The Hidden Cost of Prenatal Heat Stress Exposure: Evidence on Psychological Well-Being in China

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I. Introduction

The fetal origins hypothesis (FOH) posits that in utero shocks can permanently affect health and welfare outcomes (Almond and Currie 2011). Evidence shows that prenatal health shocks have persistent life-cycle consequences (Currie and Vogl 2013; Currie and Rossin-Slater 2015), from increased infant mortality (Banerjee and Maharaj 2020) and low birth weight (Le and Nguyen 2021) to impaired physical development (Randell, Gray, and Grace 2020; Farris, Porter, and Maredia 2021) and long-term health deterioration (Strauss and Thomas 2007). As psychological well-being (PWB) becomes increasingly central to welfare assessment (McGuire, Kaiser, and Bach-Mortensen 2022), understanding whether and how prenatal shocks affect mental health outcomes is crucial.

Environmental shocks, particularly extreme heat, warrant special attention in developing countries where adaptive capacity is limited (Kahn 2016). Heat stress can increase mortality and morbidity (Deschênes and Greenstone 2011; Agarwal et al. 2021), compromise pregnancy outcomes (Chen et al. 2020), and

We are grateful to the associate editor Alessandro Tarozzi, three anonymous referees, Marianne Page, as well as the participants at the 2024 Population Association of America Annual Meeting for their constructive suggestions. We express thanks for the financial support from the Fundamental Research Funds for the Central Universities and the Research Funds of Renmin University of China (24XNF068). The authors contributed equally to this work and are listed in alphabetical order. Any errors are our own. Declarations of interest: none. Contact the corresponding author, Yinghao Pan, at panyinghao@ruc.edu.cn.

Electronically published August 27, 2025

Economic Development and Cultural Change, volume 74, number 1, October 2025.

https://doi.org/10.1086/735375

reduce both physical and cognitive performance (Somanathan et al. 2021). While recent work documents immediate mental health effects of high temperatures (Mullins and White 2019), the long-term psychological consequences of prenatal heat stress exposure (PHSE) remain poorly understood.[1]

We examine the long-term psychological effects of prenatal exposure to extreme heat by combining individual data from the China Labor Force Dynamics Survey with climate data from the Chinese Academy of Sciences. We exploit each individual's birth year/month and birthplace to construct exposure to weather conditions during the prenatal period. Our identification strategy relies on plausibly random variations in temperature distribution across birth locations and timing, controlling for other climatic conditions, demographic characteristics, and multiple fixed effects. We find that prenatal heat stress significantly reduces adult PWB. A 10-day increase in exposure to temperatures above 90°F (32.22°C) during gestation increases unhappiness ($b = 0.055$; 95% confidence interval [CI]: [0.014, 0.097]), life dissatisfaction ($b = 0.072$; 95% CI: [0.020, 0.124]), and depression ($b = 0.049$; 95% CI: [0.016, 0.082]). These translate into increases of 5.93%, 7.56%, and 8.35% standard deviations, respectively, and are concentrated in the second and third trimesters—critical periods for brain and neurologic development (Wilson et al. 2021).

The adverse effects are particularly pronounced among women and individuals from disadvantaged backgrounds, including those born in rural areas with limited health-care access or raised in unfavorable family environments characterized by parental absence, low educational attainment, and disadvantaged occupational status. These findings persist across numerous robustness checks, including alternative measures of heat exposure, different outcome specifications, additional controls for temperature variations, various clustering approaches, multiple hypothesis testing, and controls for early-life exposure to major historical events (Great Famine and Cultural Revolution), differential mortality rates by gender at birth, sibling effects, and temperature adaptation.

Beyond biological explanations, we find that prenatal heat exposure affects PWB through human and social capital formation. A 10-day increase in extreme heat exposure reduces adult physical health by 9.21%, hourly income by 7.02%, social trust by 6.26%, and social support by 9.64% standard deviations. These results suggest that prenatal heat stress compromises PWB by undermining both human and social capital development.

[1] Prenatal heat stress may affect adult mental well-being through two primary channels. First, it can disrupt fetal brain development by altering maternal glucocorticoid secretion (Lupien et al. 2009). Second, by negatively affecting educational attainment, earnings, and social preferences (Almond and Currie 2011; Cecchi and Duchoslav 2018), prenatal heat exposure may impair human and social capital formation, ultimately compromising adult mental health.

This paper makes two main contributions to the literature. First, we extend the FOH to mental health by documenting substantial psychological welfare costs of prenatal heat exposure. While previous research shows that extreme prenatal temperatures can impair infant and child health (Banerjee and Maharaj 2020; Randell, Gray, and Grace 2020), cognitive function (Hu and Li 2019), educational attainment (Wilde, Apouey, and Jung 2017), earnings (Isen, Rossin-Slater, and Walker 2017), labor market outcomes (Majid 2015), cooperation (Cecchi and Duchoslav 2018), and marriage prospects (Caruso and Miller 2015), the long-term mental health implications remain unexplored. Our analysis of PWB provides new evidence on how prenatal climate shocks affect lifetime welfare.

Second, we advance our understanding of environmental determinants of mental health. While previous work has examined how early-life experiences affect adult well-being (Danzer and Danzer 2016; Adhvaryu, Fenske, and Nyshadam 2018; Singhal 2019) and how climate change affects mental health (Berry et al. 2018; Obradovich et al. 2018), we focus specifically on the gestational period. Building on the analysis of adolescent outcomes in China by Ai and Tan (2023), we provide novel evidence on long-term psychological effects among labor force participants aged 15 and above. Moreover, we demonstrate how birthplace conditions and early-life family circumstances moderate these effects, highlighting the crucial interaction between prenatal shocks and childhood environments in determining adult mental health.

The remainder of this paper is organized as follows. Section II describes the data and variables. Section III presents the statistical methods. Section IV covers the main results and discusses heterogeneity and robustness checks. Section V discusses the possible underlying mechanisms, and section VI concludes.

II. Data, Variables, and Descriptive Patterns

A. Data and Sample Construction

China Labor Force Dynamics Survey (CLDS). We use individual data from two waves (2016 and 2018) of the CLDS collected by the Center for Social Science Survey at Sun Yat-Sen University in China.[2] The CLDS encompasses a nationally representative sample of the Chinese labor force aged 15 and above and uses multistage stratified probability proportional-to-size sampling to draw data from approximately 21,000 individuals in nearly 14,000 households across 29 provinces.

[2] The baseline survey was conducted in 2012 and there were three follow-up waves (2014, 2016, and 2018). We exclude the first two waves because they measured only proneness to depression and did not include comprehensive tools to assess mental health, such as the Center for Epidemiological Studies Depression (CES-D) Scale.

The advantages of the CLDS in our research setting are two-fold: First, the CLDS documents detailed information on labor market outcomes of Chinese labor forces, including health status, work performance, social connections, and so forth, which can be used to investigate health outcomes in adulthood and relevant mechanisms. The CLDS has also been widely used in economics, sociology, and public health research (e.g., Lu, Zeng, and Zeng 2016; Cao 2020; Gao et al. 2023). Second, the CLDS provides detailed information on birth (e.g., birth year/month, birthplace, and birth hukou) and childhood life (e.g., parental occupations and marital status at age 14), as well as other demographic characteristics and household backgrounds, which can facilitate comprehensive explorations of the PHSE-PWB nexus.

