (age) is regressed on cumulative temperature exposures during multiple periods of a child's life denoted by $C_{i,a}$. $\gamma_{a,(age)}$ identifies the effect of HDD in period a on $Y_{i,(age)}$, measured at (age). This identifies Eq. (2) while being more precise about the time in which the outcome is realized.

We estimate Eq. (5) 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 (indexed by 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 $bw = 0.5$.

We also estimate age-varying temperature effects using subsample analysis. We do this by estimating Eq. (4) for outcomes realized at different points in time in subsamples. We consider four subsamples, each including observations whose outcome variables are realized in one of the following age ranges: $[0, 2]$, $[1, 3]$, $[2, 4]$, $[3, 5]$. For example, for a subsample defined by age range $[0, 2]$, the outcome variable is realized at some point in time between ages 0 and 2, whereas HDD covers the entire period of a child's life considered in Eq. (4).

Temperature exposures may directly disrupt children's performance on tasks that require cognitive functioning. This process can undermine children's human capital development by undermining children's own learning. Further, even without directly affecting children's development, temperature can interfere with children's performance at cognitive skills measurement. In this case, the effects of exposure to temperature changes would be observed immediately. No author to our knowledge have simultaneously examined the immediate and delayed effects of early childhood exposure to temperature variations. 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 follows:

$$Y_{it} = \alpha + \sum_{p\in P}\sum_{b\in B} \gamma_{pb} \sum_{d\in p_{it}} \mathbb{1}(T_d \in b) + x'_{it}\beta + \lambda_{\text{village-year}} + \nu_i + \rho_t + \epsilon_{it}. \tag{6}$$

$\mathbb{1}(T_d \in b)$ is defined as in Eq. (3). $p \in P \equiv \{\text{day of survey, past week, past month, past year}\}$ is the window (time period) of temperature exposure relative to the time of survey. p_{it} is the set of days in the time period p. 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 children's age, gender, and the number of siblings interacted with birth order; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; two dummy variables indicating whether the cognitive scale is from BSID, WPPSI for children younger than 4 years old, or WPPSI for children aged 4 years and above; and sunlight duration, precipitation, and $PM_{2.5}$ in each exposure window. ϵ_{it} is the idiosyncratic error term clustered at the village level.

We analyze the effect of temperature exposures on home environment using this equation as well, using the "past year" time window. We do not use Eq. (4) as in the case of children's cognitive skills because home environment would be mostly determined by caregivers whose responses to temperature changes need not necessarily be different over time.

Table 2
Effects of 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	0.048	0.079	0.052	0.065	−0.034
	(0.104)	(0.110)	(0.100)	(0.166)	(0.160)
HDD/100, 1st Year Before Birth	−0.171	−0.290†	−0.204	−0.391	−0.380
	(0.152)	(0.157)	(0.170)	(0.252)	(0.240)
HDD/100, 1st Year After Birth	−0.350*	−0.510**	−0.553***	−0.691***	−0.832***
	(0.136)	(0.151)	(0.162)	(0.180)	(0.219)
HDD/100, 2nd Year After Birth	−0.331***	−0.399***	−0.329**	−0.471**	−0.563**
	(0.075)	(0.097)	(0.109)	(0.147)	(0.209)
Village-Year FE and Test Version Dummies	✓	✓	✓	✓	✓
Year×Month FE, Day of Week FE, Examiner FE		✓	✓	✓	✓
Age, Gender, Siblings, Mom's Educ, Asset, Heating			✓	✓	✓
Indicators for Birth Month and Year 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 heating degree days for each day within each 12-month period c: $HDD_c = \sum_{d \in D_c} \max\{(18.33 - x_d), 0\}$, where x_d is the temperature in day d. Subscript c is omitted in the table. "Test version dummies" includes two dummy variables indicating whether the cognitive scale is from BSID, WPPSI for children younger than 4 years old, or WPPSI for children aged 4 years and above.

Throughout these analyses, 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, is associated with both cognitive skill development and weather. It would also be violated if some households migrate out of the sampling area in response to temperature variations, leading to selective attrition. We test for these possibilities but do not find evidence to reject the identification assumption (Section 8).

6. Effects on cognitive skills

6.1. Main results

Fig. 3 shows the estimates based on Eq. (3). According to the results, the negative effects of cold temperature are concentrated on those from daily average temperature below 5 °C. The effects of high temperature are negative but not significant. The subfigure in the upper-left corner of Fig. 3 shows that the effects of temperature exposures 2 years before birth are small and insignificant, serving as placebo tests. These results are robust to using smaller temperature bins (Figure A9). Incidentally, the magnitude of the negative effects increases approximately linearly as the temperature decreases. This is consistent with the implicit restriction imposed on Eq. (4) used to estimate the main results.

Our main results on Table 2, based on Eq. (4), show that exposure to low temperature during early childhood period has negative and significant effects on cognitive skills measured at ages 2 to 5 years. The effects are greater for exposures during the first year after birth than for those during the year before birth and the second year after birth. The effects of exposure during the *in utero* period are negative but mostly not significant.

In Table 3, we further show that exposures to high temperature do not significantly impact cognitive skills in wave 2 in our sample by jointly estimating the effects of HDD (low temperature exposure) and the effects of CDD (high temperature exposure). Columns (2), (3), and (4) show that CDD effects are small and insignificant, and controlling for CDD does not meaningfully affect estimates of main HDD effects shown in column (1). In addition, we control for 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. As Table 3 shows, the effects of exposure to low temperature are robust to adding these variables.

