Too Hot to Handle: The Effects of High Temperatures during Pregnancy on Adult Welfare Outcomes

Abstract

This paper studies the long-term effects of high temperatures during pregnancy on later outcomes for Chinese adults. We find that adults who experienced a one-standard-deviation more high-temperature days (about 36 days) during pregnancy attain 0.56 fewer years of schooling, have a higher risk of being illiteracy by 6.47%, are 17.25% standard deviations lower for word-test score, and are 0.85 cm shorter. The impacts are concentrated in the first and second trimesters. Additionally, income effects are one important channel to explain the adverse effects of hot weather. Back-of-the-envelope predictions suggest that by the end of the 21st century, *ceteris paribus*, losses in education years and height will be 0.14-0.54 years and 0.21-0.84 cm, respectively, caused by global warming.

Keywords: Global warming, high temperatures, prenatal period, educational attainments, height

1 Introduction

A growing literature in economics finds that hot weather during pregnancy causes negative effects on birth outcomes.[1] An important question that has yet to be answered is whether the adverse effects of hot weather during the prenatal period on birth outcomes are further related to adult welfare outcomes, and to what extent. To fill this gap, in this study we examine the effects of high temperatures on educational attainment and height for Chinese individuals born in rural areas between 1950 and 1994.

Evaluating the adverse impacts of hot weather is highly relevant in China and other developing countries, especially for rural residents, because they have limited access to avoidance behaviors such as air conditioners (Brooks et al. 2005; Feng et al. 2010). Specifically, for about 600 million rural residents in China, each household owned only 0.39 air conditioning units (*China Statistical Yearbook 2016*). In contrast, around 87% households in the United States were equipped with at least one air conditioning unit in 2015 (*2015 Residential Energy Consumption Survey*). The limited access to avoidance behaviors may amplify the impacts of high temperatures in rural China. Additionally, according to the National Aeronautics and Space Administration (NASA), by the end of the 21st century, average global temperatures are expected to be 0.5°F to 8.6°F higher than 2000 levels due to greenhouse gas emissions (Intergovernmental Panel on Climate Change 2013). Figure 1 contrasts the daily maximum near-surface air temperature on the

[1] Some recent papers that study the adverse effects of high temperatures during pregnancy on birth outcomes include Deschenes et al. (2009), Barreca et al. (2015), and Barreca et al. (2016). See Deschenes (2014) for a comprehensive review.

1 July 2000 (panel a) and 2100 (panel b) across the world. It shows that in 2100 the predicted high temperatures in some places (e.g., China, Arabian Peninsula, North Africa, and USA) could reach beyond 310 K (around 98°F) without controlling greenhouse gas emissions. To design rational climate-change-mitigation policies, estimating the costs related to climate change is of great importance for policy makers.

To study the effects of hot weather during pregnancy on adult outcomes, we combine individual information from the China Family Panel Studies (CFPS) with weather information from the China Meteorological Administration and the National Oceanic and Atmospheric Administration (NOAA).[2] Exploiting the information on each individual's birth date and place, we are able to measure the weather conditions during her/his prenatal period. We estimate a model controlling individual characteristics and a rich set of fixed effects. Our identification relies on plausibly random variations in the temperature distribution for a given county and calendar month.

We find that hot weather during pregnancy triggers significant reductions in adult welfare in multiple dimensions. Specifically, adults who experienced one standard deviation more high-temperature days (around 36 days) during the prenatal period attain 0.56 fewer years of schooling, have a higher risk of being illiteracy by 6.47%, are 17.25% standard deviations lower for word-test score, and are 0.85 cm shorter. In addition, the impacts seem to be concentrated in the first and second trimesters. High temperatures in the third trimester do not have statistically significant effects. Furthermore, we find a large effect

[2]The CFPS is a biennial survey, designed to be complementary to the Panel Study of Income Dynamics (PSID) in the United States. See data section for details on the CFPS.

on their birth weight for high temperatures during pregnancy. A one standard deviation increase in the number of high-temperature days leads to a loss of 91.41 grams of birth weight (17.94% standard deviation). Given the strong relationship between birth weight and children's development and adult outcomes (e.g., Behrman and Rosenzweig 2004; Black et al. 2007), this finding suggests that the adverse high-temperature effect on birth weight may be one possible channel for high-temperature effects on adult outcomes.[3]

Such effects, however, have not been taken into account when calculating the costs of global warming. Based on climate projections provided by the National Aeronautics and Space Administration (NASA), we perform back-of-the-envelope predictions for adult outcomes of individuals born in rural areas of China in 2100. Compared to those born in 2000, *ceteris paribus*, people born at the end of the 21st century will attain 0.14-0.54 fewer education years and be 0.21-0.84 cm shorter.[4]

We propose three hypotheses that may explain why hot weather affects birth outcomes: (1) biological effects. Due to the extra physical strain, a pregnant woman is more susceptible to ambient heat stress. By influencing the physical health conditions of pregnant women, high temperatures play an important role in fetal size and development;[5] (2) behavioral effects. Hot weather may induce changes in daily activities of pregnant

[3]We acknowledge that birth weight is only a proxy for infant health. The real mechanism that how hot weather during pregnancy affects adult outcomes may not necessarily be the birth weight. High temperatures may cause some other health problems. For instance, as Young (2002) suggests, the development of the sympathetic nervous system is quite sensitive to modification by exposures during neonatal life, in particular environmental exposures stemming from temperature.

[4]We acknowledge that our predictions strongly rely on the assumption that all other related factors will remain constant. See discussion section for details.

[5]For details, see discussion section.

women and further affect birth outcomes. For instance, Herman (1993) documents that ambient heat could reduce appetite and alter food selection, which are critical for fetal development (Figlio et al. 2009); (3) income effects. High temperatures affect household resources and nutrition for pregnant women by influencing crop yields—the main income source in rural areas—and further influence the health condition of newborns;[6] Exploiting the variation of the crops' sensitivity to heat, we test the existence of income effects. We find that areas with high proportions of heat-tolerant crops (corn and sugarcane) statistically significantly mitigate the adverse effects of high temperatures during pregnancy. To be specific, when the proportion of heat-tolerant crops reaches about 30%, the adverse effects of hot weather during pregnancy are muted. This evidence suggests that temperatures' effects on crop output—and thus household income—may be an important explanation for our findings. But as our data do not contain information on individual activities during pregnancy, we cannot rule out the existence of biological or behavioral effects.

Our paper contributes to the literature in several ways. First, our paper provides the first evidence for the long-term persistent effects of high temperatures during the prenatal period on adult outcomes, along with two working papers by Carrillo et al. (2015) and Isen et al. (2015). Deschenes et al. (2009) use data from 49 states in the U.S. and find that exposure to days above 85°F during pregnancy has a moderate negative effect on birth

[6] Some recent literature that documents the relationship between high temperatures and crop yield includes Hollinger and Angel (2009), Schlenker and Roberts (2009), and Burgess et al. (2011). For instance, Schlenker and Roberts (2009) find that temperatures above about 85°F cause damages to corn and soybeans yields.

weight. Whether the effect is further related to adult outcomes (e.g., human capital, physical conditions, etc.), as the authors claim, is an important—but unanswered—question. Using a developing country context—China, our study shows that adults' educational attainment and height are negatively affected by hot weather in *utero*. As the current air-conditioner-penetration-rate in China is still relatively low, our findings should raise both the public and policy makers' attention.

To compare, Isen et al. (2015) employ the U.S. data and find that hot weather during pregnancy reduces annual income but does not affect educational attainment. Another study by Carrillo et al. (2015) shows that 1°C increase in average temperature during pregnancy reduces income and education attainment in Ecuador. Additionally, besides educational attainment, we also examine the effects of high temperatures on physical conditions (height). Furthermore, our study provides a detailed discussion of the potential mechanisms that explain why hot weather affects birth outcomes. We find the evidence which supports that income effects are one of the key channels.

Second, our study contributes to a growing literature which studies the relationships between early life conditions and later outcomes (see Currie and Almond 2011 for a comprehensive review). Several influential studies have examined the consequences of early life shocks, such as the influenza pandemic (Almond 2006), Chernobyl disaster (Almond et al. 2009), and hurricanes (Currie and Rossin-Slater 2013), and find that such shocks have persistent and profound effects on well-being in later life. The unusual nature of these events, however, raises concern about the generalizability (Maccini and Yang 2009;

Almond and Mazumder 2011). Recent studies start to examine the effects of typical events in early life, such as rainfall (Maccini and Yang 2009), alcohol availability (Nilsson 2017), and nutrition restriction caused by Ramadan (Almond and Mazumder 2011). We complement this strand of literature by investigating the effects of high temperatures during pregnancy—another typical variation in early life—on later outcomes.

Lastly, from a broader perspective, our findings may add to the literature that explains the positive correlation between latitude and economic development. Many scholars have found convincing evidence that economic activities are correlated with geography indirectly through historical channels (see Wacziarg and Spolaore 2013 for a review). Some studies, however, show alternative direct explanations for such phenomena, e.g., a high burden of disease and the pests and parasites that thrive in hot climates. Based on our findings, we may provide another explanation, i.e., high temperatures affect newborn endowment, and further human capital, which is crucial for economic development.

Section 2 describes our data and variable definitions. Section 3 introduces the econometric approach. Section 4 presents the main findings, while Section 5 discusses the possible channels behind the impacts, implements robustness checks, and predicts the effects of global warming. We conclude in Section 6.

2 Data and descriptive analysis

2.1 Data source

Welfare outcomes and birth weight. Our major source of data on adult outcomes is the China Family Panel Studies (CFPS) 2010, a nationally representative, annual longitudinal survey of Chinese communities, families, and individuals. The studies were launched in 2010 by the Institute of Social Science Survey (ISSS) of Peking University and cover 25 provinces that represent 95% of the total population of China (Xie 2012).[7]

A few adult outcomes are included in the survey—e.g., years of schooling, word-test score, and height. Specifically, the interviewers investigate individuals' education levels, which consist of eight categories, i.e., illiterate/semi-illiterate, primary school, junior middle school, senior middle school, junior college, college, master's degree, and doctoral degree. The year of schooling is then imputed on the basis of the education levels by the survey. The word-test score is another measurement on individuals' educational attainment. In the word test designed by the CFPS, respondents are required to read as many Chinese characters as possible.[8] For the sake of interpretation, the score has been standardized in our empirical analyses. Height reflects individuals' physical conditions.