Weather conditions dataset. We obtain weather data from the Institute of Geographic Sciences and Natural Resources Research at the Chinese Academy of Sciences. The dataset contains consecutive daily weather records from 2,479 monitoring stations across 31 Chinese provinces from 1950 to 2006 (the latest birth year of the participants in our sample), including daily temperature, precipitation, relative humidity, and sunshine duration. We measure city-level daily climatic conditions by taking a weighted average of all weather variables from stations within a 200-km radius of each city's centroid, where the weights are the inverse of their squared distance to each city so that more distant stations are given less weight (as in Deschênes and Greenstone 2011).

Sample construction. Because no participants in the CLDS for the 2016 wave were followed up in 2018, we construct pool data from two repeated cross-sectional waves. We retain the sample of individuals born after 1951 because climatic data have been available since 1950. We also drop observations missing information on demographic traits and socioeconomic conditions. The final sample in our analysis consists of 10,842 individuals in 7,490 households from 487 communities/villages across 29 provinces.[3] Our sample cohort ranges from 1951 to 2003, covering 294 cities. Figure 1 presents the geographic distribution of the CLDS participants' birthplaces.

Our analysis of cohort distributions reveals no concerning patterns of selection in the sample. As shown in figure A1 (figs. A1–A5 are available online), births are fairly evenly distributed across both years and months, with no systematic seasonal clustering during summer months (June–August). While

[3] We did not restrict our sample to either urban residents or rural residents. There are 39.55% urban residents and 60.45% rural residents in our sample. By use of birth hukou to inform birth residence, we find 79.29% of individuals were born in rural areas (holding agricultural hukou) and the other 20.71% were born in urban areas (holding nonagricultural hukou). Therefore, in any case of living residence and birth residence, the sample selection issue should not occur in this study, allowing us to capture the overall effect of PHSE on PWB in equilibrium.

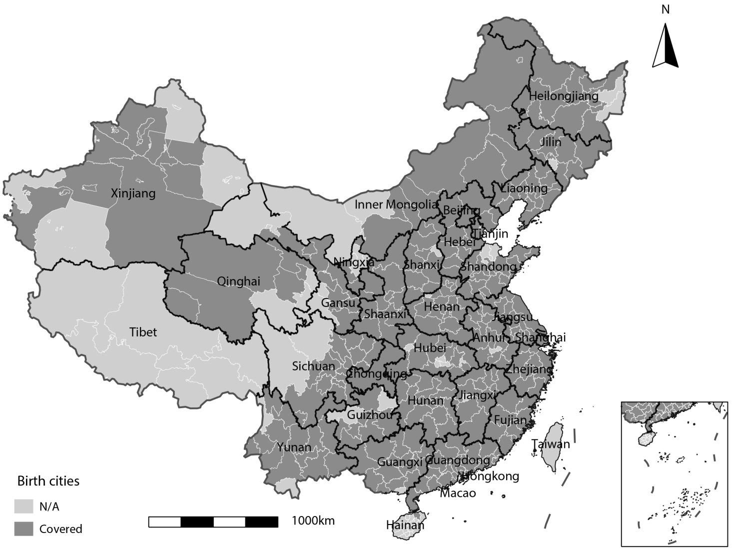

Figure 1. Birth cities covered in the China Labor Force Dynamics Survey. Individuals surveyed in the CLDS were born across 294 cities in China.

cohorts born between 1955 and 1975 (aged 41–63 at the time of survey) are somewhat larger, there are no sharp spikes in any particular birth year that might bias our estimates.

B. *Variables*

1. Explained Variables: PWB

Happiness and life satisfaction. PWB is traditionally assessed by two types of measures—evaluative and emotional—on the basis of Benjamin et al. (2014), Krueger and Stone (2014), and Li (2021). Happiness reflects short-term and specific perceptions of daily life, whereas life satisfaction captures long-term and broader feelings about life experiences (Lim and Putnam 2010). In the CLDS, happiness and life satisfaction are both measured on a 5-point scale. For example, the participants are asked “Overall, how happy do you feel in life?” They can choose from 1 = very unhappy, 2 = unhappy, 3 = fair, 4 = happy, or 5 = very happy. Another question is “Overall, how satisfied are you with your life?” They can choose from 1 = very unsatisfied, 2 = unsatisfied, 3 = fair, 4 = satisfied, or 5 = very satisfied. In analysis, we recode measures of happiness and life satisfaction to unhappiness and life unsatisfaction, with higher points indicating lower PWB.

Depression. Additionally, we choose depressive symptoms, measured by the CES-D Scale, as an emotional proxy (Radloff 1977). The CLDS uses the Chinese version of the CES-D Scale, containing 20 items that gauge the frequency of different aspects of depressive symptoms experienced in the previous week. We calculate the total CES-D score, ranging from 0 to 60, according to a 4-point scale: 0 = rarely or never (less than 1 day); 1 = little or sometimes (1–2 days); 2 = moderate or occasionally (3–4 days); and 3 = most or always (5–7 days). The average CES-D score ranges between 0 and 3. Higher scores indicate greater depressive symptoms, which in turn suggest lower levels of PWB.

In primary analyses, to facilitate the interpretation of results, we treat the raw well-being measures as continuous variables because Ferrer-i-Carbonell and Frijters (2004) and Li (2021) found that PWB analyses are insensitive to whether PWB indicators take a cardinal or ordinal form.

2. Key Explanatory Variables: PHSE

We use the weighted average of the number of prenatal high-temperature days for all weather stations at distances of no more than 200 km from the birth city's centroid. We evaluate heat stress exposure at the city level for two main reasons. First, the cohort of our sample covers the period from 1951 to 2003, when intracity migration in China was more evident, especially prior to the nationwide hukou reform (which started in 2014) and construction of the national expressway network, which was preliminarily completed in 2007 (Bosker, Deichmann, and Roberts 2018). Second, the CLDS anonymizes the county codes of birthplaces within cities.

In line with recent work on extreme weather in China (Hu and Li 2019) and the United States (Graff Zivin and Neidell 2014; Park et al. 2020), we define the prenatal period as 9 months (i.e., about 270 days) prior to birth on the basis of each individual's birth year and birth month, and we define high-temperature days as the number of days with maximum temperatures exceeding 90°F. We also apply a different threshold of 85°F for high-temperature days for the robustness checks.

To validate our findings, we construct two more indicators to measure hot weather for the robustness checks: (1) the number of days during the prenatal period with a mean temperature exceeding 90°F (Barreca et al. 2015), and (2) cooling degree days (CDD), which equal the sum of the difference between 65°F and each hot day's (>65°F) mean temperature throughout the year (Albouy et al. 2016).

To account for potentially confounding factors, we add a vector of climatic, demographic, and parental covariates to alternative regression models. The climatic covariates include total precipitation, average relative humidity, and daily sunshine duration during pregnancy. Demographic covariates include gender, ethnicity, age and its square, birth order, and number of siblings. Parental covariates include parents' average education years and father's and mother's hukou status at birth. Table 1 presents summary statistics for the main variables.

Figure 2 shows the time trend of extreme heat events in Chinese cities from 1951 to 2004, covering all birth dates in our sample. Figures 2*A* and 2*B* jointly indicate a large spatial dispersion in the mean exposure to heat waves combined with a large within-city variation in high-temperature events, which allows us to empirically test the effects of extreme heat stress in China. Figure 2*C* portrays the distribution of monthly mean temperature across years, implying a significant trend of global warming over the period of 55 years in China.

C. Descriptive Patterns

This section describes the empirical patterns of gestational exposure to hot weather and later-life PWB. By leveraging city-level interannual fluctuations in temperature, we account for the potentially confounding effects of spatial differences in economic opportunities and health facilities. Specifically, we regress each outcome variable of later-life PWB and the number of high-temperature days (maximum > 90°F, in units of 10 days) during pregnancy on multiple sets of fixed effects (birth city by birth year, birth city by birth month, birth year by birth month, and province by year) and predict the regression residuals.