Our main results imply that mild temperature variations can have a sizable impact on cognitive development in early childhood. An additional ten days of exposure to temperature colder by 1 °C during the first year of a child's life (an increase in HDD by 10) is predicted to lower cognitive skill in wave 2 by 0.0832 in standard deviation unit, as shown in column (5) of Table 2. This is similar in magnitude to the effects of a Nicaraguan program that transferred approximately 15% of per capita expenditure each year on early childhood cognitive skills (Macours et al., 2012). Alternatively, the effects of about 2 months of exposure to temperature colder by 1 °C (an increase in HDD by 60) 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).[12]

We show the heterogeneity of effects in Table 4 using interaction models so that the significance of the interaction terms provides tests of heterogeneity. We examine the heterogeneity by child's gender in column (1), but the differences are not significant.

Table 3
Effects of temperature exposures with additional control variables.

	Cognitive score in wave 2			
	(1, Baseline)	(2)	(3)	(4)
HDD/100, 2nd Year Before Birth	−0.035 (0.160)	−0.091 (0.161)	−0.034 (0.188)	−0.037 (0.179)
HDD/100, 1st Year Before Birth	−0.381 (0.240)	−0.462† (0.241)	−0.424† (0.247)	−0.373 (0.237)
HDD/100, 1st Year After Birth	−0.831*** (0.219)	−0.868*** (0.208)	−0.852*** (0.212)	−0.918*** (0.214)
HDD/100, 2nd Year After Birth	−0.562** (0.209)	−0.578** (0.209)	−0.526* (0.227)	−0.515* (0.222)
CDD/100, 2nd Year Before Birth		−0.273 (0.267)	−0.396 (0.293)	−0.354 (0.295)
CDD/100, 1st Year Before Birth		−0.092 (0.247)	−0.174 (0.268)	−0.072 (0.259)
CDD/100, 1st Year After Birth		−0.117 (0.263)	−0.168 (0.281)	−0.244 (0.286)
CDD/100, 2nd Year After Birth		0.163 (0.255)	0.212 (0.252)	0.186 (0.246)
Other Baseline Controls and Having AC	✓	✓	✓	✓
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 heating degree days for each day within each 12-month period c: $HDD_c = \sum_{d \in D_c} \max\{(18.33 - x_d), 0\}$, where x_d is the temperature in day d. Subscript c is omitted in the table. CDD is the sum of cooling degree days 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 temperature $t_{d,max}$, $t_{d,min}$, 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; two dummy variables indicating whether the cognitive scale is from BSID, WPPSI for children younger than 4 years old, or WPPSI for children aged 4 years and above; children's age, gender, and the number of siblings by birth order; indicators for month of birth; indicators for year 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. "Having AC" is a binary variable indicating whether the household had an air conditioner at home during wave 0.

The effect on boys for the low temperature exposure during pregnancy is now borderline significant. Column (2) shows that the differences in effects by the household asset level at baseline are negligible, perhaps because the sample consists of mostly disadvantaged households without much variation in assets that help them adapt to the cold. Column (3) shows that the effects are not significantly different by whether the child is born during winter months. The difference in effect for the low temperature exposure during the year before birth is borderline significant. Column (4) examines heterogeneity by mother's education level and column (5) by the caregiver's level of parenting knowledge.[13] These may be related to the caregiver's ability in helping their children adapt to the cold. The differences are mostly insignificant and inconsistent in sign, however.

Column (6) shows the heterogeneity by the type of heating devices available at home. The heterogeneity is based on whether the households own firewood heaters or coal heaters without ventilation pipes, regardless of whether they have other types of heating devices. Such heating devices are associated with heavy indoor air pollution which can negatively impact the health and cognitive development of household members (Chen et al., 2018; Tian et al., 2009). Note that we merely have information about the availability of each type of device, not whether or how often they are used in the household. Further, this information is available for only a subset of the sample, so that the sample size is reduced for the analysis in the last column.

The results show that the negative effects of low temperature exposure one year after birth do not differ significantly in magnitude by the type of heating devices available at home. Compared to the baseline estimate of −0.832 in Table 2 for the effects of temperature during the first year, the effects are barely greater for households that are likely to suffer more indoor air pollution because they own firewood heaters or coal heaters without ventilation pipes (−0.915). We provide more analyses and discussion on potential confounding by indoor air pollution in Section 8.4.

[12] 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 measured at the end of the program. 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 a 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 at age 8 by 0.57 in standard deviation unit. This is equivalent to about 66 days of exposure to low temperature.