The data set provides ample information on demographic status as well, such as date

[7] The 25 provinces are Beijing, Tianjin, Hebei, Shanxi, Liaoning, Jilin, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, and Gansu. Figure 2 in the appendix shows their geographic distribution.

[8] See the CFPS (2010) user's manual for a detailed description.

of birth (month and year), gender, race, county of birth, birth order, number of siblings, and parental characteristics—e.g., age, educational attainment, etc. Based on the date of birth, we define each individual's prenatal period as nine months before the birth, or around 270 days in total.[9] The whole period is typically divided into three trimesters. Socio-economic information may help us capture family heterogeneity across different areas with different climates.[10]

In addition, relying on interviewees' own birth weight data, we examine the high-temperature effects on the birth outcome. During the survey, interviewees were required to report their own birth weight if they remembered. It is a custom in China that doctors tell the parents their newborn's birth weight. Thus people could know their own birth weight from their parents.[11]

Weather data. Weather data are from the China Meteorological Administration and the National Oceanic and Atmospheric Administration (NOAA) and include 1,509 different weather stations across China. The data set contains daily maximum and minimum temperature and precipitation. High-temperature days are defined as the number of days with daily maximum temperatures higher than 85°F.[12] To ensure the accuracy of

[9]The nine-month gestation period is supported by Deschenes et al. (2009). In addition, Patel et al. (2004) find that the median gestational age at delivery is about nine months in Asians. We acknowledge that the prenatal period is inevitably measured with error, as the exact birthdate and gestational length are not available. But as long as the measurement errors are not correlated with our core explanatory variable, they would not bias our estimates.

[10]For instance, Buckles and Hungerman (2013) find that the relationship between season of birth and later outcomes is driven by maternal characteristics.

[11]In the data set, a limitation is that only one third of the interviewees remembered their birth weight. In the results section, we document the relationship between the missing birth weight and personal characteristics.

[12]To test the sensitivity of the estimates to the temperature threshold, we apply different thresholds,

the weather readings, our key variable is defined as the average of the number of high-temperature days of all the weather stations whose distance to the county's centroid are less than 80km and that do not vary in elevation by more than 200 meters.[13] Hereafter, we refer simply to "high-temperature" or "hot-weather" days. In our sample, a representative rural pregnant woman is exposed to about 53.12 hot-weather days out of nine months of pregnancy. Other meteorological controls include the number of low-temperature days and total precipitation during pregnancy. Low-temperature days are defined as the number of days with daily minimum temperatures lower than 32°F.

In our analysis, we restrict our sample to individuals born in rural areas, which comprise 84.05% of the original CFPS sample. Since individuals in rural areas in general work outside frequently and have limited ways to avoid ambient heat, such as air conditioners, they are more likely to suffer from hot weather. Furthermore, observations without exact information on birth place are excluded. The remaining sample contains 9,041 individuals in 141 counties across 25 provinces. Sample statistics are summarized in Table I.

2.2 Descriptive regional patterns

If ambient heat stress during the prenatal period is an important determinant of welfare outcomes, we would expect that individuals in warmer regions have worse adult outcomes on average. In this subsection, we first depict the relationships between temperature and

ranging from 70°F to 90°F. See the main results section for detailed analysis.

[13] Using alternative distance thresholds, such as 70 km and 60 km, does not change our main results. Corresponding results are summarized in Table A.II and A.III in the appendix.

adult outcomes across provinces. Next, we examine the correlations between temperature and birth weight across provinces, as the high-temperature effects on adult outcomes are possibly caused by the high-temperature effects on birth weight.[14]

Welfare outcomes against temperature. Panels (a) through (d) in Figure 3 plot the mean years of schooling, illiteracy dummy, word-test score, and height, respectively, against the number of hot-weather days (>85°F) for a representative gestational period across provinces.[15] Relative to the southern provinces (blue circle markers in Figure 3), provinces in the north (red square markers) suffer hot weather less frequently.[16] The four figures indicate that hot weather during pregnancy may be further related to welfare losses in adulthood. Specifically, Panels (a)-(c) display interesting regional patterns that adults born in warmer places (lower latitudes in general) have fewer schooling years, a higher probability of being illiteracy, and lower word-test scores. Panel (d) shows the same regional pattern that the warmer the area, the greater the loss in height. This phenomenon in China—the higher the latitude, the taller the people—is also documented by Buxton (2013). Our findings suggest that the high temperatures during pregnancy may explain this geographical distribution of height to some extent.

Birth weight against temperature. In Figure 3, Panels (e) and (f) plot mean birth

[14]Importantly, the correlations depicted below only serve as the motivation for this project. They do not imply any causal interpretations. They could be explained by other factors. For instance, northerners in China are on average taller than Southerners, and this may be explained by differences in cuisine or genetics, rather than high temperatures.

[15]Beijing is excluded from these panels, since the average years of schooling and word- and math-test scores for individuals in Beijing are far beyond those in other provinces.

[16]We use an official geographical dividing line—the Huai River-Qin Mountains—to define northern and southern China provinces.

weight and low-birth-weight likelihood (<2,500 grams, LBW hereafter) for each province against the number of high-temperature days in a representative gestational period. The regional pattern of birth weight is striking and consistent with that of adult outcomes: Typically, babies born in the southern provinces gain less weight and are more likely to suffer from LBW. For perspective, Guangdong and Guangxi provinces, which are located in the southest China, are the warmest areas of China, with around 100 days with a maximum temperature higher than 85°F in a typical year. Compared to a representative baby in other regions of China, babies born in these two provinces weigh less by 8.7% and 11.4%, respectively.

3 Empirical framework

To identify the causal effect of high-temperature exposure during pregnancy on adult outcomes, our model relies on plausibly random variations in the temperature distribution for a given county and calendar month. To partial out potential confounding factors, we exploit the panel nature of our data to account for unobserved differences in counties, months, and years by estimating the following specification:

$$\begin{aligned} Y_{icmy} &= \beta HighTemp_{icmy} + W'_{icmy}\gamma + X'_i\delta \\ &\quad + county_c \times year_y + county_c \times month_m + month_m \times year_y + \epsilon_{icmy}. \end{aligned} \tag{1}$$

Here, *i* references individual, *c* represents county, and birth month and year are denoted by *m* and *y*, respectively. The dependent variables, Y_{icmy}, are adult outcomes, including schooling years, illiteracy dummy, standardized word–test score, and height. The variable of interest in Equation (1) is $HighTemp_{icmy}$, the number of hot-weather days during the gestational period. Other meteorological factors (W_{icmy}), such as the number of cold-weather days and total precipitation during the gestational period are controlled. We add a vector of individual characteristics, X_i, including gender, race, birth order, number of siblings, and parental age at delivery and educational attainment, to capture individual heterogeneity.

To isolate the causal effect, the specification includes all three sets of two-way fixed effects, i.e., county-by-year, county-by-month, and year-by-month fixed effects: (1) County-by-year fixed effects could capture the nonlinear changes in the determinants of human capital formation. As during our sample period, China enacted several policies that likely created nonlinear region-specific differences over time, for instance, the collectivization of land (late 1950s), the Three Years of Great Chinese Famine (1959-1961), the Cultural Revolution (1966-1976), and 9-year Compulsory Education (1986); (2) County-by-month fixed effects account for permanent unobserved county-by-month factors that may be correlated with both temperature and early-life health, e.g., seasonal employment. These fixed effects ensure that our model is identified from the presumed random annual fluctuations in the distribution of temperatures in a given county and calendar month; (3) Year-by-month fixed effects captures any shocks that are common to all regions.

ϵ_{icmy} denotes an idiosyncratic random error term. In our main results, standard errors are clustered at the county level. To check the robustness of the inference, we randomly assign individuals born in a placebo time and place, and re-estimate Equation (1) 1,000 times. If the standard errors were consistent, the rejection rate of the null hypothesis of no effect should be around 5% of the time when the threshold for the absolute t-statistic is 1.96. As shown in Figure 4, cases with an "effect" significant at the 5% level are around 5% of all placebo estimates. To allow for potential temporal and spatial autocorrelations, we use a number of other methods for inferences, including clustered at the province level (bootstrap-based), two-way clustering (county and year), and spatial clustering (Cameron et al. 2008; Hsiang 2010; Cameron et al. 2011; Barrios et al. 2012). As shown in Table A.IV, the inferences change slightly.

As suggested by the epidemiological literature, high-temperature exposure in different trimesters may have heterogeneous effects on birth weight and then further on adult outcomes. In the following specification, we allow for such heterogeneity:

$$Y_{icmy} = \sum_{T=1}^{3} \beta^T HighTemp_{icmy}^T + \sum_{T=1}^{3} \gamma^T W_{icmy}^{'T} + X_i' \delta$$
$$+ county_c \times year_y + county_c \times month_m + month_m \times year_y + \epsilon_{icmy}, \quad (2)$$

where $HighTemp_{icmy}^T$ denotes the number of hot-weather days in each trimester. $T = 1$, 2, and 3 denote the first, second, and third trimester, respectively. W_{icmy}^T consists of the number of cold-weather days and total precipitation in each trimester. The other notations are the same as those in Equation (1).

4 Main Results

This section reports estimates of the effects of ambient heat stress during pregnancy on later-life well-being, including educational attainment and height. Moreover, the heterogeneous effects of high temperatures across trimesters and family background on all outcomes are outlined. At last, we examine the high-temperature effects on birth weight.

4.1 Effects on adult outcomes

Before proceeding to report our main findings, we first validate our main specification. Specifically, we regress personal characteristics on high-temperature days during pregnancy including the sets of fixed effects in Equation (1). If high-temperature days are not associated with the observable characteristics conditional on the sets of fixed effects, it would support the exogeneity of high-temperature days in our main specification. The results in Table II show that all coefficients of high-temperature days are neither economically nor statistically significant at the traditional level, indicating that the high-temperature days are not correlated with any observable characteristics conditional on the sets of fixed effects. This finding suggests that the high-temperature days in our main specification are exogenous. Additionally, most coefficients on low-temperature days and precipitation are not statistically significant, either.[17]

Next, we begin our analysis by presenting the effect of ambient heat during pregnancy on adult outcomes, which are shown in Table III.[18] All columns includes other weather controls, personal characteristics, and three sets of two-way fixed effects.