Figure 3 shows the relationship between residual PWB status later in life and heat stress exposure during pregnancy. We observe a clear, robust, and negative relationship between the residuals of the evaluative indicators of PWB (unhappiness and life unsatisfaction) and prenatal exposure to extremely hot weather. Moreover, the predicted residuals of depressive symptoms are positively correlated with exposure to extreme temperatures during the prenatal period. Our findings suggest that PHSE may be negatively associated with future PWB.

III. Empirical Framework

To identify the effect of PHSE on acquired PWB in adulthood, we exploit the panel nature of our cohort dataset to partial out unobserved confounding factors in birth cities, seasonality across different birth months, and common shocks across birth cohorts. We estimate our model using the following specifications:

$$\begin{aligned} Y_{i,p,y,bc,bm,by} = \beta_0 &+ \beta_1 HighTemp_{bc,bm,by} + \varphi_{bc,by} + \varphi_{bc,bm} + \varphi_{by,bm} \\ &+ \varphi_{p,y} + \varepsilon_{i,p,y,bc,bm,by}, \end{aligned} \tag{1}$$

where i refers to individual, y indicates the survey year, p denotes province of residence, bc represents cities of birth, and the birth month and year are denoted as

TABLE 1
DESCRIPTIVE STATISTICS

Variable	Mean	SD	Minimum	Maximum	Observations
			A. PWB		
Unhappiness	2.216	.927	1	5	11,913
Satisfaction	2.320	.953	1	5	11,913
Depression	.454	.587	0	3	11,913
			B. Demographic Characteristics		
Age	42.322	13.964	15	67	11,913
Female	.511	.500	0	1	11,913
Han ethnicity	.908	.289	0	1	11,911
Birth order	2.137	1.271	1	13	11,913
Sibling	2.572	1.992	0	12	11,913
			C. Parental Socioeconomic Status		
Parental education years	4.580	3.873	0	19.5	9,173
Paternal agricultural hukou	.852	.355	0	1	11,913
Maternal agricultural hukou	.865	.342	0	1	11,913
			D. Climatic Conditions during Pregnancy		
High-temperature days (maximum > 90°F, 10s)	2.305	3.702	0	16.023	11,913
High-temperature days (maximum > 85°F, 10s)	4.989	5.239	0	20.470	11,913
High-temperature days (mean > 90°F)	.552	1.894	0	29.434	11,913
CDD (65°F, 100s)	13.013	7.967	0	40.616	11,913
Precipitation	7.858	.565	2.308	8.796	11,913
Humidity	4.263	.148	3.456	4.468	11,913
Sunshine	5.800	1.436	1.544	9.626	11,913
Wind	2.375	.737	.260	7.693	11,913
			E. Mechanism		
Physical illness	.111	.315	0	1	11,913
Hourly income	2.293	1.809	0	10.974	11,913
Social trust	3.443	1.070	1	5	11,913
Social support	1.908	1.462	0	4.605	11,913

Note. The sample contains 11,913 individuals from 8,068 households across 29 provinces. Panel A: Happiness and satisfaction are rated on 5-point scales measuring participants' levels of happiness and life satisfaction (from 1 = very unhappy/unsatisfied to 5 = very happy/satisfied). Depression is the average score of the 20-item CES-D Scale. Panel B: Age is age in years. Female is an indicator of being female. Han is an indicator of having Han ethnicity. Birth order is the sequence of births within the family. Sibling is the number of siblings. Panel C: Parental education years is the average year of education for fathers and mothers. Paternal agricultural hukou is the indicator of holding agricultural hukou for fathers at birth. Maternal agricultural hukou is the indicator of holding agricultural hukou for mothers at birth. Panel D: High-temperature days are defined as the number of days (10s, or in units of 10 days) with daily temperature (maximum or mean) exceeding a certain threshold during pregnancy. CDD is the sum of the difference in temperature (100s, or in units of 100 degrees) between threshold temperature and each hot day's (exceeding the threshold) mean temperature over the year. Precipitation is the total precipitation during pregnancy (unit: mm, in logarithm). Humidity is the mean relative humidity during pregnancy (unit: %, in logarithm). Sunshine is the mean number of daily hours of insolation during pregnancy (unit: hour). Wind is the mean speed of wind during pregnancy (unit: m/s). Panel E: Physical illness is an indicator of having experienced diagnosed hospitalization in the previous year. Hourly income is calculated by dividing the sum of annual wages and business income by annual working hours (unit: Chinese yuan, in logarithm). Social trust is measured on a 5-point scale (from 1 = completely untrustworthy to 5 = completely trustworthy) that measures participants' degree of trust in their neighborhood and other residents in the community/village. Social support is the number of close friends/acquaintances from whom participants can obtain support and help (unit: person, in logarithm). Conversion equation for temperature: °F = °C × 1.8 + 32.

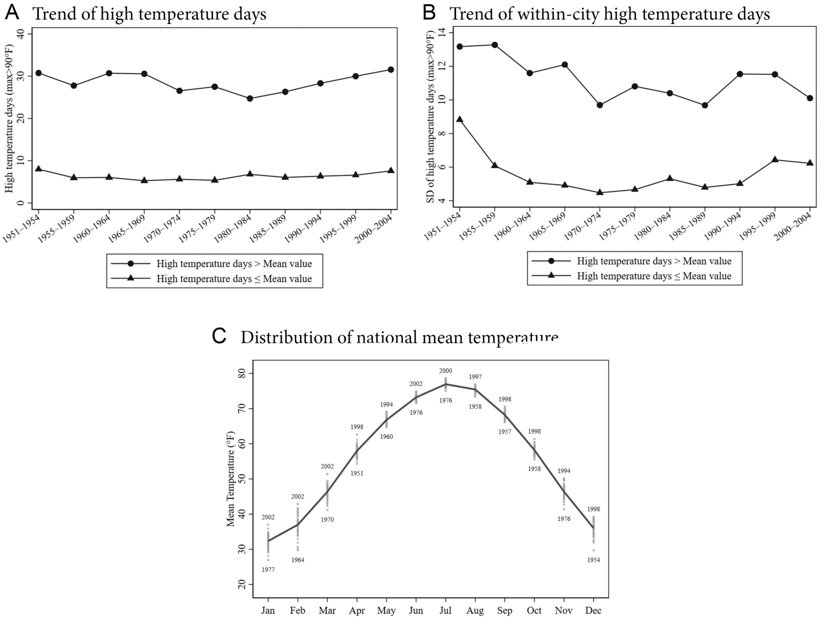

Figure 2. High-temperature days by period. *A* and *B*, We divided Chinese cities into two groups on the basis of whether the yearly number of days with a maximum temperature higher than 90°F exceeded the mean value of the specific period. Then, we calculated the within-city standard deviation of high-temperature days as the standard deviation of the predicted residuals from the regression of the yearly number of high-temperature days on city fixed effects. *C*, Dots denote the monthly mean temperature across years between 1951 and 2004; the years of minimum and maximum values are labeled. The solid line represents the mean value of the monthly mean temperature. Conversion equation for temperature: °F = °C × 1.8 + 32. Source: Data from Institute of Geographic Sciences and Natural Resources Research at the Chinese Academy of Sciences.

bm and *by*, respectively. The outcome variable $Y_{i,p,y,bc,bm,by}$ refers to adult PWB, including evaluative (unhappiness and life unsatisfaction) and emotional (depressive symptoms) measures. $HighTemp_{bc,bm,by}$ denotes the number of high-temperature days during pregnancy. The coefficients of this key explanatory variable, indicated by β_1, capture the effect of PHSE on later-life PWB. The error term is $\varepsilon_{i,p,y,bc,bm,by}$.