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

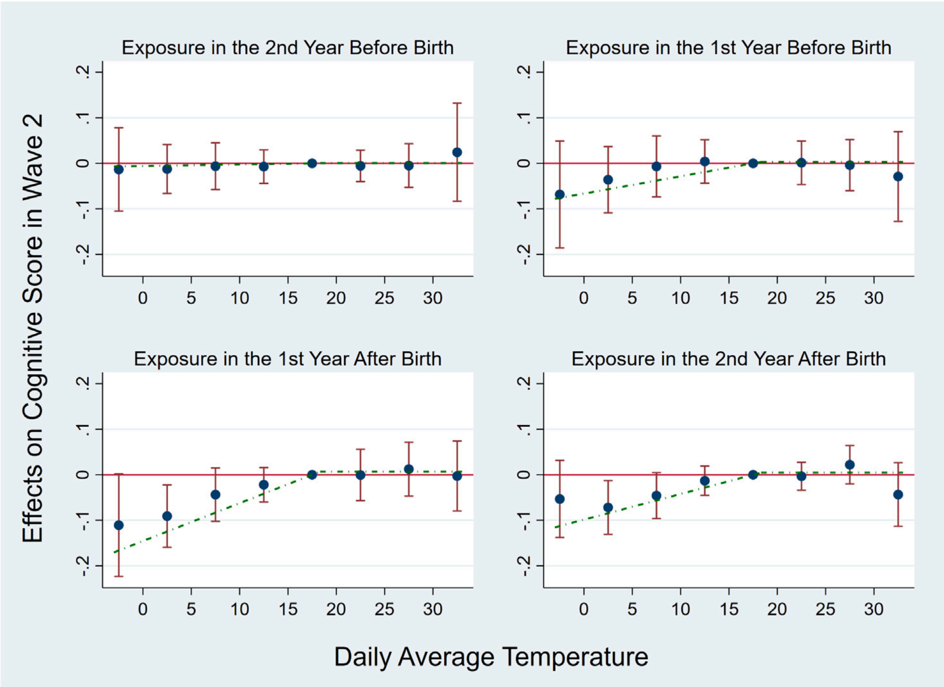

Fig. 3. Effects of temperature exposure on cognitive skills in early childhood.
Notes: Error bars indicate 95% confidence intervals. Standard errors are clustered at the village level. Circles represent estimates based on Eq. (3). Dotted lines represent estimates of a linear spline model with a knot 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; two dummy variables indicating whether the cognitive scale is from BSID, WPPSI for children younger than 4 years old, or WPPSI for children aged 4 years and above; children's age, gender, and the number of siblings by birth order; indicators for month of birth; indicators for year 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.

6.2. Immediate and delayed effects of temperature exposure

Results in the previous section were based on outcomes measured in the last wave, covering ages from 3 to 5. In this section, we pin down the age in which the outcome is measured to determine more precisely when the effects of temperature exposures start to emerge in children's lives. Specifically, we use locally weighted regression based on Eq. (5) for outcomes measured at different ages. We find that the effects of temperature exposures in the first year of life are large and significant on cognitive skills measured at ages 3 and 4 (Figure A10, lower left subfigure). The effects of exposure in the second year of life are also significant only in the third year after birth (lower right subfigure). We do not find effects on outcomes at age 1 under any specification. Also, the effects of temperature exposures before birth, including exposures during pregnancy, are not significant on outcomes at any age. Subsample analyses shown in Table A2 replicate these results: significant, negative effects are concentrated on outcomes observed at ages 2–5 years, and only for exposures after birth (columns (3) and (4)). Exposures during the first year after birth do not significantly affect outcomes at ages 0–3 years (columns (1) and (2)). 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 using panel regression based on Eq. (6). Even though children's performance at cognitive tasks may be vulnerable to temperature exposures similar to adults, results in Fig. 4 show insignificant effects of temperature exposures on the day of the survey and for the 7 days and 30 days leading up to the survey date. The significant effects are observed only for the temperature exposures during the 365 days leading up to the survey date, and for days of average temperature below 0 °C. Therefore, the temperature exposure effects are unlikely to be explained by temporary disruptions on children's cognition at the time of measurement.[14] These results, based on children in early childhood, complement the evidence showing that temperature variation can impact same-day cognitive performance of adolescents and adults (e.g., Graff Zivin et al., 2018).

[14] It is possible that the "true" damage on children was inflicted immediately, but the measurement of this damage occurred only later. This is a common problem in the literature of measuring unobservable skills (Almlund et al., 2011).