Educational Attainment. We start with presenting the effect of ambient heat during pregnancy on educational outcomes, including education years, the probability of being illiteracy, and the standardized word-test score.[19] Column (1) shows that the effect of high temperatures during pregnancy on education years is negative and statistically significant at the 7% level. The coefficient indicates that a one standard deviation increase in high-temperature days (35.94 days) lowers the average years of schooling by 0.56(=0.0155*35.94) years (13.46% standard deviation). From another perspective, in column (2), we find that hot weather in the prenatal period statistically significantly increases the risk of being illiteracy. A one standard deviation rise in high-temperature days shifts up the probability of being illiteracy by 6.47 percentage points. In column (3), we examine the adverse effects of hot weather on the standardized word-test score. The point estimate indicates that adults who experienced one standard deviation more high-temperature days in the prenatal period are 17.25% standard deviations lower for word-test score. And the effect is statistically significant at the 5% level.

[17] In contrast, Wilde et al. (2016) find that because of fetal selections in Sub-Saharan African, hot weather around the time of conception induces better educational attainment later in life and lowers child mortality.

[18] Individuals who did not survive due to exposure to ambient heat in the prenatal period are not included in our sample. We may underestimate welfare losses because of such selection (Black et al. 2007).

[19] Individuals who did not survive due to exposure to ambient heat in the prenatal period are not included in our sample. We may underestimate welfare losses because of such selection (Black et al. 2007).

We also notice that cold weather and precipitation does not have statistically significant effect on education years, the probability of being illiteracy, or the standardized word-test score. Additionally, males and individuals with higher educational achievements parents tend to have longer years of schooling. Younger children in one family are less likely to be illiteracy, consistent with the findings in Black et al. (2005).

We have thus far defined the "high temperature" as a daily maximum temperature higher than 85°F. We acknowledge that this threshold is arbitrary to some degree. To test the sensitivity of the estimates to the temperature threshold, we apply different thresholds, ranging from 75°F to 90°F. Panels (a)-(c) in Figure 6 summarize the coefficients and confidence intervals for estimates of the effects on schooling years, the probability of being illiteracy, and the standardized word-test score using thresholds from 75°F to 90°F, respectively. As can be seen, the coefficients for high-temperature days are significantly negative when the threshold is beyond 85°F, implying that the effects of high temperatures during pregnancy are not sensitive to the temperature thresholds.

Height. Column (4) in Table III shows the impact of ambient heat during pregnancy on height. The coefficient implies that hot weather during pregnancy has statistically significantly negative effect on height. The point estimate shows that a one standard deviation increase in high-temperature days lowers the average height by 0.85 cm (11.07% standard deviation). Similar to the analyses on educational attainment, we also generate a dummy indicating that an adult's height falls in the bottom 10% of the sample distribution. The estimate presents that high temperatures in the prenatal period statistically significantly increase the risk of growing into a lower tail height by 5.75 percentage points.

Panels (d) and (e) in Figure 6 show that the negative effect of high temperatures on height is not sensitive to the temperature threshold. Additionally, we find that cold weather and rainfall during pregnancy do not have statistically significant effects on height.

Urban Sample. To compare, we also examine the effects of high temperatures during the gestational period for urban-born individuals. In the CFPS, urban-born individuals occupy only a relatively small proportion (15.95%). As the sample has only 1,910 observations, we cannot control for the three sets of two-way fixed effects as in Equation (1).[20] Instead, we employ the following less stringent specification to estimate the hot weather impacts for urban-born individuals:

$$\begin{aligned} Y_{icmy} &= \beta HighTemp_{icmy} + W^{'}_{icmy}\gamma + X^{'}_{i}\delta + county_c \\ &\quad + province_p \times year_y + province_p \times month_m + month_m \times year_y + \epsilon_{icmy}. \end{aligned} \tag{3}$$

Here, p denotes province. Compared to Equation (1), we replace the county-by-year and county-by-month fixed effects with province-by-year and province-by-month fixed effects.[21] We find that high-temperature days have no effect on adult outcomes for urban individuals, either statistically or economically (even no systematic direction of the

[20]For the urban sample, county-by-year, county-by-month, and year-by-month fixed effects have 1,321, 916, and 413 regressors. The total regressors are larger than the number of observations. Therefore, for urban sample, we are not able to use Equation (1).

[21]In Equation (3), the county, province-by-year, province-by-month, and year-by-month fixed effects have 126, 614, 283, and 413 regressors, respectively. The high-temperature effects can be identified.

impacts; see Table VII for related results). This is possibly because living conditions—e.g., housing quality and the availability of cooling tools—in urban areas are much better than those in rural areas. Also, urban individuals typically work outside less frequently, and thus are less likely to be directly exposed to ambient heat. However, based on the time use data, Peterman et al. (2013) find that in rural China, the time spent on agricultural work for the women during pregnancy is not statistically different from that for non-pregnant women. It implies that pregnant women in rural China are exposed to ambient heat more frequently and directly. Therefore, we will focus on the rural sample from this point on.

4.2 Trimester heterogeneity

In this subsection, we allow for heterogeneous effects of ambient heat across trimesters. Table IV illustrates the effects of high temperatures in each trimester. In each regression, we include all other weather controls, personal demographic characteristics, and three sets of two-way fixed effects. Columns (1) through (5) present the results for adult outcomes.

Noticeably, the adverse effects of hot weather in the second trimester are more statistically significant and larger for all educational outcomes.[22] Specifically, individuals who were exposed to one standard deviation more high-temperature days in the second trimester (around 23.02 days) attain 0.40 fewer education years, have a 5.99% higher

[22] Although the coefficients for education years are not statistically significant at the traditional level, we conduct a Wald test which shows that the overall effect of the high temperatures during the three trimesters on education years is statistically significant at the 10% level.

probability of being illiteracy, are 12.43% standard deviations lower for word-test score. For height, the effects in both the first and the second trimester are pronounced. Individuals who were exposed to one standard deviation more high-temperature days in the first and the second trimester are 1.29 and 0.95 cm shorter, respectively. However, high temperatures in the third trimester do not have statistically significant effects on these adult outcomes. Such sensitivity to temperature fluctuation during the first and second trimesters has also been documented by medical research (Murray et al. 2000 and Elter et al. 2004). However, as we do not have precise birth date or gestational length, trimesters are defined with errors. Therefore, we cautiously conclude that pregnant women are more sensitive to ambient heat in the first two trimesters.

4.3 Heterogenous effects across family background

Next, we explore the heterogenous effects of hot weather across family background, e.g., parental education. We hypothesize that better-educated parents should be able to avoid or mitigate the adverse effects of high temperatures during pregnancy. To test this hypothesis, we conduct two analyses. First, as suggested in Buckles and Hungerman (2013), parents with good education background tend to select their conception time to avoid bad weather conditions. If so, we would expect that parental education years are correlated with the number of high-temperature days during pregnancy. In columns (3) and (5) of Table 2, we regress father and mother's education years on the number of high-temperature days during pregnancy, respectively, and find that the correlations are not statistically significantly different from zero. Therefore, we conclude that there is no adaption in the sense that better-educated parents can select better conception time to avoid bad weather conditions.

Second, in response to early-life health shocks, parents may make compensatory and reinforcing investments in different dimensions of human capital across children. For perspective, we suppose that two individuals from two families, A and B, experienced the same hot-weather shock during the prenatal period. Parents in family A have better educational attainments than those in family B. So, parents in family A are more likely to make compensatory and reinforcing investments on their child. To test this story, we can add an interaction term between parental education years and the number of hot-weather days. As can be seen in Table V, the interaction terms are statistically insignificant across outcomes. One possibility explanation for this finding is that the adverse effects of high temperatures during prenatal period may not be compensatory. As Young (2002) suggests, environmental exposures (e.g., temperatures) at early life stage may permanently alter sympathoadrenal function for people, providing a basis for developmental origins of pediatric and adult disease.

4.4 Effect on birth weight

In this subsection, we examine the effect of ambient heat during pregnancy on birth weight—a possible important channel explaining high-temperature effects on adult outcomes. As only one third of the interviewees remembered their birth weight, our sample has 3,223 observations. Given the small sample size, we use Equation (3) to estimate the adverse effects of high temperatures on birth weight.

The adverse effect of ambient heat during pregnancy on birth weight is presented in Table VI. Column (1) reveals a large effect of hot weather in the prenatal period on birth weight. In particular, the coefficient indicates that birth weight is 2.54 grams (around 0.08%) lower for one additional high-temperature day. And the effect is statistically significant at the 10% level. To compare, Deschenes et al. (2009) find that each additional day>85°F lowers birth weight by 0.0025%. The magnitude is much smaller than our estimate, which is possibly because living conditions in the US were much better than those in China during the sample period. Such adverse influence is not negligible. A one standard deviation increase in high-temperature days leads to a 91.41 grams drop in birth weight, which is about 17.94% standard deviation. Moreover, cold weather does not have significant effect on birth weight, whereas high rainfall affects it negatively. Column (2) presents for effects of high temperatures on LBW incidence. The coefficient indicates one extra hot-weather day during pregnancy significantly increases the risk for LBW by 0.13 percentage points, though the estimate is not precise.

We also run sensitivity checks by using different definitions of high-temperature days. Panels (e) and (f) in Figure 6 show the coefficients and 90% confidence intervals for estimates of birth weight and low-birth-weight incidence using thresholds from 70°F to 90°F, respectively. As can be seen, the effects of high temperatures during pregnancy are not sensitive to the temperature thresholds.

We then examine the correlations between birth-weight-missing indicator and demographic status. Table A.I shows that individuals whose parents are better educated have a higher probability to remember their birth weight. This implies that the adverse effects of high temperatures during pregnancy on birth weight may be underestimated in this study, because the effects are likely to be larger for individuals with worse family background.

5 Discussion

5.1 Mechanisms

Our results thus far have presented the effects of high temperatures during pregnancy on adult outcomes and birth weight. Several channels may account for such impacts. One possibility is that hot weather has adverse physiological influences on pregnant women due to physical and mental strain.[23] By affecting the pregnant woman's health, heat stress further triggers negative impacts on newborns—e.g., low birth weight. In addition to biological effects, hot weather may induce changes in daily activities (behavioral effects). For instance, Herman (1993) documents that ambient heat could reduce appetite and alter food selection. Food intake and selection are critical for fetal development. Furthermore, high temperatures may also cause damage to crop yields (Hollinger and Angel 2009; Schlenker and Roberts 2009; Burgess et al. 2011), which determine family resources in

[23]Strand et al. (2011) suggest that a pregnant woman may be sensitive to heat stress because (i) the capacity to lose heat by sweating is lessened due to the reduced ratio of surface area to body mass, (ii) weight gain triggers more heat production, (iii) core temperature increases with accumulated fat deposition, and (iv) the increased body composition and metabolic rate of the fetus cause a rise in maternal heat stress.

rural areas and influence newborns' endowment through income effects, as suggested by Maccini and Yang (2009). As the data do not contain information on individual activities during pregnancy, we cannot test the existence of biological or behavioral effects. But we do can test the channel of income effects.