In order to isolate the causal effect, we include the following sets of fixed effects: (1) birth city by birth year fixed effects ($\varphi_{bc,by}$) that capture nonlinear, birth-city-specific differences over time (e.g., changes in city-level events or policies that might affect human capital formation)[4]; (2) birth city by birth month

[4] During our study period, China underwent significant historical events and policy changes. Two major events were the Great Chinese Famine (1959–61) and the Cultural Revolution (1966–76). These events had far-reaching effects on Chinese society. Research shows these events influenced fertility choices and child development (Zhou and Hou 1999; Gørgens, Meng, and Vaithianathan 2012). To account for these effects, we use birth year by birth month fixed effects in our analysis. Furthermore, different regions of China experienced these events with varying intensity. For example,

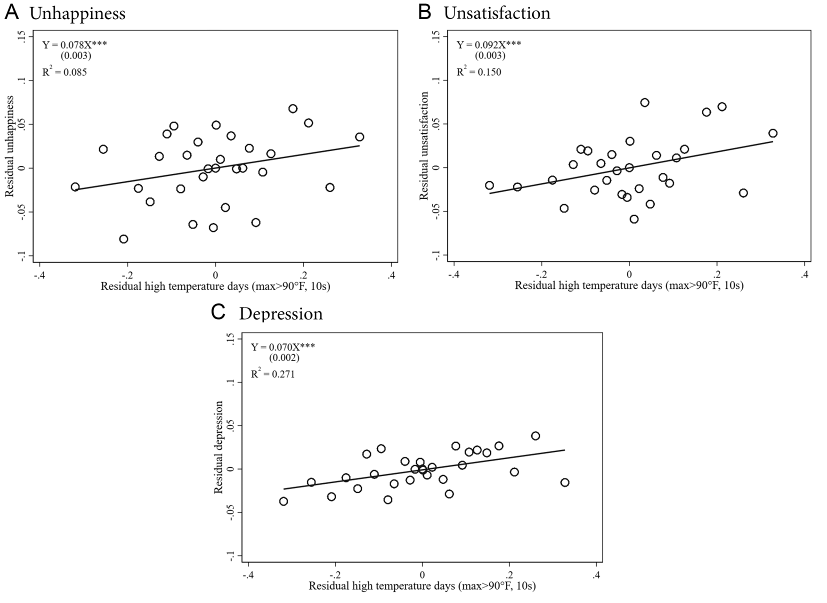

Figure 3. PHSE and later-life PWB. We obtained residuals of outcome variables from the regression of indicators of happiness, satisfaction, and depression on multiple sets of fixed effects (birth city by birth year, birth city by birth month, birth year by birth month, and province by year) and other climatic conditions (precipitation, humidity, sunshine). We obtained residuals of high-temperature days from the regression of the number of days (10s, or in 10 days) with a maximum temperature >90°F during pregnancy on the same sets of fixed effects. We grouped the observations into 50 groups according to the quantile of the residuals of high-temperature days. We dropped the minimum and the maximum values of residual dependent and independent variables to avoid outliers. The *y*-axis denotes the mean value of the residuals of PWB in each quantile, and the *x*-axis indicates the mean value of residuals of high-temperature days in each quantile. The solid line is for a linear regression that fits on the scatter plot. Conversion equation for temperature: °F = °C × 1.8 + 32.

fixed effects ($\varphi_{bc,bm}$) that capture unobserved monthly changes in the outcomes common to all births in a city (e.g., seasonal employment); (3) birth year by birth month fixed effects ($\varphi_{by,bm}$) that account for any year-specific seasonal shocks correlated with both temperature and birth outcomes in all cities; and (4) province by year fixed effects ($\varphi_{p,y}$) that capture unobservable factors fluctuating by survey year at the provincial level (e.g., economic shocks that may affect residents' well-being).

One potential concern is that after including all sets of the fixed effects in the model, the variation left for indicators of PWB and PHSE might be too little to identify the effects. Figure A2 indicates that there is sufficient variation left in PWB and PHSE variables, thereby validating our analytic strategy.

some areas faced more severe famine conditions than others. The Cultural Revolution also had uneven effects across the country. To address these regional differences, we include birth city by birth year fixed effects in our model.

IV. Results

In this section, we present the empirical results of how PHSE is associated with later-life PWB, including evaluative (unhappiness and life unsatisfaction) and emotional (depressive symptoms) measures. We outline heterogeneous effects across trimesters and nonlinear temperature-bin effects, as well as heterogeneous effects across individuals' characteristics and early-life circumstances. We also discuss the robustness of our main findings.

A. Effects of In Utero Heat Stress Exposure on Later-Life PWB

Table 2 displays the primary estimations of equation (1). The effects of PHSE on later-life PWB in the adult labor force are negative and statistically significant. Specifically, one additional 10-day instance of exposure to extremely high temperatures (maximum > 90°F) during the prenatal period raises the level of unhappiness and life unsatisfaction in adulthood by 0.055 (95% CI: [0.014, 0.097]) and 0.072 (95% CI: [0.020, 0.124]) units, respectively, and increases depressive symptoms by 0.049 units (95% CI: [0.016, 0.082]). The point estimates also imply that one additional 10-day increase in PHSE leads to an increase in the standard deviation of later-life unhappiness, unsatisfaction, and depressive symptoms by 5.93% (= 0.055/0.927), 7.56% (= 0.072/0.953), and 8.35% (= 0.049/0.587), respectively. In other words, these results correspond to 2.48% (= 0.055/2.216), 3.10% (= 0.072/2.320), and 10.79% (= 0.049/0.454) of the mean of each dependent variable, respectively.

We also apply alternative specifications, including (1) alternative sets of fixed effects, (2) inclusion of linear and quadratic time trend of birth provinces to account for the possibility of regional adaptation to extreme temperatures, and (3) controls of other climatic conditions during pregnancy, demographic traits,

TABLE 2
BASELINE RESULTS: PHSE AND PWB IN ADULTHOOD

	Unhappiness (1)	Unsatisfaction (2)	Depression (3)
High-temperature days (maximum > 90°F, 10s)	.055***	.072***	.049***
	(.021)	(.026)	(.017)
Observations	11,913	11,913	11,913
R^2	.686	.686	.700
Mean of dependent variable	2.216	2.320	.454
SD of dependent variable	.927	.953	.587
SD of high-temperature days	3.702	3.702	3.702

Note. Ordinary least squares (OLS) estimates include multiple fixed effects (birth city by birth year, birth city by birth month, birth year by birth month, and province by year). High-temperature days are defined as the number of days (10s, or in units of 10 days) with daily temperature (maximum or mean) exceeding a certain threshold during pregnancy. Robust standard errors are in parentheses, clustered at the birth-city level. Conversion equation for temperature: °F = °C × 1.8 + 32.
*** $p < .01$.