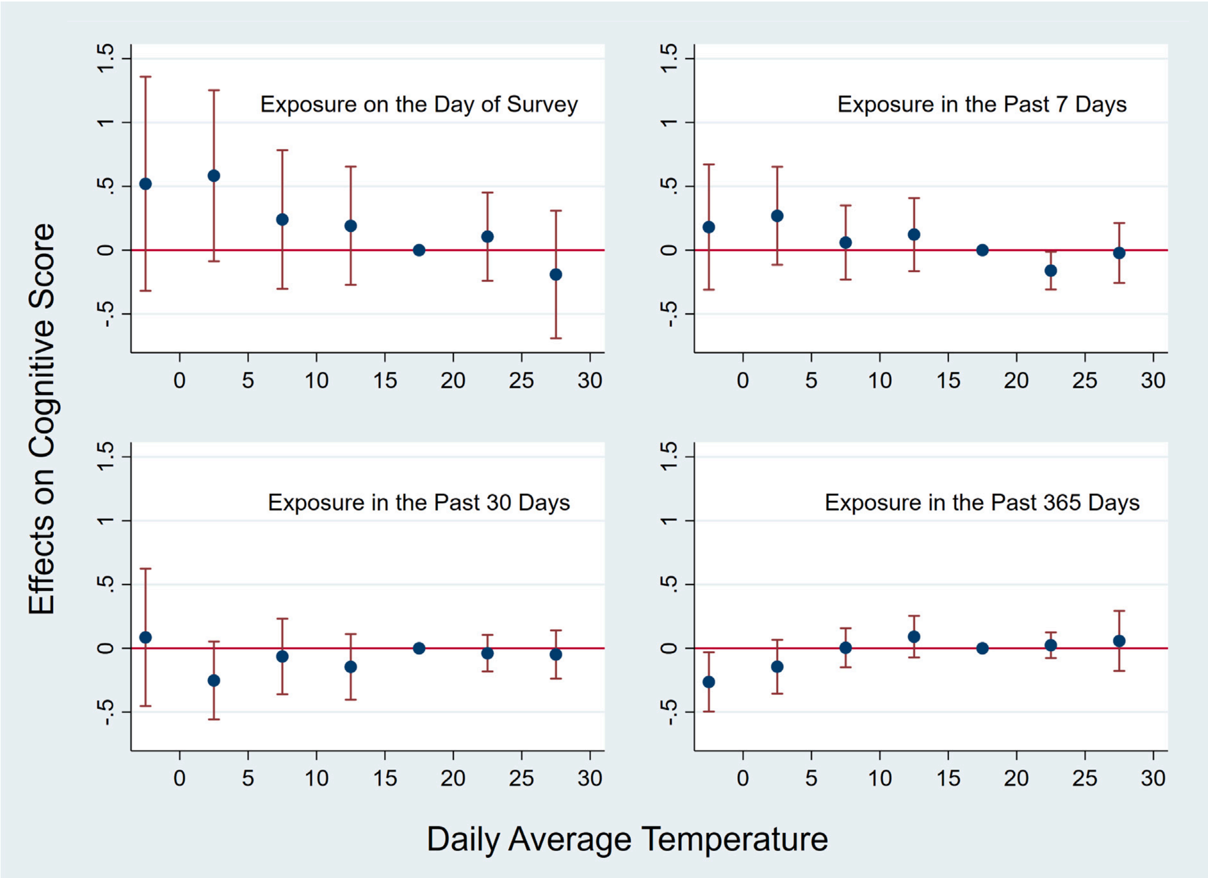

Fig. 4. Panel regressions of temperature effects on cognitive scores.
Notes: Error bars indicate 95% confidence intervals. Standard errors are clustered at the village level. Other control variables include: child fixed effects; wave fixed effects; village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; two dummy variables indicating whether the cognitive scale is from BSID, WPPSI for children younger than 4 years old, or WPPSI for children aged 4 years and above; children's age, gender, and the number of siblings by birth order; precipitation, sunshine and $PM_{2.5}$ during each period.

7. Effects on home environments

In this section, we examine whether temperature exposures affect the home environment, a key determinant of short- and long-term child development (Caldwell and Bradley, 1979; Heckman and Mosso, 2014). Caregivers may try to compensate for the disadvantages suffered by the children, implying that home environments may improve in response to cold temperature exposures, whereas the disruptive effects of temperature on parents imply that home environments may worsen. Results show that investments in children as measured by home environments are *lower* in households exposed to lower temperature. As seen in Table 5, the coefficient estimates of the HDD variable are negative on the overall home environment score and the two subscores covering caregiver–child interactions ("activities") and material investments into the home environment ("books and toys"), although the estimate is significant at the conventional levels only for the model with the overall score. Fig. 5 shows, however, that both the overall score and the activities subscore are significantly lower for children exposed to temperature below 5 °C, based on nonparametric regression models. These results are consistent with the intuition that, compared to material investments, the interaction between parents and children may be more directly shaped by changes in parents' behaviors exposed to low temperature. Panel regression estimates on the material investments subscore are negative but not significant.

These results do not support the implications of parents making adequate compensating investments in response to children's health disadvantages reported in the literature (Almond and Mazumder, 2013; Yi et al., 2015). As discussed in Section 3, caregivers may be directly undermined by the temperature, preventing them from adequately compensating for their children with interactions and care. Because childhood home environments are important predictors of subsequent skill development, temperature changes in early childhood may have persistent, long-term effects through the childhood home environment.

Analysis of each item of caregiver–child activities that comprises the home environment shows that the negative estimates are concentrated on subscales related to "playing outdoors" and "telling stories" (Table A3, Figure A11, and Figure A12). These are physically and cognitively demanding tasks that may be more vulnerable to temperature changes than other activities in the measure.