To test the income effects, we exploit the variation of the crops' sensitivity to heat. Hollinger and Angel (2009) find that heat stress is more likely to cause damage to crops when temperatures approach or exceed 85 °F. Moreover, how crops respond to hot weather varies. Specifically, C4 plants, including corn, sugarcane, and sorghum, are more adaptable to hot weather due to the efficient way they retain water in a hot environment. In contrast, C3 plants (barley, rice, wheat, etc.) are more sensitive to heat stress. If income effects matter, people living where C4 (C3) plants are widely cultivated would be less (more) affected by high temperatures during pregnancy. To test the income channel, we employ the following specification:

$$Y_{icmy} = \beta HighTemp_{icmy} + \zeta C4PlantArea_{py} + \kappa HighTemp_{icmy} * C4PlantArea_{py}$$
$$+ W'_{icmy}\gamma + X'_i\delta + + county_c \times year_y + county_c \times month_m + month_m \times year_y + \epsilon_{icmy}. \quad (4)$$

Here, p references province. $HighTemp_{icmy}$ denotes number of days with a daily maximum temperature higher than 85°F during pregnancy. $C4PlantArea_{pt}$ represents the corn and sugarcane proportion of crop acreage within each province-year cell.[24] The

[24]County-level plant area data are not available before 1997. Instead, we use plant-area da-

other notations are the same as those in Equation (1). If high temperatures affect people through the income channel, we would expect the coefficient of interaction term κ to be significantly positive. As shown in Table VIII, the interaction terms are statistically significantly positive for most outcomes. When the proportion of heat-tolerant crops reaches about 30%, the adverse effects of hot weather during pregnancy are muted.[25] The results provide support for the existence of income effects. But we cannot rule out the biological or behavioral effects.

5.2 Nonlinear effects of hot weather

In this subsection, we explore the nonlinear effects of high temperatures on adult outcomes. If ambient heat adversely affected embryos (or fetuses) only beyond a certain level of accumulated high-temperature days, it would change welfare implications, since high frequency of high-temperature days is not that common. We employ the partially linear model, allowing the key variable to be nonlinear:[26]

$$Y_{icmy} = f(X_{icmy}) + Z^{'}\gamma + \epsilon_{icmy}. \tag{5}$$

where X_{icmy} represents the number of hot-weather days during pregnancy. $f(.)$ is the unspecified nonlinear component, estimated by kernel regression with optimal band-

ta from the Thematic Database for Human-earth System (http://www.data.ac.cn/zrzy/DH55.asp?name-=&pass=&danwei=). It provides the plant area of each crop within each province from 1949 to 2000. There are two C4 crops (corn and sugarcane) in the dataset; the other 8 crops are C3 plants.

[25] On average, the proportion of C4 crops is 13.30% in our sample. One standard deviation is 9.11%.

[26] The partially linear model was first applied by Engle et al. (1986).

width.[27] Z represents other controls and fixed effects in Equation (1). To estimate Equation (5), we use the Robinson difference estimator (Robinson 1988).

Panels (a) through (e) of Figure 5 present the adult welfare outcomes estimates from Equation (5).[28] The y-axis represents the dependent variable partialled out from the parametric fit. The relationships shown in the figure are striking (significant at the 1% level): When the number of high-temperature days during pregnancy increases, years of schooling, the risk of being illiteracy, the word-test score, and height decrease monotonically.

5.3 Effects of high temperatures before conception and after birth

In this subsection, we first provide falsification tests by examining the impacts of high temperatures before conception on adult outcomes. In general, adult outcomes should not be influenced by before-conception temperatures. As shown in columns (1)-(5) in Table X, the effects of high temperatures during nine months before conception are not statistically significant at the traditional level.[29] Additionally, low temperatures and precipitation do not affect any adult outcomes, either. The falsification tests provide support to our main specification.

Besides the *in utero* stage, the early life conditions after birth are also critical for hu-

[27] The Epanechnikov kernel function is applied here.

[28] As Robinson (1988) points out, the nonparametric estimators of $E(Y|X_{icmy})$ and $E(Z|X_{icmy})$ are not reliable if the density of X_{icmy} is close to zero at x. Therefore, all regressions in Figure 5 are performed on a trimmed sample, in which 3% observations with the lowest estimated density are excluded.

[29] Six months before conception is defined as ten to fifteen months before conception. Such results are also robust to three months and nine months before the conception. The results are very similar by examining three months and six months before conception.

man capital development as well (Almond et al. 2009). In Table IX, we simultaneously control for weather conditions during pregnancy and nine months after birth. As displayed in columns from (1) through (5) in Table IX, the coefficients on the number of high-temperature days during nine months after birth are negative but not statistically significantly associated with any adult outcomes. Moreover, the coefficients on the number of hot weather days during pregnancy remain statistically significant. This comparison indicates that relative to high temperatures after birth, they matter more during pregnancy. Another interesting finding is that cold weather in nine months after birth statistically significantly affects educational attainment, indicating that newborns are more sensitive to low temperatures relative to high temperatures. This finding is consistent with Deschenes and Moretti (2009). They find that infants are vulnerable to extreme cold weather.

5.4 Predicting the impacts of climate change on birth weight and adult outcomes

The effects of high temperatures during pregnancy have not been taken into account when calculating the costs of global warming. Based on climate projections provided by the National Aeronautics and Space Administration (NASA), we perform back-of-the-envelope predictions for adult outcomes of individuals born in rural areas of China in 2100. Our predictions strongly rely on the assumption that all other related factors will remain constant. We acknowledge that individuals can adapt to changing environment and mitigate the potential negative effects of increasing temperatures. Moreover, access to air conditioners have been drastically increasing in China and other developing countries in recent years. But back-of-the-envelope predictions here can provide us a concrete figure, indicating without the technology progress and adaption what the specific effects of global warming are.

Assuming that greenhouse gas emissions will peak around 2040 (RCP 4.5 scenario), we predict that, holding all else equal, adults born in rural areas of China in 2100, on average, will suffer 0.14 fewer years of schooling and 0.21 cm decrease in height, compared to those born in 2000 due to global warming.[30] In an even more pessimistic case (RCP 8.5 scenario), greenhouse gas emissions will peak around 2100.[31] Likewise, losses in education years and height will increase to 0.54 years and 0.84 cm, respectively. Again, the above predictions are based on a strong assumption that all other related factors will remain constant—i.e., the same purchasing power, medical technologies, and access to air conditioners (Barreca et al. 2016 and Zivin et al. 2015). As other factors are being improved in China, however—especially in rural areas—the effects of global warming may be alleviated.

[30] RCPs are possible greenhouse-gas-concentration trajectories adopted by the Intergovernmental Panel on Climate Change (IPCC). Specifically, RCP 4.5 presumes that global annual greenhouse gas emissions (measured in CO2-equivalents) will peak around 2040, then decrease. In RCP 8.5, emissions keep increasing throughout the 21st century. Under the RCP 4.5 scenario, the number of high-temperature days during pregnancy increases by 12.35 days on average. As cold weather in the analysis does not have significant effects on most outcomes, it is not taken into account in this back-of-the-envelope predictions.

[31] Under the RCP 8.5 scenario, the number of high-temperature days during pregnancy increases by 47.87 days on average.

6 Conclusions

In this paper, we examine the long-term effects of high temperatures during the prenatal period on education attainment and height. Additionally, we investigate whether prenatally exposed children have worse endowments—birth weight. Our results indicate that hot weather in early life not only trigger adverse birth outcomes, but have persistent and profound effects in later life. By enduring one additional standard deviation of hot-weather days *in utero*, individuals attain 0.56 fewer years of schooling, have a higher risk to be illiteracy by 6.47%, are 17.25% standard deviations lower for word-test score, and are 0.85 cm shorter. The impacts seem to be concentrated in the first and second trimesters. Moreover, children who were prenatally exposed to frequent heat stress have statistically significant lower birth weight. We also examine the possible mechanisms behind the adverse effects of hot weather during pregnancy. The results indicate that the income effects are one important channel through which high temperatures during pregnancy affect birth weight and further adult outcomes.

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Table I: Summary statistics

Variable	Mean	Std. Dev.	N
Education Years	6.62	4.14	9,041
Illiteracy	0.21	0.41	9,041
Standardized Word-test Score	0	1	9,041
Height (cm)	164.47	7.66	9,041
Height in Bottom 10%	0.13	0.33	9,041
Birth Weight (gram)	2,977.54	509.60	3,223
Low Birth Weight Dummy (<2500 grams)	0.09	0.29	3,223
Age	36.86	10.41	9,041
Female	0.47	0.5	9,041
Han Chinese	0.9	0.3	9,041
Mother's Education Years	2.24	3.49	9,041
Father's Education Years	4.37	4.26	9,041
Mother's Age at Birth	27.21	6.15	9,041
Father's Age at Birth	29.77	6.91	9,041
Birth Order	2.27	1.48	9,041
Number of Siblings	2.74	1.75	9,041
High Temp Days	53.12	35.94	9,041
High Temp Days (1st trimester)	16.86	22.69	9,041
High Temp Days (2nd trimester)	17.99	23.02	9,041
High Temp Days (3rd trimester)	18.27	23.66	9,041
Low Temp Days	60.76	51.26	9,041
Low Temp Days (1st trimester)	20.84	29.58	9,041
Low Temp Days (2nd trimester)	18.99	28.2	9,041
Low Temp Days (3rd trimester)	20.94	29.82	9,041
Precipitation	6.26	0.91	9,041
Total Precipitation(1st trimester)	4.79	1.32	9,041
Total Precipitation(2nd trimester)	4.86	1.28	9,041
Total Precipitation(3rd trimester)	4.79	1.34	9,041

Note: The sample contains 9,041 individuals in 141 counties across 25 provinces. All individuals in the sample were born in rural areas. High-temperature days are defined as those with a daily maximum temperature higher than 85°F. For convenience of interpretation, word-test scores are standardized.