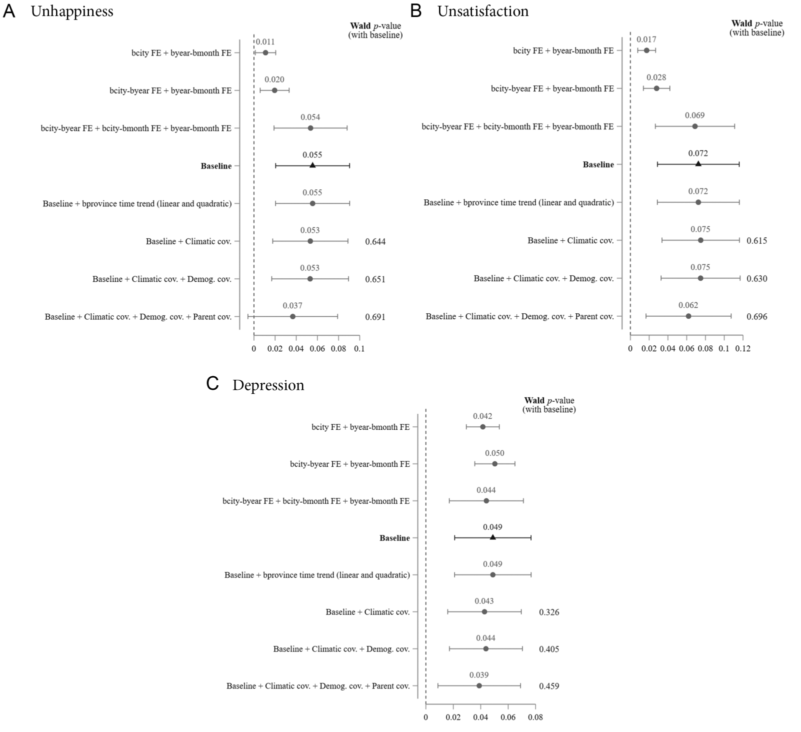

Figure 4. Estimation for PHSE-PWB nexus by using alternative specifications. Dots and triangles denote the estimated coefficients on the number of high-temperature days (maximum > 90°F, 10s) during pregnancy. High-temperature days are defined as the number of days (10s, or in units of 10 days) with daily temperature (maximum or mean) exceeding a certain threshold during pregnancy. Solid lines represent the 95% CI. The term *bcity* denotes birth city, *byear* denotes birth year, *bmonth* denotes birth month, and *bprovince* denotes birth province. *Climatic cov.* refers to climatic covariates, including precipitation, humidity, sunshine, and wind speed. *Demog. cov.* refers to demographic covariates, including gender, ethnicity, age and age-squared, birth order, and number of siblings. *Parent cov.* refers to parental covariates, including parental education years, paternal hukou status, and maternal hukou status. The definition and descriptive statistics of these variables are shown in table 1. Robust standard errors are clustered at the birth-city level. Conversion equation for temperature: °F = °C × 1.8 + 32.

and parental socioeconomic status. Results in figure 4 are almost statistically significant (except unhappiness after controlling for parental covariates), but the point estimates for unhappiness and unsatisfaction are substantively smaller in the first two flexible models with fewer fixed effects. There might be more confounding at the birth city by birth month level for the evaluative indicators of PWB (unhappiness and life unsatisfaction) that significantly affects the estimation.

Trimester heterogeneity. Furthermore, we investigate the effects of ambient heat stress across the trimesters of pregnancy on later-life PWB. Figure 5 shows the estimated coefficients. Notably, the adverse effects of PHSE on later-life PWB portray an increasing trend from the first trimester to the third trimester and are greater and more statistically significant in the second and third trimesters (except the coefficient on depressive symptoms in the second semester).

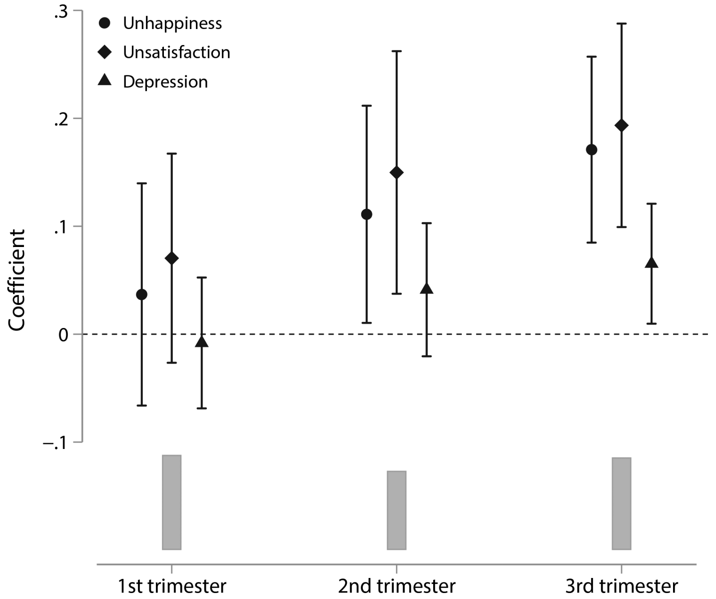

Figure 5. Effect of PHSE on later-life PWB by trimester. Dots, diamonds, and triangles denote the estimated coefficients on high-temperature days (maximum > 90°F, 10s) in each trimester. High-temperature days are defined as the number of days (10s, or in units of 10 days) with daily temperature (maximum or mean) exceeding a certain threshold during pregnancy. Solid lines represent the 95% CI. Bars refer to the mean value of the prenatal exposure to extreme high temperature in each trimester (number of days, 10s). The OLS estimates include multiple fixed effects (birth city by birth year, birth city by birth month, birth year by birth month, and province by year). Robust standard errors are clustered at the birth-city level. For unhappiness, diff [2nd Trimester − 1st Trimester] = 0.074 (p = .022); diff [3rd Trimester − 1st Trimester] = 0.134 (p = .004); and diff [3rd Trimester − 2nd Trimester] = 0.060 (p = .131). For unsatisfaction, diff [2nd Trimester − 1st Trimester] = 0.079 (p = .060); diff [3rd Trimester− 1st Trimester] = 0.123 (p = .000); and diff [3rd Trimester − 2nd Trimester] = 0.044 (p = .238). For depression, diff [2nd Trimester − 1st Trimester] = 0.049 (p = .059); diff [3rd Trimester − 1st Trimester] = 0.073 (p = .008); and diff [3rd Trimester − 2nd Trimester] = 0.024 (p = .282). Conversion equation for temperature: °F = °C × 1.8 + 32.

However, heat stress in the first trimester does not have a statistically significant effect on adult PWB. The statistically significant differences in coefficients between the first trimester and the other two trimesters are also documented (see the caption of fig. 5). Such sensitivity to high-temperature fluctuations in the last two trimesters has been documented in several studies (Isen, Rossin-Slater, and Walker 2017; Fishman, Carrillo, and Russ 2019; Hu and Li 2019). Our results provide indirect evidence for the biological effects of extreme prenatal temperature shocks on later-life PWB because the brain and neurologic functions develop during the second and third trimesters (Wilson et al. 2021).

Nonlinear effects. Following Deschênes and Greenstone (2011), we employ 10-degree temperature bins to investigate the nonlinear effects of daily maximum temperatures during pregnancy, with 50°F–60°F as the reference group. Figure 6 portrays the results. The estimated coefficients in figures 6*A*–6*C* represent the effect of one additional instance of 10 days of exposure to a