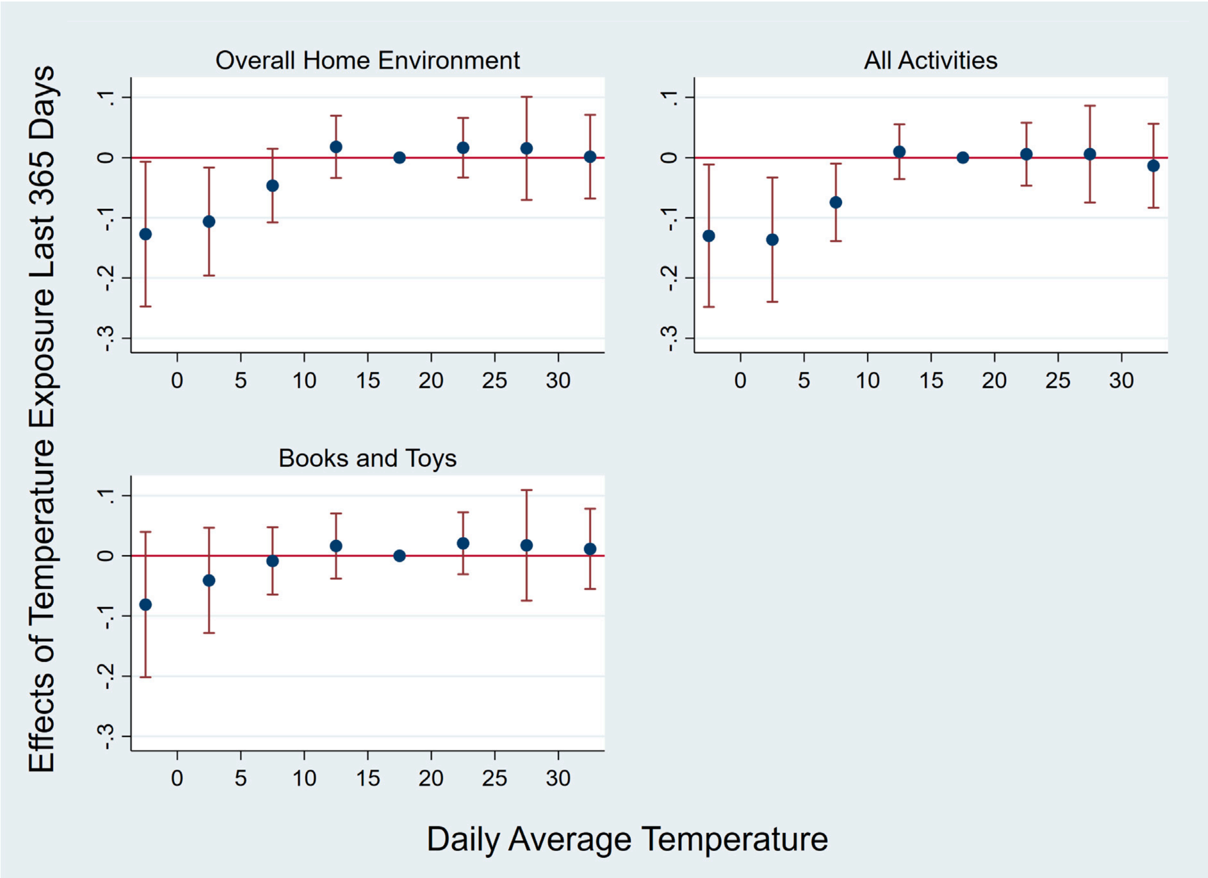

Fig. 5. Panel regressions of home environment on last year's temperature.
Notes: Error bars indicate 95% confidence intervals. Standard errors are clustered at the village level. Other control variables include: child fixed effects; wave fixed effects; village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; two dummy variables indicating whether the cognitive scale is from BSID, WPPSI for children younger than 4 years old, or WPPSI for children aged 4 years and above; children's age, gender, and the number of siblings by birth order; precipitation, sunshine and $PM_{2.5}$ in the past 365 days.

Although "telling stories" likely occurs indoors, rural China is known for inadequate heating at home (Ma et al., 2021; Niu et al., 2010). Further, the literature shows that outside temperature can impact cognitive functioning indoors even with adequate climate control (Cook and Heyes, 2020; Heyes and Saberian, 2019). Households exposed to low temperature are also lower in many of the individual measures of material investment, but the estimates are mostly not significant.[15]

Heterogeneity analysis on home environment in Table A4 shows that the estimates do not significantly differ by the same subgroups we consider for children's cognitive skills. These results are broadly consistent with the lack of heterogeneity we found for the cognitive skills. It is possible that the home environment may be a channel explaining the effects of temperature exposures on cognitive skills we observe, although we cannot directly confirm this mechanism.

Finally, we investigate whether children's screen time differ by exposure to suboptimal temperatures. Excessive screen time predicts negative developmental outcomes such as high BMI and low academic achievements (Duch et al., 2013), but can be limited by parental monitoring (Gentile et al., 2014). We find that children's screen time is not significantly associated with temperature exposures (Figure A13).

8. Robustness

8.1. Accounting for attrition

Our study relies on the analysis of panel data which can produce biased estimates if there is systematic attrition. Whereas the attrition rate is relatively modest at 18.31% in the last wave (wave 2), we use linear regression to examine sources of attrition and

[15] We do not have information to distinguish whether material investment measures are lower because parents are less willing to purchase materials for their children. We later investigate but do not find evidence that household income was affected by the temperature.

Table 4
Heterogeneous effects by subgroups.

	Cognitive score in wave 2					
Group B ⟶	Being Female (1)	Assets ≥ Median (2)	Being Born in Sep–Feb (3)	Mother Finished High School (4)	Knowledge in Wave 0 ≥ Median (5)	Having Firewood or Coal w/o Pipe (6)
HDD/100, 2nd Year Before Birth	−0.011	−0.038	−0.316	0.007	−0.152	0.370
	(0.148)	(0.195)	(0.258)	(0.170)	(0.198)	(0.320)
×Group B	−0.033	0.007	0.265	−0.168	0.244*	−0.135
	(0.123)	(0.116)	(0.182)	(0.171)	(0.119)	(0.242)
HDD/100, 1st Year Before Birth	−0.436†	−0.375	−0.211	−0.369	−0.372	0.080
	(0.237)	(0.240)	(0.244)	(0.241)	(0.240)	(0.384)
×Group B	0.140	−0.014	−0.330†	−0.091	0.137	−0.159
	(0.127)	(0.137)	(0.178)	(0.191)	(0.123)	(0.228)
HDD/100, 1st Year After Birth	−0.765**	−0.828***	−0.838***	−0.890***	−0.692**	−0.915*
	(0.239)	(0.240)	(0.247)	(0.209)	(0.227)	(0.359)
×Group B	−0.139	−0.017	−0.002	0.253	−0.226	0.120
	(0.166)	(0.159)	(0.205)	(0.161)	(0.154)	(0.284)
HDD/100, 2nd Year After Birth	−0.582**	−0.573**	−0.636**	−0.558**	−0.462*	−0.416
	(0.211)	(0.213)	(0.226)	(0.210)	(0.228)	(0.362)
×Group B	0.012	0.022	0.075	−0.066	−0.155*	0.170
	(0.088)	(0.090)	(0.107)	(0.130)	(0.077)	(0.146)
Other Baseline Controls	✓	✓	✓	✓	✓	✓
Observations	1245	1245	1245	1245	1239	737