Table II: Balanced check on observable characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	Female	Han	ME	MA	FE	FA	Birth Order	No. of Siblings
High Temp Days	-0.0012	-0.0000	0.0055	-0.0170	0.0157	-0.0066	0.0050	0.0010
	(0.0014)	(0.0006)	(0.0087)	(0.0180)	(0.0129)	(0.0193)	(0.0038)	(0.0043)
Low Temp Days	0.0003	-0.0004	0.0248	-0.0301	-0.0164	-0.0340	-0.0045	-0.0002
	(0.0028)	(0.0010)	(0.0175)	(0.0325)	(0.0199)	(0.0348)	(0.0077)	(0.0075)
Precipitation	-0.0040	-0.0064	0.2649	-0.3161	0.0499	-0.0601	-0.1111*	-0.0235
	(0.0243)	(0.0066)	(0.2043)	(0.3087)	(0.1816)	(0.3329)	(0.0640)	(0.0695)
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9041	9041	9041	9041	9041	9041	9041	9041
R-Squared	0.541	0.805	0.663	0.569	0.656	0.575	0.603	0.722

Note: The dependent variables in columns (3)-(6) are mother's education years and age at birth and father's education years and age at birth, respectively. An observation is an individual born in a rural area. High- and low-temperature days are defined as those with daily maximum temperatures higher than 85°F and with daily minimum temperatures lower than 32°F. Ordinary least squares estimates for all columns. Standard errors in parentheses, clustered by county. ***Significant at 1%, **significant at 5%, *significant at 10%.

Table III: The impact of high temperatures during pregnancy on adult outcomes

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	Eduy	Illiteracy	Word Test	Height	Bottom 10%
High Temp Days	-0.0155*	0.0018**	-0.0048**	-0.0236*	0.0016**
	(0.0093)	(0.0009)	(0.0022)	(0.0140)	(0.0008)
Low Temp Days	-0.0007	-0.0012	0.0023	0.0158	-0.0007
	(0.0156)	(0.0017)	(0.0038)	(0.0241)	(0.0015)
Precipitation (log)	0.0309	0.0038	-0.0358	-0.0192	-0.0200
	(0.1842)	(0.0218)	(0.0488)	(0.3448)	(0.0172)
Demographics Controls	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes
County-Month FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Observations	9041	9041	9041	9041	9041
R-Squared	0.715	0.657	0.705	0.795	0.620

Note: An observation is an individual born in a rural area. High- and low-temperature days are defined as those with daily maximum temperatures higher than 30°C (85°F) and with daily minimum temperatures lower than 0°C (32°F). Demographic controls include gender, race, birth order, number of siblings, and parents' education years and age at delivery. Ordinary least squares estimates for all columns. Bottom 10% is a dummy indicating that an adults height falls in the bottom 10% of the sample distribution. Ordinary least squares estimates for all columns. Standard errors in parentheses, clustered by county. ***Significant at 1%, **significant at 5%, *significant at 10%.

Table IV: The impacts of high temperatures during pregnancy on adult outcomes by trimester

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	Eduy	Illiteracy	Word Test	Height	Bottom 10%
High Temp Days (1st trimester)	-0.0167	0.0026*	-0.0044	-0.0568**	0.0039***
	(0.0145)	(0.0015)	(0.0035)	(0.0251)	(0.0014)
High Temp Days (2nd trimester)	-0.0173	0.0032**	-0.0054*	-0.0412**	0.0003
	(0.0132)	(0.0013)	(0.0032)	(0.0202)	(0.0013)
High Temp Days (3rd trimester)	-0.0148	0.0004	-0.0051	0.0297	0.0008
	(0.0143)	(0.0015)	(0.0035)	(0.0219)	(0.0012)
Weather Controls	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes
County-Year	Yes	Yes	Yes	Yes	Yes
County-Month FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Observations	9041	9041	9041	9041	9041
R-Squared	0.715	0.658	0.706	0.796	0.621

Note: An observation is an individual born in a rural area. High- and low-temperature days are defined as those with daily maximum temperatures higher than 85°F and with daily minimum temperatures lower than 32°F. Each trimester consists of three months. Demographic controls include gender, race, birth order, number of siblings, and parents' education years and age at delivery. Ordinary least squares estimates. Standard errors in parentheses, clustered by county. ***Significant at 1%, **significant at 5%, *significant at 10%.

Table V: Heterogeneous effect by parental education

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	Eduy	Illiteracy	Word Test	Height	Bottom 10%
High Temp Days	-0.0132	0.0015*	-0.0039*	-0.0202	0.0014*
	(0.0101)	(0.0009)	(0.0023)	(0.0143)	(0.0008)
High Temp Days × Father's Education Years	-0.0004	0.0000	-0.0002*	-0.0004	0.0000
	(0.0005)	(0.0000)	(0.0001)	(0.0006)	(0.0000)
High Temp Days × Mother's Education Years	-0.0003	0.0000	0.0000	-0.0008	0.0000
	(0.0005)	(0.0001)	(0.0001)	(0.0008)	(0.0000)
Father's Education Years	0.1850***	-0.0133***	0.0472***	0.0284	-0.0029
	(0.0299)	(0.0029)	(0.0078)	(0.0452)	(0.0025)
Mother's Education Years	0.1176***	-0.0063*	0.0145	0.0733	-0.0011
	(0.0347)	(0.0033)	(0.0097)	(0.0618)	(0.0026)
Demographic & Weather Controls	Yes	Yes	Yes	Yes	Yes
County-Year	Yes	Yes	Yes	Yes	Yes
County-Month FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Observations	9041	9041	9041	9041	9041
R-Squared	0.715	0.657	0.705	0.795	0.620

Note: An observation is an individual born in a rural area. High- and low-temperature days are defined as those with daily maximum temperatures higher than 85°F and with daily minimum temperatures lower than 32°F. Ordinary least squares estimates for all columns. Standard errors in parentheses, clustered by county. ***Significant at 1%, **significant at 5%, *significant at 10%.

Table VI: The impact of high temperatures during pregnancy on birth weight

	(1)	(2)
Dependent Variable:	Birth Weight	LBW
High Temp Days	-2.5433*	0.0013
	(1.4920)	(0.0010)
Low Temp Days	-0.1099	0.0004
	(1.9406)	(0.0014)
Precipitation (log)	-85.1418**	0.0494**
	(33.0864)	(0.0210)
Han	22.8328	0.0467
	(99.5235)	(0.0416)
Female	-148.8190***	0.0173
	(32.8197)	(0.0211)
Mother's Education Years	2.4723	-0.0027
	(4.4656)	(0.0025)
Father's Education Years	6.2274	-0.0035
	(4.2606)	(0.0027)
Mother's Age at Birth	-5.3991	0.0027
	(3.4883)	(0.0025)
Father's Age at Birth	1.0195	-0.0009
	(3.4167)	(0.0019)
Birth Order	15.9821	0.0001
	(16.6660)	(0.0130)
Number of Siblings	-21.4430	0.0054
	(14.0839)	(0.0087)
County FE	Yes	Yes
Province-Year FE	Yes	Yes
Province-Month FE	Yes	Yes
Year-Month FE	Yes	Yes
Observations	3223	3223
R-Squared	0.590	0.511

Note: An observation is an individual born in a rural area. High- and low-temperature days are defined as those with daily maximum temperatures higher than 85°F and with daily minimum temperatures lower than 32°F. Ordinary least squares estimates for all columns. Standard errors in parentheses, clustered by county. ***Significant at 1%, **significant at 5%, *significant at 10%.

Table VII: The impacts of high temperatures during pregnancy on adult outcomes for urban-born individuals

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	Eduy	Illiteracy	Word Test	Height	Bottom 10%
High Temp Days	0.0038	0.0003	0.0070	-0.0562	-0.0003
	(0.0226)	(0.0012)	(0.0050)	(0.0374)	(0.0019)
Low Temp Days	0.0172	-0.0004	0.0074	0.0373	0.0008
	(0.0269)	(0.0013)	(0.0080)	(0.0538)	(0.0022)
Precipitation	0.3172	-0.0415	0.1781	-1.8489	0.0376
	(0.6918)	(0.0558)	(0.1966)	(1.2913)	(0.0642)
Demographics Controls	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes	Yes
Province-Month FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Observations	1910	1910	1910	1910	1910
R-Squared	0.843	0.810	0.820	0.884	0.779

Note: An observation is an individual born in an urban area. High- and low-temperature days are defined as those with daily maximum temperatures higher than 85°F and with daily minimum temperatures lower than 32°F. Demographic controls include gender, race, birth order, number of siblings, and parents' education years and age at delivery. Ordinary least squares estimates for all columns. Standard errors in parentheses, clustered by county. ***Significant at 1%, **significant at 5%, *significant at 10%.

Table VIII: Does a high proportion of heat-tolerant crops mitigate the adverse effects of high temperatures during pregnancy on adult outcomes?

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	Eduy	Illiteracy	Word Test	Height	Bottom 10%
High Temp Days	-0.0313***	0.0034**	-0.0094***	-0.0520**	0.0035***
	(0.0118)	(0.0013)	(0.0033)	(0.0211)	(0.0013)
High Temp Days X C4	0.0011*	-0.0001*	0.0003	0.0018*	-0.0001*
	(0.0006)	(0.0001)	(0.0002)	(0.0010)	(0.0001)
Demographic & Weather Controls	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes
County-Month FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Observations	9022	9022	9022	9022	9022
R-Squared	0.715	0.657	0.705	0.795	0.620

Note: An observation is an individual born in a rural area. C4 Plant Area represents corn and sugarcane proportion of crop acreage within the province. High-temperature days are defined as those with daily maximum temperatures higher than 85°F. 19 observations are missing from the main regression sample, because crop-area information is missing for Shanghai in 1993. Demographic controls include gender, race, birth order, number of siblings, and parents' education years and age at delivery. Weather controls include low-temperature days and total precipitation during pregnancy. Ordinary least squares estimates. Standard errors in parentheses, clustered by county. ***Significant at 1%, **significant at 5%, *significant at 10%.