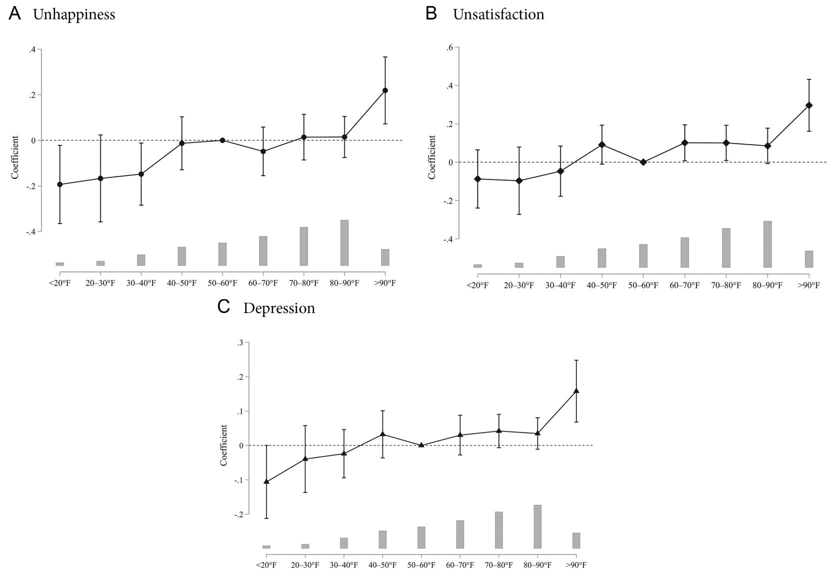

Figure 6. Nonlinear effects of temperature exposure, estimated by the 10-degree temperature-bin approach (the number of days with a daily maximum temperature in each bin, in 10 days, 50°F–60°F as the reference) on adults' PWB. Dots, diamonds, and triangles denote the estimated coefficients on the number of days falling into each 10-degree temperature bin during pregnancy. Solid lines represent the 95% CI. Bars refer to the mean value of the prenatal exposure to each temperature bin (number of days, in 10 days). The OLS estimates include multiple fixed effects (birth city by birth year, birth city by birth month, birth year by birth month, and province by year). Robust standard errors are clustered at the birth-city level. Conversion equation for temperature: °F = °C × 1.8 + 32.

specific temperature bin on the outcomes of interest relative to days with temperatures ranging from 50°F to 60°F. In general, the increase in days of exposure to extremely high temperatures of 90°F or above during the prenatal period is significantly associated with higher levels of unhappiness and life unsatisfaction, as well as a higher propensity for depressive symptoms. The coefficients are reasonably monotonic with increasing temperature bins, with 90°F and above presenting the largest magnitudes. We alternatively use the 5-degree temperature-bin approach for daily maximum temperatures, and we apply the 10-degree temperature-bin method to daily mean temperature; the results suggest that toxicity to mental health is most profound among the high-temperature bins (see figs. A3 and A4).[5]

[5] The monotone instead of U-shaped trends in fig. 6 and fig. A3 could be interpreted by the fact that higher maximum temperatures are associated with lower levels of PWB throughout the temperature spectrum, while higher maximum temperatures may benefit well-being for temperatures below the "optimum." These monotone trends of bin analysis by use of daily maximum temperature are consistent with previous studies (e.g., Hu and Li 2019, their fig. 4). In addition to daily maximum temperature, we also plot the temperature bin analysis for daily mean temperature (shown in fig. A4). These trends

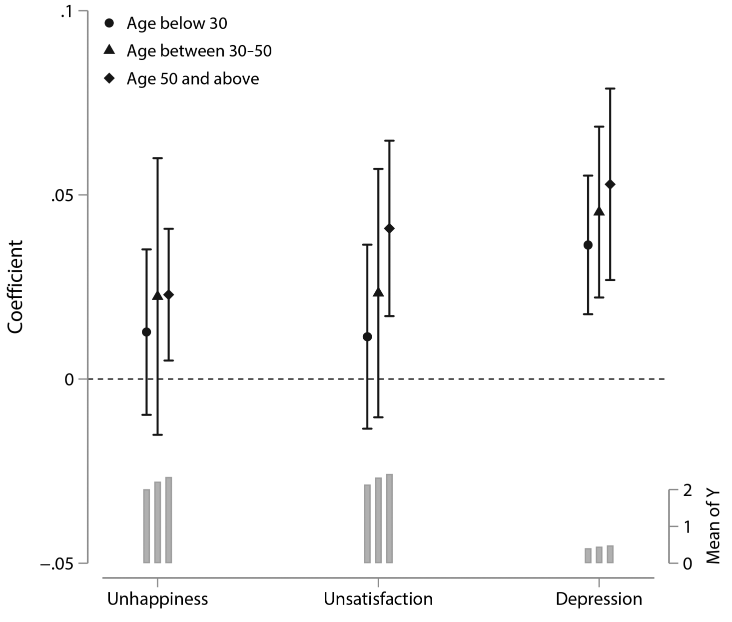

Figure 7. Cumulative effects of PHSE during gestation on adult PWB. Dots, triangles, and diamonds denote the estimated coefficients on the number of high-temperature days (maximum > 90°F, in 10 days) during pregnancy. Solid lines represent the 95% CI. Bars refer to the mean value of outcome variables. The OLS estimates include multiple fixed effects (birth city, birth year by birth month, and province by year). Robust standard errors are clustered at the birth-city level. Bootstrap (with 500 replications) and permutation tests for difference in coefficients between two groups are employed: For unhappiness, diff [Age between 30–50 − Age below 30] = 0.009 (p = .170); diff [Age 50 and above − Age below 30] = 0.010 (p = .120); and diff [Age 50 and above − Age between 30–50] = 0.001 (p = .830). For unsatisfaction, diff [Age between 30–50 − Age below 30] = 0.012 (p = .250); diff [Age 50 and above − Age below 30] = 0.029 (p = .020); and diff [Age 50 and above − Age between 30–50] = 0.018 (p = .150). For depression, diff [Age between 30–50 − Age below 30] = 0.009 (p = .140); diff [Age 50 and above − Age below 30] = 0.016 (p = .010); and diff [Age 50 and above − Age between 30–50] = 0.008 (p = .310). Conversion equation for temperature: °F = °C × 1.8 + 32.

Cumulative effects by age. We divide individuals into three groups (age below 30, age between 30 and 50, age 50 and above) on the basis of their age at survey and examine the heterogeneous effects of PHSE by age. Figure 7 portrays the results. The estimates on the exposure to extremely high temperatures and the mean values of PWB indicators increase with age, potentially implying a cumulative trend (which is considered the cumulative effect). For unsatisfaction and depressive symptoms, the statistically significant differences in coefficients on PHSE between older adults (age 50 and above) and younger adults (age below 30) are also documented (see the caption of figure 7). Our findings of greater adverse effects of early-life health shocks in older people are consistent

are not monotone; the largest effects are in the bins of extreme high temperature (>90°F). The effects of coldness (<20°F, 20°F–30°F) are slightly larger than the reference group though insignificant.

with the previous studies (Lindeboom, Portrait, and Van den Berg 2010; Gould, Lavy, and Paserman 2011; Duque and Schmitz 2023).[6]

Validity of the identification assumption. The validity of our identification strategy depends on the exogeneity of environmental shocks during pregnancy; that is, they should not interfere with the observable demographic traits conditional on the sets of fixed effects in equation (1). Owing to the idiosyncratic temperature shocks that remain, the net location and birth cohort means are plausibly exogenous, and our estimates can be interpreted as the causal effects of PHSE. In addition, we conduct a series of balance tests (see table A1; tables A1–A13 are available online) by regressing the demographic traits and parental socioeconomic status on high-temperature days during pregnancy, including the same sets of fixed effects in equation (1). The results indicate that all coefficients of extremely high-temperature exposure in relation to demographic traits are neither substantively nor statistically significant at the conventional level. This finding implies that significant fetal selection does not exist in our sample, which may have biased our estimates, thus supporting the randomness of extremely high-temperature exposure during the prenatal period.

B. Heterogeneous Effects across Gender, Birthplace, and Early-Life Conditions

To explore whether the relationships between PHSE and PWB outcomes in adulthood differ across critical sociodemographic factors, we interact high-temperature days with binary indicators of the interested sociodemographic variables in equation (1); the estimated coefficients reflecting between-group variations are listed in table 3. In addition, we interact high-temperature days with indicators for each subgroup such that the coefficient of each interaction term represented the estimated effect for the specified subgroup. The results are depicted in figure A5.