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 heating degree days for each day within each 12-month period c: $HDD_c = \sum_{d \in D_c} \max\{(18.33 - x_d), 0\}$, where x_d is the temperature in day d. Subscript c is omitted in the table. "×Group B" represents the interaction between HDD/100 during the corresponding one-year exposure period and the group specified in the column header. "Other baseline controls" include: village-by-year fixed effects; year-by-month fixed effects; day-of-week fixed effects; examiner fixed effects; two dummy variables indicating whether the cognitive scale is from BSID, WPPSI for children younger than 4 years old, or WPPSI for children aged 4 years and above; children's age, gender, and the number of siblings by birth order; indicators for month of birth; indicators for year 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.

Table 5
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	−0.339*	−0.285	−0.288
	(0.170)	(0.219)	(0.174)
Village-Year FE, Test Version Dummies	✓	✓	✓
Age, Individual FE, 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 heating degree days for each day within each 12-month period c: $HDD_c = \sum_{d \in D_c} \max\{(18.33 - x_d), 0\}$, where x_d is the temperature in day d. Subscript c is omitted in the table. "Test version dummies" includes two dummy variables indicating whether the cognitive scale is from BSID, WPPSI for children younger than 4 years old, or WPPSI for children aged 4 years and above.

predict retention probabilities. Table A5 shows no significant association between baseline characteristics and attrition probabilities except for the effects of the number of siblings of children. Further, Table A6 shows that our main results are robust to adjusting for attrition, based on the regression of Eq. (4) with observations weighted by the inverse of retention probabilities (inverse probability weighting).

8.2. 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. We show in Table A7 that the survey date is likely not determined in favor of one household over another because none of the baseline household characteristics we examine is significantly associated with the HDD on the day of the survey and days surrounding it.

The identification assumption can also be violated because of endogenous migration, either across or out of villages, in response to temperature variation. Table A8 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 exposure to low temperature and parental migration decisions, separately by the mother and the father (Table A9).

8.3. Other robustness checks

Control variables. We first recall some of the robustness checks already shown in Section 6 alongside the main results. We show in Table 2 that the main results are robust to removing various control variables. In addition, we account for the effects of exposure to temperature other than the low temperature as measured by HDD by accounting for the effects of CDD. Table 3 shows that the effects of exposure to high temperature as measured by CDD are small and insignificant, and the inclusion of CDD does not affect the effects of HDD. These results are robust to controlling for the range of temperature variation as well, as shown in the set of control variables shown in the last panel of Table 3.

Temperature effects may be confounded by caregivers' climate-adaptive behaviors not considered in our models. Because such behaviors are likely correlated with the behaviors and characteristics of caregivers at home, we additionally control for the identity of the primary caregiver[16] and whether parents visit local daycare centers.[17] We also estimate results without controlling for the availability of heating devices at home. Table A10 shows that the main results are robust to these controls.

HDD base temperature. 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 explained by exposures to a limited range of temperature. We examine this possibility by lowering the baseline temperature in constructing the HDD variable. If the temperature range that drives the effects is located right below the base temperature, then the estimates using HDD with lower baseline temperature will be small and insignificant. As shown in Table A11, however, our results are robust to using lower base temperature to define HDD, as one would expect if the effects increase with greater exposure to the temperature of 0 °C or below.

Time window surrounding birth. Main results are based on models that include the outcomes of children measured up to two years before and after birth. 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 models with exposure 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 A12). The magnitudes of effects are smaller for exposures nearer to the time of measurement, continuing the pattern we observe for the main results.

Cognitive skill outcomes. For the main results, we use normalized scores of cognitive skills. 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. In Table A13, 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.

Language skill outcomes. Further, as a different outcome measure, we examine the temperature exposure effects on the children's language skills (Table A14 and Figure A14). Language skills are different from cognitive skills because 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 language subscore is available for the entire sample, shown in column (1). The receptive and expressive language subscores shown in columns (2), (3) and (4) are measured only in BSID, limiting the statistical power of the model. The coefficient signs and magnitudes are nonetheless consistent throughout, and the effects of first- and second-year exposures are significant except for the effects on the expressive language scale.

Daily minimum and maximum temperature. Finally, we account for the possibility that the results in this study are explained not by the daily average temperature but by the "extreme" temperature within the range of temperature variation in our sample. To this end, we use daily maximum and daily minimum temperature to estimate the effects of temperature exposure. The results in Figure A15 using daily maximum temperature are consistent in sign but weaker in significance. The results from daily minimum temperature closely follow our main results, consistent with our explanation that the negative effects of low temperature exposures explain the effects.

8.4. Other outcomes and alternative channels

Household income. 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., 2020b; 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 or the occupation of caregivers at home. Instead, we

[16] Studies show that biological parents in China tend to provide better childcare than grandparents do (e.g., Feng et al., 2022).

[17] Formal daycare is nonexistent for most households in the study area. The daycare provided as a part of the study is to watch the children while their parents receive parenting training, a part of the survey study not considered in this paper (Sylvia et al., 2021). In other words, daycare is an occasional arrangement rather than a primary form of childcare.

searched news media looking for mentions of unusual weather in the sampling area. On April 6–7, 2018, severe cold currents in northwestern China including Shaanxi province caused widespread frost damage to fruit crops such as apples (Gilleski, 2018; Inouye, 2018; Wang, 2018).[18] 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 A15 shows that our results are robust to this manipulation, confirming that the effects are not driven by the cold spell in April 2018 that plausibly reduced agricultural income. We remind the reader, however, that we are unable to distinguish sources of household income because of data limitation, and that this test does not rule out all possibilities of income channel.