Table IX: The impacts of high temperatures during nine months after birth on adult outcomes

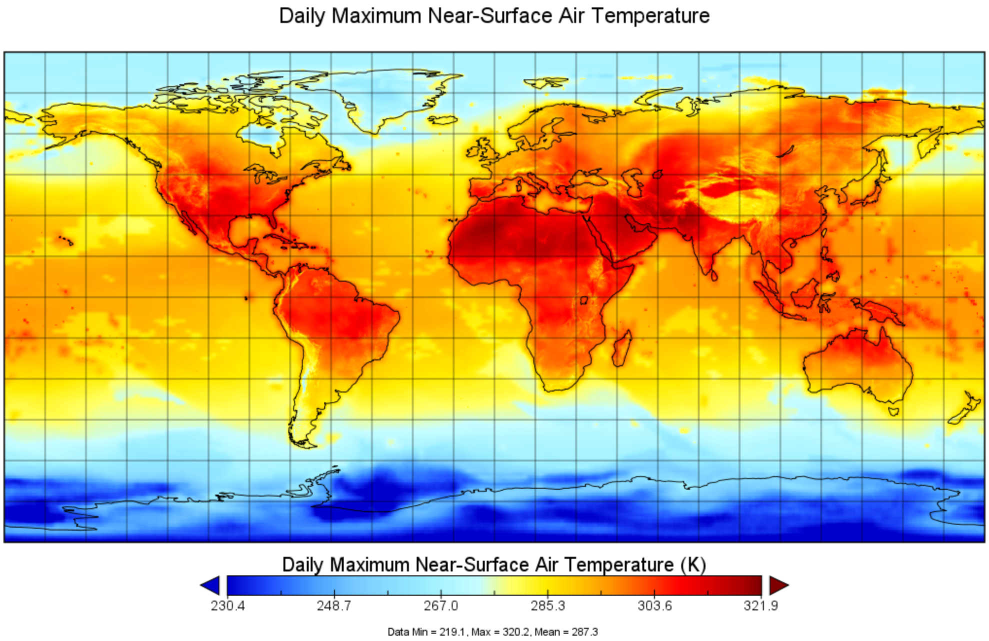
Dependent Variable:	(1) Eduy	(2) Illiteracy	(3) Word Test	(4) Height	(5) Bottom 10%
High Temp Days (9 Mon After Birth)	-0.0002	0.0008	-0.0018	-0.0202	0.0006
	(0.0114)	(0.0013)	(0.0030)	(0.0153)	(0.0010)
Low Temp Days (9 Mon After Birth)	-0.0481***	0.0042**	-0.0028	-0.0185	0.0013
	(0.0156)	(0.0017)	(0.0040)	(0.0349)	(0.0015)
Precipitation (9 Mon After Birth, log)	0.0008	-0.0000	-0.0001	-0.0003	0.0000
	(0.0005)	(0.0001)	(0.0001)	(0.0008)	(0.0001)
High Temp Days (During Pregnancy)	-0.0205**	0.0023**	-0.0054**	-0.0316**	0.0018*
	(0.0102)	(0.0010)	(0.0024)	(0.0160)	(0.0010)
Low Temp Days (During Pregnancy)	-0.0126	-0.0001	0.0014	0.0088	-0.0003
	(0.0156)	(0.0016)	(0.0037)	(0.0264)	(0.0015)
Precipitation (During Pregnancy, log)	0.0730	0.0024	-0.0380	-0.0242	-0.0195
	(0.1855)	(0.0222)	(0.0501)	(0.3471)	(0.0166)
Demographics Controls	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes
County-Month FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Observations	9041	9041	9041	9041	9041
R-Squared	0.716	0.657	0.705	0.795	0.620

Note: An observation is an individual born in a rural area. High- and low-temperature days are defined as those with daily maximum temperatures higher than 85°F and with daily minimum temperatures lower than 32°F. Demographic controls include gender, race, birth order, number of siblings, and parents' education years and age at delivery. Ordinary least squares estimates. Standard errors in parentheses, clustered by county. ***Significant at 1%, **significant at 5%, *significant at 10%.

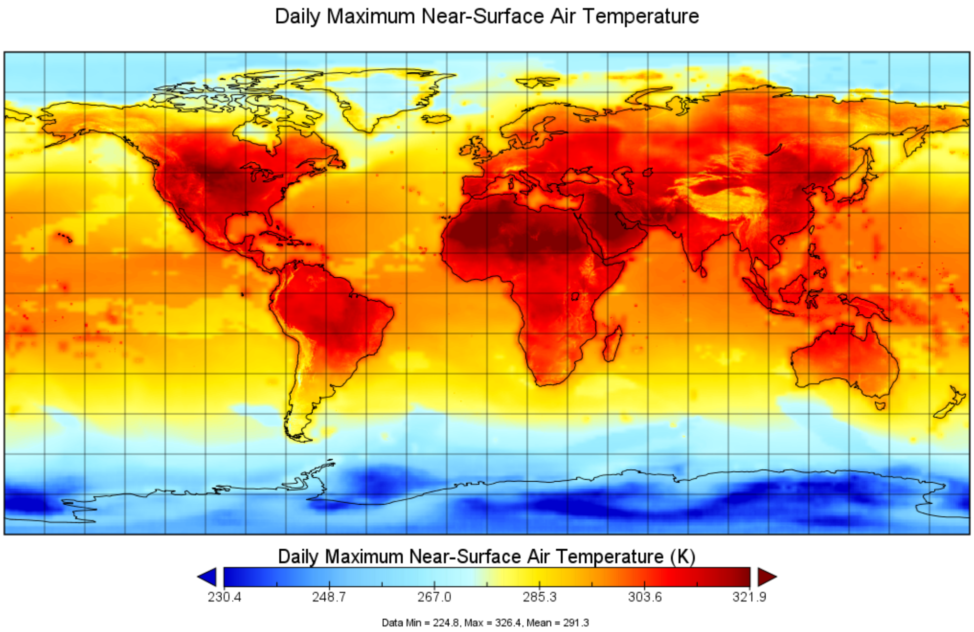
Table X: The impacts of high temperatures during nine months before conception on adult outcomes

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	Eduy	Illiteracy	Word Test	Height	Bottom 10%
High Temp Days (9 Mon Before Conception)	0.0101	-0.0017	0.0022	0.0331	-0.0007
	(0.0126)	(0.0015)	(0.0029)	(0.0206)	(0.0012)
Low Temp Days (9 Mon Before Conception)	-0.0061	0.0021	-0.0036	-0.0329	-0.0008
	(0.0164)	(0.0020)	(0.0042)	(0.0204)	(0.0012)
Precipitation (9 Mon Before Conception, log)	-0.0004	0.0000	-0.0001	0.0009	-0.0000
	(0.0005)	(0.0001)	(0.0002)	(0.0008)	(0.0001)
Demographics Controls	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes
County-Month FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Observations	8908	8908	8908	8908	8908
R-Squared	0.715	0.657	0.705	0.801	0.621

Note: An observation is an individual born in a rural area. High- and low-temperature days are defined as those with daily maximum temperatures higher than 85°F and with daily minimum temperatures lower than 32°F. Nine months before conception is defined as ten to eighteen months before birth. 133(=9041-8908) individuals in our sample do not have weather information in nine months before conception. Demographic controls include gender, race, birth order, number of siblings, and parents' education years and age at delivery. Ordinary least squares estimates. Standard errors in parentheses, clustered by county. ***Significant at 1%, **significant at 5%, *significant at 10%.



(a) 2000



(b) 2100

Figure 1: The global daily maximum near-surface air temperature on the 1st July, 2000 (panel a) and 2100 (panel b).

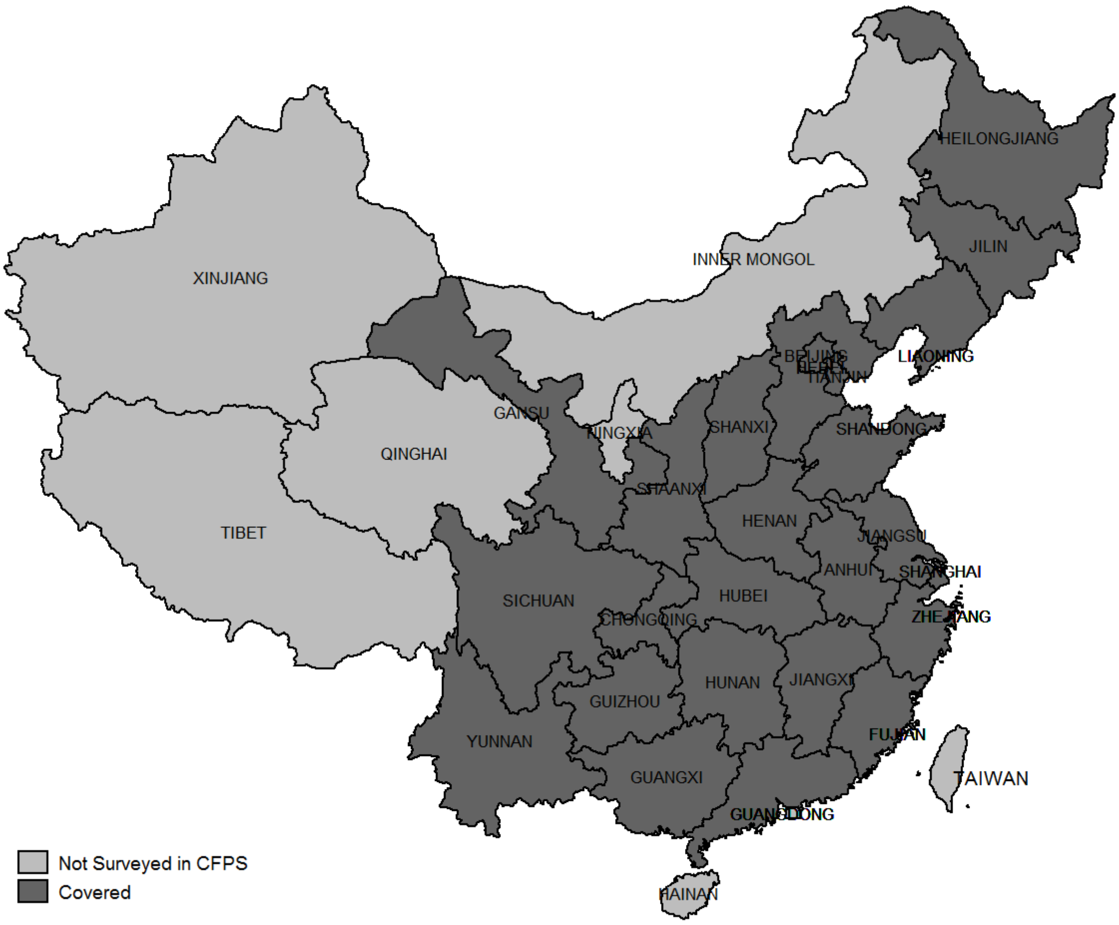
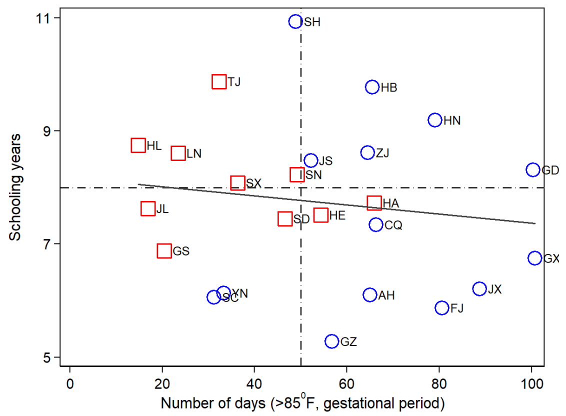
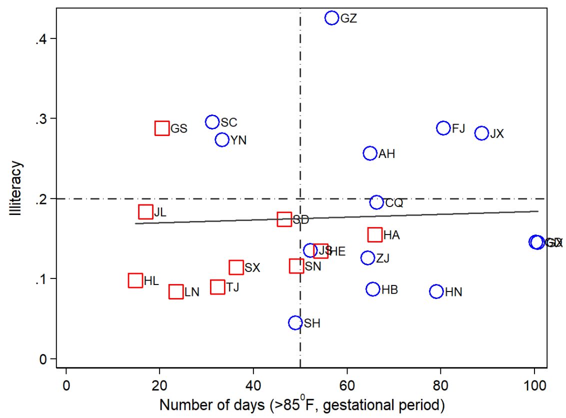