Gender. The results in panel A of table 3 show that both male and female adults' PWB suffers from PHSE, and the adverse effects are more prominent and statistically significant among women.

Living conditions of birthplace. The outcomes in panel B of table 3 show that rural-born individuals are more vulnerable to heat stress, which is consistent with Hu and Li (2019), Banerjee and Maharaj (2020), and Garg, Jagnani, and

[6] Specifically, Duque and Schmitz (2023) found that the adverse effects of early-life exposure to the Great Depression on later-life labor market and health outcomes become more pronounced as surviving cohort members age in the United States. Lindeboom, Portrait, and Van den Berg (2010) used Dutch data and found that exposure to the famine in early life negatively affects survival at ages older than 50, while they did not document any significant long-term effect at ages younger than 50. Gould, Lavy, and Paserman (2011) found that Yemenite children who were placed in a more modern environment had better socioeconomic outcomes in later life, and older women experienced much larger effects.

TABLE 3
HETEROGENEOUS EFFECTS OF PHSE ACROSS DEMOGRAPHIC CONDITIONS

	Unhappiness (1)	Unsatisfaction (2)	Depression (3)
	A. Heterogeneity by Gender (Female = 1)		
High-temperature days (maximum > 90°F, 10s)	.048**	.067**	.045***
	(.021)	(.026)	(.017)
High-temperature days (maximum > 90°F, 10s) × Female	.013**	.011*	.008**
	(.006)	(.006)	(.004)
R^2	.686	.686	.702
	B. Heterogeneity by Birth Hukou (Agricultural Hukou = 1)		
High-temperature days (maximum > 90°F, 10s)	.038*	.057**	.033
	(.022)	(.028)	(.021)
High-temperature days (maximum > 90°F, 10s) × Birth hukou	.018**	.017*	.018**
	(.009)	(.010)	(.008)
R^2	.687	.687	.702
	C. Heterogeneity by Health-Care Resources in One's Birthplace (under Mean = 1)		
High-temperature days (maximum > 90°F, 10s)	.026	.014	.022
	(.023)	(.029)	(.018)
High-temperature days (maximum > 90°F, 10s) × Medical personnel	.040***	.067***	.034***
	(.013)	(.018)	(.010)
R^2	.701	.705	.712
	D. Heterogeneity by Parental Absence before Age 14 (Divorce or Death = 1)		
High-temperature days (maximum > 90°F, 10s)	.027	.034	.034*
	(.022)	(.025)	(.018)
High-temperature days (maximum > 90°F, 10s) × Parental absence	.036***	.052***	.024***
	(.010)	(.011)	(.007)
R^2	.689	.691	.702
	E. Heterogeneity by Paternal Education (under High School = 1)		
High-temperature days (maximum > 90°F, 10s)	.009	.034	−.052***
	(.038)	(.028)	(.019)
High-temperature days (maximum > 90°F, 10s) × Paternal education	.039*	.043**	.102***
	(.021)	(.021)	(.015)
R^2	.775	.769	.790

TABLE 3 (*Continued*)

	Unhappiness (1)	Unsatisfaction (2)	Depression (3)
	F. Heterogeneity by Paternal Occupational Class before Age 14 (Primary or Intermediate Classes = 1)		
High-temperature days (maximum > 90°F, 10s)	.033	.044	.036**
	(.025)	(.033)	(.016)
High-temperature days (maximum > 90°F, 10s) × Paternal occupation	.033***	.042***	.027***
	(.011)	(.013)	(.006)
R^2	.716	.717	.730

Sources. For panel C, data sources are the *Comprehensive Statistical Data and Materials on 50 Years of People's Republic of China*, *China Compendium of Statistics 1949–2008*, and provincial statistical yearbooks.
Note. Binary heterogeneous indicators are also included in the regressions. High-temperature days are defined as the number of days (10s, or in units of 10 days) with daily temperature (maximum or mean) exceeding a certain threshold during pregnancy. In panel C, we constructed the number of medical technical personnel per 10,000 people to measure health-care resources in the province of birth. The CLDS dataset involves an eight-category scheme for paternal occupation at age 14 according to the major group classifications used by the Chinese National Bureau of Statistics (*People's Republic of China Classification of Occupations Ceremony*). In panel F, we categorized these eight occupational categories into three classes: (1) the primary class, i.e., workers in the farming, forestry, animal husbandry, and fishery industries (64.5%), other unclassified staff and workers (6.35%), and those without an occupation (0.93%); (2) the intermediate class, i.e., office workers and related staff (3.0%), commercial and service workers (4.6%), and production, transportation, and related workers (6.7%); and (3) the advanced class, i.e., administrators in government, parties, social organizations, enterprises, and institutions (7.2%), and scientific and technical staff (6.7%). We defined a binary variable of lower occupational class that equals 1 if paternal occupation belongs to the primary or intermediate classes. OLS estimates include multiple fixed effects (birth city by birth year, birth city by birth month, birth year by birth month, and province by year). Robust standard errors in parentheses are clustered at the birth-city level. Conversion equation for temperature: °F = °C × 1.8 + 32.
* $p < .10$.
** $p < .05$.
*** $p < .01$.

Taraz (2020). The more negative effects of extreme weather in rural areas could also explain the income effects, through which the PHSE might affect the main economic security (i.e., agricultural production) for pregnant mothers' and fetuses' nutrition. The results in panel C of table 3 suggest that the effects of hot weather are more salient for individuals born in areas with poor medical and health-care facilities.

Early-life family background. Panels D–F of table 3 display heterogeneous effects across different early-life family backgrounds, including household integrity, parental educational attainment, and occupational class. The findings consistently demonstrate that the negative outcomes of PHSE matter more for broken families (panel D), households with lower educational attainment (panel E), and individuals belonging to lower occupational classes (panel F).

C. Robustness Checks

Alternative measures of extremely hot weather. We use alternative measures of high-temperature days to examine the link between hot weather and PWB, including daily maximum temperatures higher than 85°F, daily mean temperatures higher than 90°F, and CDD with a natural normalization temperature of 65°F. The directions of the coefficients presented in table A2 are consistent with our primary analyses and are statistically significant, thereby validating our main finding that PHSE can significantly reduce individuals' PWB in adulthood.

Dichotomous measures of PWB. We define two dichotomous variables for PWB outcomes on the basis of their mean and median values. We code responses above the mean or median as 1 and the rest as 0. As argued by Li (2021), the dichotomous definition has two essential advantages: (1) it does not require considering a cardinal or ordinal conception of individuals' responses to PWB questions, and (2) the distributional skewness and fairly low degree of variability in responses to PWB questions can be tackled. Table A3 suggests that most findings remain consistent with our primary analyses when dichotomizing the dependent variables (except unhappiness and depression using mean value and median value as cutoff points, respectively), thereby highlighting the robustness of our findings.

Additional controls. First, we include the number of extremely cold days with a minimum temperature below 20°F during pregnancy (Deschênes and Greenstone 2011) in the specifications to assess whether adult PWB is vulnerable to prenatal exposure to waves of extreme cold. Table A4 shows that the effects of cold weather are statistically insignificant, and our results remained stable.[7] Second, we add the number of extremely high-temperature days 3 months prior to conception and 9 months after childbirth to our specifications, accounting for the potential effects of heat waves on the frequency of sexual activity and children's human capital development (Lam and Miron 1996; Garg, Jagnani, and Taraz 2020). The estimates in table A5 suggest that only PHSE can significantly influence later-life well-being, which is consistent with Hu and Li (2019).