Dietary intake. We also examine whether children's dietary intake is affected by temperature. Bhattacharya et al. (2003) show that low-income households in the US reduced food expenditure as their fuel expenditure increased during cold weather. Similarly, parents may have been persuaded to reduce the cost of food provided to children during low temperature days. Figure A16 and Table A16 show that exposure to low temperature in the previous year increases provisions of rice and beans but reduces dairy, meat, eggs, vitamin supplements, and fruits. Children are also less likely to consume four or more different kinds of foods. While this pattern is consistent with the existence of negative impacts of temperature 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 do not account for multiple hypothesis testing but doing so would further weaken already insignificant results.

Indoor air pollution. Given that the negative effects of temperature exposures are driven by low temperature, an important alternative explanation is the air pollution caused by using dirty heating devices at home. Studies show that air pollution can undermine health and cognitive development (Chen et al., 2013; Chen, 2024) and that indoor coal burning in China increases ambient air pollution (Almond et al., 2009; Chen et al., 2013).

We first confirm that days of low temperature are positively associated with air pollution in our sample. Figure A17 shows that lower temperature days are associated with higher levels of ambient $PM_{2.5}$, although the coefficient estimates are not significantly different from zero and declining temperature does not monotonically predict more air pollution.

We then examine whether air pollution can explain the temperature effects. The primary source of potential confounding by air pollution in our study is indoor heating by using heating devices that can cause significant air pollution, such as heaters using firewood or coal heaters without ventilation pipes. Studies in China show that indoor air pollution is significantly higher if the heating is done by firewood, "crop residue" (straws), and coal than by natural gas or electricity (Chen et al., 2018). As for the distinction between coal heaters with or without ventilation pipes, our reasoning is that a ventilation pipe would direct most of the smoke out of the house, thereby reducing indoor air pollution. According to Tian et al. (2009), air pollution is significantly lower if a chimney is installed above coal-heated stove than if the chimney is blocked.

As a part of our heterogeneity analysis, Table 4 in Section 6 already showed that the main results do not depend greatly on whether households own polluting devices including heaters using firewood and coal heaters without ventilation pipes. In addition, the main results are robust to not controlling for the availability of heating devices at home, as shown in Table A10 in Section 8.3.

We then estimate the effects of exposure to low temperature by allowing the effects to differ by whether households have each type of heating devices at home.[19] We estimate the same model used for the heterogeneity analysis, in which the interaction term estimates provide tests of heterogeneity in effects. The interaction term equals 1 if the households do not own the heating device in question. Table A17 in the appendix shows the results. The first column shows heterogeneity by whether households own heaters using electricity or natural gas, which cause minimal indoor air pollution. Focusing on the third panel, showing effects of exposure during the first year after birth, the effects are worse if the households do not own heating devices based on electricity or natural gas. Because other types of heating devices are potentially more polluting, the results are consistent with the possible role of indoor air pollution. The estimate is borderline significant, however. Column (2) shows results based on owning coal heaterS with ventilation pipes, column (3) based on coal heaters without ventilation pipes, and column (4) based on owning firewood heaters. The differences based on these devices are small in magnitude and not significant, even though coal heaters without ventilation pipes and firewood heaters are known to cause heavy indoor pollution. Effects of low temperature exposure during the second year after birth also do not show heterogeneity by the ownership of different heating devices.

Ambient air pollution, precipitation, and sunlight exposure. More direct tests are shown in Table A18 on whether air pollution affects children's cognitive skills development. The estimated effects of exposures to air pollution as measured by $PM_{2.5}$ at any 1-year time intervals between two years before birth and two years after birth are all close to zero and insignificant on children's cognitive skills outcomes measured in wave 2. Although our air pollution measure is based on ambient, outdoor air pollution, studies show that ambient air pollution increases in response to indoor coal burning in China (Almond et al., 2009; Chen et al., 2013).

Table A18 shows effects of other weather variables as well. The first panel shows the effects of precipitation, which can affect household income by crop yields (Beuermann and Pecha, 2020; Yamashita and Trinh, 2022). The second panel shows the effects of sunlight exposure, which can affect health (Brunekreef and Holgate, 2002; Moan et al., 2008) and crop yields. The effects of precipitation and sunlight exposures are small and insignificant on children's outcomes.

[18] According to Inouye (2018), "In early April, a severe frost struck the major apple-producing provinces in northwest China, including Shaanxi, Gansu, and Shanxi Provinces. This greatly affected the apple crop blossom. As a result, Shaanxi Province, the leading apple producing province, is expected to produce 20–30 percent less apples than last year".

[19] As explained in Section 6, we do not have information on whether the devices are actually used.

Children's health. Exposure to low temperature 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). The respondents report the number of days the children were sick during the 2 weeks prior to the interview. As Figure A18 shows, however, we find no evidence showing that temperature exposure has an effect on the number of days children were sick.