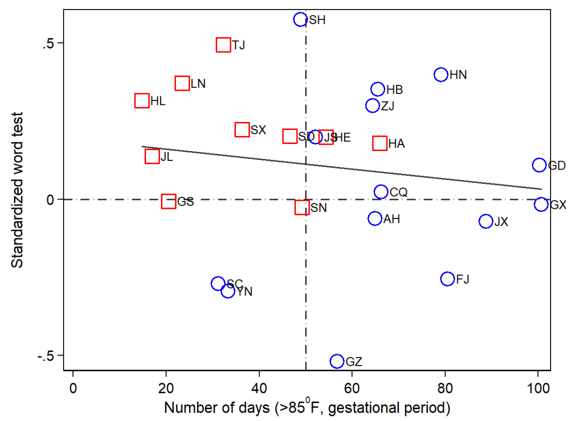
Figure 2: Provinces covered in the CFPS sample.



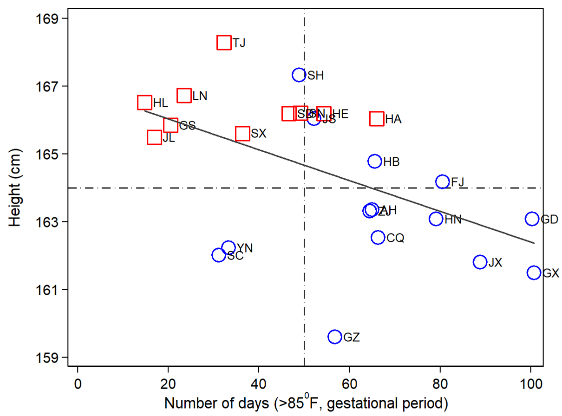
(a) Education years



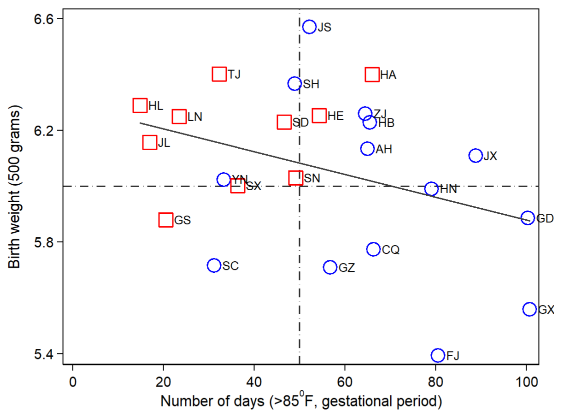
(b) Illiteracy



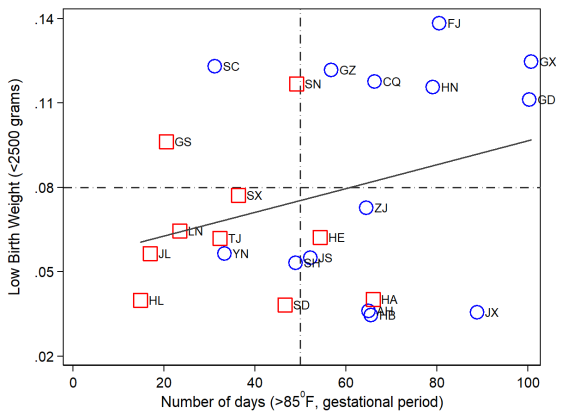
(c) Word-test score



(d) Height



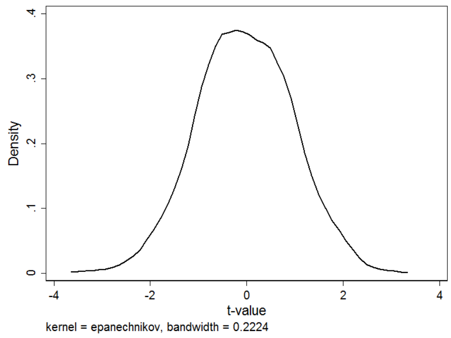
(e) Birth weight



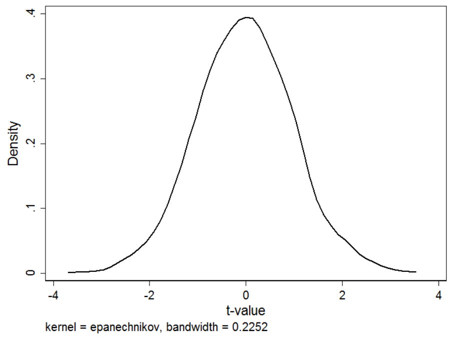
(f) LBW

Figure 3: Adult outcomes and birth weight against number of high-temperature days (>85°F) for typical gestational period by province.

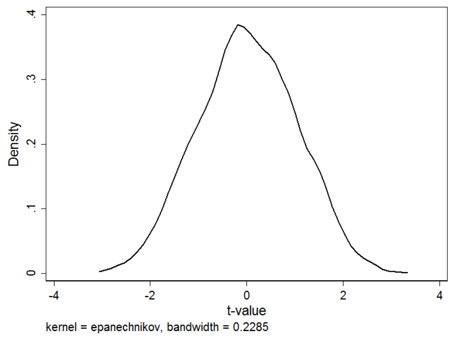
Note: Red square and blue circle markers represent provinces in the north and south, respectively. The solid line is fitted using OLS.



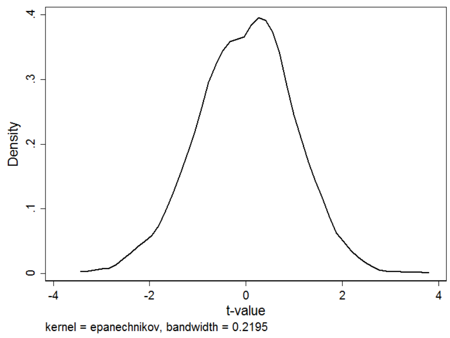
(a) Schooling years



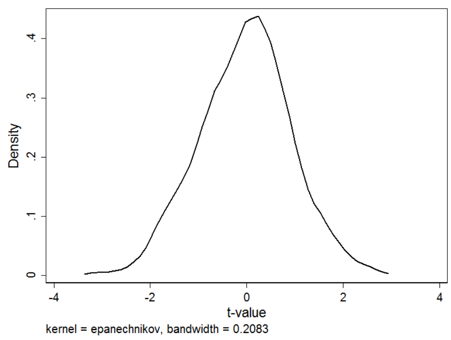
(b) Word-test score



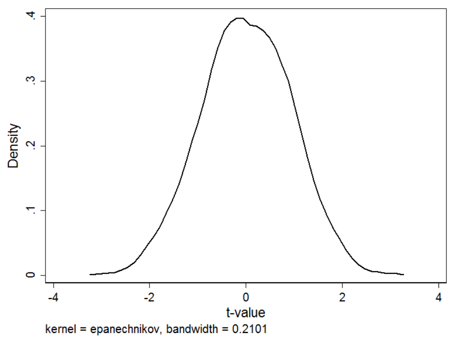
(c) Math-test score



(d) Height

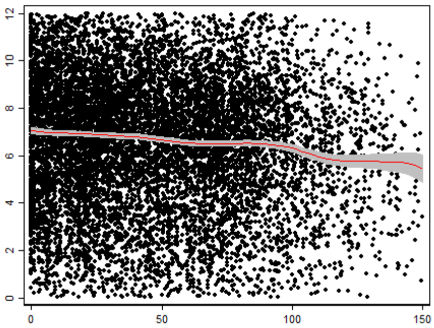


(e) Birth weight

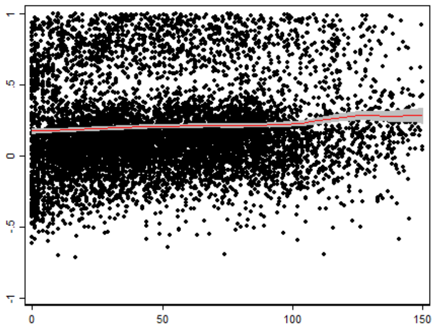


(f) LBW

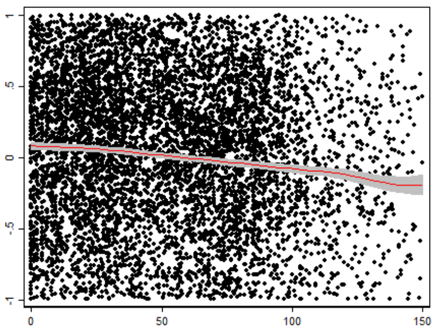
Figure 4: Distribution of t-statistic for high-temperature days of 1,000 estimates for Equation (1) with placebo birth time and place.