Indoor and outdoor activities. Temperature variation may make it stressful for the child to explore indoor or outdoor local environments, a critical part of children's cognitive development (Gibson, 1988). Children's outside activities can be discouraged by bad weather (e.g., Hesketh et al., 2017). Indoor activities can be similarly affected if the children were exposed to outside temperature prior to indoor activities (Cook and Heyes, 2020; Heyes and Saberian, 2019). Such problems would be worse in rural Chinese homes that typically lack adequate heating (Ma et al., 2021; Niu et al., 2010). Our measure of temperature exposures does not distinguish indoor or outdoor exposures. If better caregivers take their children indoors to keep them warm, home environment measures based on outdoor activities would decrease and those based on indoor activities may increase, provided indoor heating is sufficient. Figure A11 and Table A3 show that exposures to low temperature have negative effects on the subscore measuring children playing outdoors, although the estimates are not significant. There is no evidence of increase in indoor activities in response to low temperature exposures.

Cognitive skill measures in early age. The main results, that exposure to low temperature lowers children's cognitive skills, are based on measures such as BSID, some of which are taken when children are only a few months old. Using such early childhood measures is unavoidable given our research question. It is important, however, to ensure that our measures have good predictive validity. Many authors in developmental psychology literature suggest that BSID generally shows good predictive validity (Lung et al., 2009), but others found its predictive validity to be moderate among rural, disadvantaged communities (Rasheed et al., 2023). Our results may be biased in unknown ways if the characteristics of these measures are unaccounted for. We respond to this concern in several ways.

First, we recall that two dummy variables for the types of cognitive measures are included in all empirical models. Further, the scores are normalized by children's age in months, so the mean effect of the outcome measure (whose use depends on the age of children) is already accounted for.

Second, we show in Figure A19 that BSID scores in wave 1 predict WPPSI scores in wave 2 as much as BSID scores in wave 1 predict BSID scores in wave 2. In other words, the predictive validity within BSID scores over time is similar to the predictive validity of using BSID scores to predict WPPSI scores (within each child), where BSID targets younger children and WPPSI is a more stable measure that targets older children.

Finally, we estimate the model separately by whether BSID or WPPSI is used as the outcome variable. Comparing the results in columns (1) and (2) in Table A19, we see that the results are concentrated on outcomes based on BSID scores which measure cognitive skills at younger ages. The effects on WPPSI scores are negative but smaller in magnitude and not significant. Column (3) shows, however, that the effects are not significantly different by whether BSID or WPPSI scores are used, based on interaction models used for the heterogeneity analysis in Section 6. Columns (4) and (5) show that the results are robust to excluding the dummy variables for the types of cognitive measures used as dependent variables.

9. Conclusion

We investigate the effects of early childhood exposures to low temperature on cognitive skills development and home environment. We overcome data limitations in earlier studies by using 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.

We find that exposures to low temperature have negative effects on children's cognitive development in early childhood. The effects are significant at 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 in cognitively demanding tasks. The effects of exposures to high temperature are negative but small and insignificant.

Further, we find that households exposed to cold temperature are lower in investments in the home environment, especially as measured by interactions with children. These results do not show that caregivers adequately help the children overcome the negative effects of temperature exposures. Because home environments predict long-term outcomes of children such as educational attainment and income, these findings suggest that the negative temperature effects may be observed on outcomes realized later in children's lives without appropriate policy responses.

We find no evidence that temperature affected household income or children's health. Also, ambient air pollution or the immediate effects of temperature exposures do not explain the temperature effects we find.

Indoor air pollution from burning fuel for heating may be an important explanation for the negative effects of exposure to low temperature. An effective policy response through this channel would be to induce households to switch to non-polluting heating devices. Although our estimates do not depend significantly on the availability of different types of heating devices at home, we are unable to directly examine whether indoor air pollution played a role in generating the negative effects of low temperature. We leave this for future research.

Our findings show that ambient temperature variations at low temperature is a source of developmental disadvantages for children in low-income households. The non-extreme range of temperature variations in our study would be felt by many households in temperate regions across the world. Further, as climate change progresses and the climate system becomes increasingly unstable, the world will experience unexpectedly hotter days and colder days at higher frequencies (Bathiany et al., 2018; Schär et al., 2004). Our findings suggest that more children would experience negative developmental effects, and the negative effects of climate change on educational outcomes (Prentice et al., 2024) may worsen over time.

There are limitations to this study. Although the dataset includes an extensive range of information on home environment and children's developmental outcomes, it does not include all outcomes that could have been impacted by weather variations such as crime, conflict, or labor productivity (Dell et al., 2014). Also, because children's cognitive skills and home environment variables are jointly determined, we cannot (and do not attempt to) determine whether the effects on home environments explain the effects on cognitive skills, or whether the effects on cognitive skills explain the effects on home environment.[20] Finally, we point out that the children in our sample are in early childhood, for whom cognitive measurements may not be as precise as those designed for subjects at older ages.

Our results imply that policies targeting families with disadvantaged home environments 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. Early childhood programs were shown to improve the developmental outcomes of children in part by providing caregivers at home with assistance and training that improve the their parenting behaviors (Campbell et al., 2014; Elango et al., 2016; Zhou et al., 2024). Therefore, helping the caregivers in disadvantaged households to protect their children from the effects of temperature can be an effective and novel policy response to the negative effects of low temperature exposures.

CRediT authorship contribution statement

Wenjie Wu: Writing – review & editing, Writing – original draft, Supervision, Data curation. **Zhe Yang:** Writing – review & editing, Writing – original draft, Formal analysis, Conceptualization. **Jun Hyung Kim:** Writing – review & editing, Writing – original draft, Conceptualization. **Ai Yue:** Resources, Project administration, Investigation, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jeem.2025.103162.

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[20] The latter scenario is possible if, for example, caregivers reinforce observed differences in outcomes across children (Dizon-Ross, 2019).

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