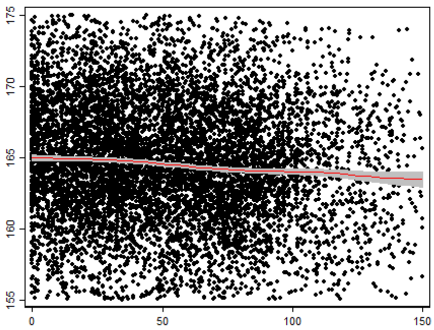
(a) Schooling years



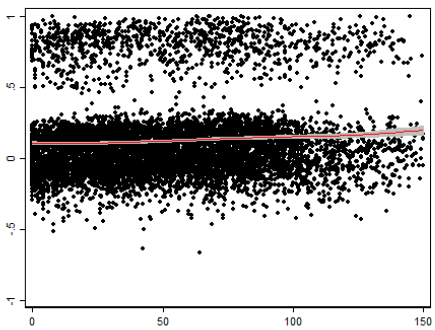
(b) Illiteracy



(c) Word-test score



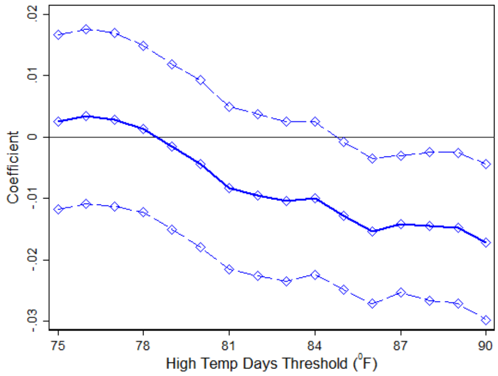
(d) Height



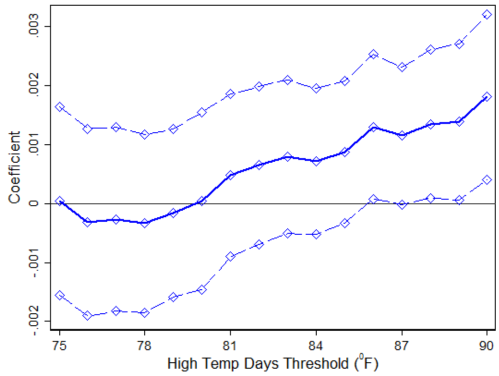
(e) Height in Bottom 10%

Figure 5: High-temperature days (>85°F) during pregnancy against adult outcomes.

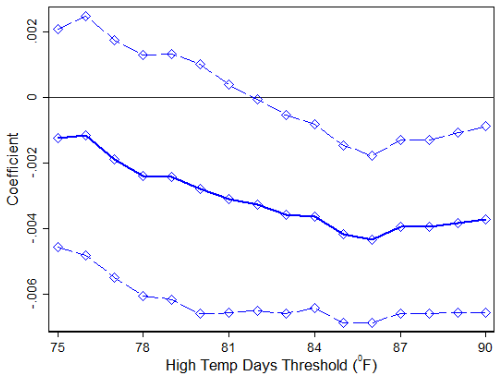
Note: The solid line shows the fitted partially linear model, and the gray area denotes the 95% confidence interval.



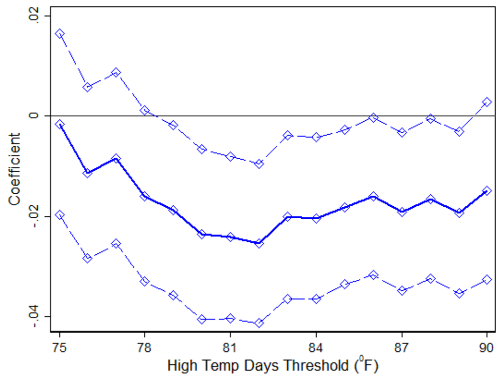
(a) Schooling years



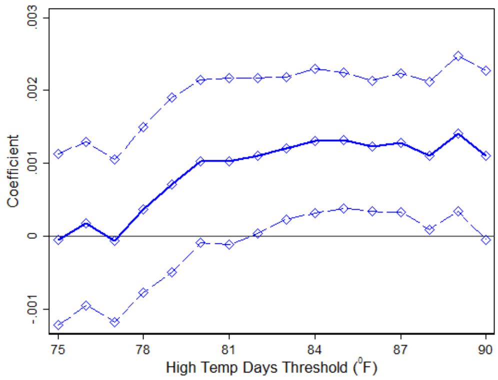
(b) Illiteracy



(c) Word-test score



(d) Height



(e) Height in Bottom 10%

Figure 6: Coefficients of high-temperature days on adult outcomes from regressions using different definitions of high-temperature days.

Note: The solid line denotes the estimated coefficients on each high-temperature day definition. Dash lines represent the upper and lower bounds for the 90% confidence interval.

A Appendix

Table A.I: The differences between individuals with and without birth weight information

	(1)
Dependent Variable:	Birth weight missing dummy
High Temp Days	0.0011
	(0.0011)
Low Temp Days	0.0010
	(0.0019)
Precipitation (log)	0.0047
	(0.0102)
Han	0.0303
	(0.0381)
Female	0.0361***
	(0.0112)
Mother's Education Years	-0.0070***
	(0.0025)
Father's Education Years	-0.0024
	(0.0017)
Mother's Age at Birth	0.0004
	(0.0021)
Father's Age at Birth	0.0009
	(0.0018)
Birth Order	-0.0076
	(0.0076)
Number of Siblings	0.0098
	(0.0069)
County-Year	Yes
County-Month FE	Yes
Year-Month FE	Yes
Observations	9041
R-Squared	0.668

Note: An observation is an individual born in a rural area. High- and low-temperature days are defined as those with daily maximum temperatures higher than 85°F and with daily minimum temperatures lower than 32°F during the nine months before birth. Ordinary least squares estimates. Standard errors in parentheses, clustered by county. ***Significant at 1%, **significant at 5%, *significant at 10%.

Table A.II: Robustness checks of the impacts of high temperatures on all outcomes using weather stations within 70 km radius

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	Eduy	Illiteracy	Word Test	Height	Bottom 10%
High Temp Days	-0.0142	0.0017**	-0.0048**	-0.0252*	0.0012*
	(0.0095)	(0.0008)	(0.0023)	(0.0142)	(0.0007)
Low Temp Days	0.0040	-0.0010	0.0045	0.0094	-0.0010
	(0.0163)	(0.0017)	(0.0040)	(0.0248)	(0.0016)
Precipitation	0.1735	-0.0103	-0.0031	-0.1551	-0.0288*
	(0.2012)	(0.0248)	(0.0573)	(0.4305)	(0.0169)
Demographics Controls	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Birth Year FE	Yes	Yes	Yes	Yes	Yes
Birth Month FE	Yes	Yes	Yes	Yes	Yes
County-Specific Linear Trend	Yes	Yes	Yes	Yes	Yes
County-Specific Linear Trend(sqr)	Yes	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	8667	8667	8667	8667	8667
R-Squared	0.720	0.660	0.701	0.804	0.630

Note: An observation is an individual born in a rural area. Each county is matched to all weather stations within 70 km. High- and low-temperature days are defined as those with daily maximum temperatures higher than 85°F and with daily minimum temperatures lower than 32°F during the eight months before birth. Demographic controls include gender, race, birth order, number of siblings, and parents' education years and age at delivery. Ordinary least squares estimates for all columns. Standard errors in parentheses, clustered by county. ***Significant at 1%, **significant at 5%, *significant at 10%.

Table A.III: Robustness checks of the impacts of high temperatures on all outcomes using weather stations within 60 km radius

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	Eduy	Illiteracy	Word Test	Height	Bottom 10%
High Temp Days	-0.0203*	0.0018*	-0.0046*	-0.0243*	0.0012
	(0.0116)	(0.0010)	(0.0027)	(0.0143)	(0.0009)
Low Temp Days	0.0044	-0.0017	0.0073	0.0200	-0.0006
	(0.0173)	(0.0018)	(0.0046)	(0.0280)	(0.0017)
Precipitation	0.2270	-0.0083	0.0105	0.0725	-0.0417**
	(0.2629)	(0.0345)	(0.0741)	(0.4330)	(0.0204)
Demographics Controls	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Birth Year FE	Yes	Yes	Yes	Yes	Yes
Birth Month FE	Yes	Yes	Yes	Yes	Yes
County-Specific Linear Trend	Yes	Yes	Yes	Yes	Yes
County-Specific Linear Trend(sqr)	Yes	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	7268	7268	7268	7268	7268
R-Squared	0.732	0.674	0.714	0.810	0.643

Note: An observation is an individual born in a rural area. Each county is matched to all weather stations within 60 km. High- and low-temperature days are defined as those with daily maximum temperatures higher than 85°F and with daily minimum temperatures lower than 32°F during the eight months before birth. Demographic controls include gender, race, birth order, number of siblings, and parents' education years and age at delivery. Ordinary least squares estimates for all columns. Standard errors in parentheses, clustered by county. ***Significant at 1%, **significant at 5%, *significant at 10%.

Table A.IV: Different inference methods

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	Eduy	Illiteracy	Word Test	Height	Bottom 10%
High Temp Days	-0.0155*	0.0018**	-0.0048**	-0.0236*	0.0016**
-County Clusters	(0.0093)	(0.0009)	(0.0022)	(0.0140)	(0.0008)
-Province Clusters	(0.0096)	(0.0010)	(0.0019)	(0.0145)	(0.0009)
-Two-way Clusters (County and Year)	(0.0091)	(0.0008)	(0.0023)	(0.0137)	(0.0009)
-Spatial Clusters (Hsiang 2010)	(0.0075)	(0.0009)	(0.0020)	(0.0135)	(0.0008)
Demographic & Weather Controls	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes
County-Month FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Observations	9041	9041	9041	9041	9041
R-Squared	0.715	0.657	0.705	0.795	0.620

Note: The entries after row 1 present different levels of clustering for standard errors. As our sample only has 25 provinces, we use the bootstrap method to obtain robust province-clustered standard errors (Cameron et al. 2008). In row 5, we adjust standard errors to account for the potential that disturbances have spatial autocorrelation of arbitrary form within 2,000 km and serial correlation over five years (Hsiang 2010) An observation is an individual born in a rural area. High- and low-temperature days are defined as those with daily maximum temperatures higher than 85°F and with daily minimum temperatures lower than 32°F during the nine months before birth. Demographic controls include gender, race, birth order, number of siblings, and parents' education years and age at delivery. Weather controls include the number of cold weather days and total precipitation during pregnancy. Ordinary least squares estimates. Standard errors in parentheses, clustered by province. ***Significant at 1%, **significant at 5%, *significant at 10%.