Alternative clustered standard errors. In addition to clustering the robust standard errors at the birth-city level in the baseline estimations, we also attempt several other ways of clustering. First, to rule out the potential events or policies that all cities within the same administrative unit (such as city tiers) or the same province may be correlated, we cluster the standard errors on the basis of Chinese administrative units, including birth-city tiers (i.e., municipality directly under the central government, subprovincial city, provincial capital city, and prefecture-level city) and birth provinces. Second, in order to allow for time variations, we cluster the standard errors (two-way) at the

[7] These results along with fig. A4 are consistent with the existing literature that documented a stronger effect of heat on human development than that of coldness in several developed and developing countries, such as the United States (Barreca et al. 2016), Japan (He and Tanaka 2023), India (Colmer 2021), China (Agarwal et al. 2021), and so forth, and even globally (LoPalo 2023).

birth city by birth year level and the birth city by birth month level. Third, to allay the concern about spatial correlation possibly caused by the ease with which extreme weather may cover a large region and spread from one city to another, we employ the standard errors adjusted for spatial autocorrelation within 300, 500, and 1,000 km, respectively (Hsiang 2010). The results are reported in table A6. The effects of PHSE remain statistically significant in these estimations.

Multiple hypothesis testing. To address the concern regarding inference for the multiplicity of outcomes, we apply several multiple hypothesis tests, including the family-wise error rate (FWER) correction approach proposed by Holm (1979), Westfall and Young (1993), Romano and Wolf (2005), and List, Shaikh, and Xu (2019), as well as the false discovery rate (FDR) correction approach proposed by Benjamini and Yekutieli (2001). The results in table A7 are robust to accounting for multiple hypotheses testing.

Excluding early-life exposure to the Great Famine and Cultural Revolution. Although we have added birth city by birth year fixed effects to account for city-specific time-varying determinants (particularly historical events or policies) of PWB at birth level, there is still a concern that individuals might have been exposed to historical shocks when they were relatively young. Ages before 3 or 5 are considered a critical stage in human capital development (Currie and Almond 2011; Behrman 2015). To further exclude the effects of historical events during birth and early-life development, we drop individuals who were born and aged 0–5 during the Great Chinese Famine (1959–61) and the Chinese Cultural Revolution (May 1966–October 1976). The results in table A8 show that our main findings remain unchanged after excluding these potential confounding factors derived from historical events or policies.

Accounting for gender-specific mortality selection at birth. Previous studies found that heat-related mortality varied by gender in different countries (e.g., Parks et al. 2020; Ballester et al. 2023) and was much higher among males in China (Yu, Lei, and Wang 2019). Moreover, our findings show that the effect of PHSE on later-life PWB was much larger among female adults.[8] Therefore, the PHSE-PWB nexus might be vulnerable to differential effects of exposure to mortality across gender types. To address this concern, we add mortality rate at birth provinces and interact it with gender indicator to account for the effect of differential mortality across gender types. We also drop individuals born and aged 0–5 during the Great Chinese Famine and the Chinese Cultural

[8] One possible reason for the stronger effects of PHSE on women might be the fact that boys are more "fragile" in early life, thus they could be more positively selected than women into surviving until adulthood.

Revolution to further account for excessive mortality caused by exposure to historical shocks. The results in table A9 imply that most findings remain robust after excluding the effect of differential mortality across gender types.[9]

Within household variation. Although our main findings remain robust after controlling parental socioeconomic status (see fig. 4), there are still many unobservable family factors that may affect later-life mental health outcomes through biological (e.g., gene) and nurturant (e.g., parental investment) channels. In this case, comparing children within the same household (i.e., sibling fixed effects) would be better to identify the real effect of PHSE than comparing children across different households (Bharadwaj et al. 2017). Therefore, we keep households that have more than one child and include sibling fixed effects (as well as birth-month fixed effects) in regressions.[10] All the estimates shown in table A11 are statistically significant, implying that the PHSE-PWB nexus exists within the same household.

Adaptation to temperature change. Given the possibility for adaptation, it may not be the number of such high-temperature days that is the relevant treatment. We refer to Cui and Zhong (2024) and incorporate a moving-average method into the cohort estimation framework to identify whether the PHSE exceeding the gradually shifting normals results in PWB outcomes. The method allows us to capture the birthplace adaptation to historical temperature change.[11] The results presented in tables A12 and A13 suggest that greater PHSE than historical normals significantly induce PWB reduction, demonstrating a strong and negative PHSE-PWB nexus under the circumstance of climatic adaptation.

V. Discussion

In this section, we additionally explore the potential nonbiological explanations through which PHSE could lead to a decline in adult PWB by harming human

[9] One related issue is that the gendered heterogeneous effects of PHSE (panel A in table 3) might also be deviated by differential exposures to mortality across gender types. We applied the same strategy to mitigate this concern. The results in table A10 suggest robust findings of prominent adverse effects of PHSE among women.

[10] In our sample, there are 56.5% (= 6,725/11,913) individuals born in multichild households.

[11] The model is specified as the following equation:

$$Y_{i,p,y,bc,bm,by} = \beta_0 + \beta_1 \mathbf{1}\left(HighTemp_{bc,bm,by} > \widetilde{HighTemp}_{bc,bm,by}\right) + \varphi_{bc,by} + \varphi_{bc,bm} + \varphi_{by,bm} + \varphi_{p,y} + \varepsilon_{i,p,y,bc,bm,by},$$

where $\widetilde{HighTemp}$ is the PHSE normals measured by averaging city-specific number of high-temperature days during pregnancy over the 10, 15, or 20 years that precede the birth, and $\mathbf{1}(HighTemp_{bc,bm,by} > \widetilde{HighTemp}_{bc,bm,by})$ is a dummy indicator to represent a greater PHSE than historical normals (the results are presented in table A12). Other indexes are the same as in eq. (1). We also displace the dummy indicator with the continuous measure (i.e., the number of days PHSE exceeded historical normals) in table A13.

and social capital formation. To examine the underlying explanations, we construct a battery of indicators: (1) human capital indicators (physical health and hourly income) and (2) social capital indicators (social trust and social support).

Human capital. Human capital formation, which is primarily reflected in physical health, education, and income, serves as a determinant of adult PWB (Benjamin et al. 2012; Lamu and Olsen 2016; Killingsworth, Kahneman, and Mellers 2023). Prenatal health shocks, including heat stress exposure, can exert strong and persistent adverse effects on life-cycle health outcomes (Currie and Vogl 2013; Currie and Rossin-Slater 2015), educational attainment (Wilde, Apouey, and Jung 2017), and workplace performance (Majid 2015; Isen, Rossin-Slater, and Walker 2017), thereby impairing PWB in the long run. Educational attainment can influence other components of socioeconomic status (e.g., income and occupational status), which may ultimately affect mental health (as shown by Muller 2002). In this case, we measured human capital by physical health status and labor market performance.

We use a binary indicator of having experienced hospitalization in the previous year to measure physical health status. Additionally, we use hourly income, calculated by dividing the sum of annual wages and business income by annual working hours (units: Chinese yuan, in logarithm), as a measure of labor market performance. For the unemployed sample, we code hourly income as 0.

Social capital. Social capital plays a vital role in adult well-being (Agampodi et al. 2015). In addition to life support and risk mitigation (Yip et al. 2007; Helliwell et al. 2017), social networks and trust can improve adults' labor market performance (Franzen and Hangartner 2006). Early-life environmental shocks can adversely influence social capital formation. First, social preferences are endogenously determined starting in the womb, and prenatal health shocks could reduce childhood and even later-life social cooperation (Cecchi and Duchoslav 2018). Second, poor early-life health is likely to affect household unity and well-being (Reichman, Corman, and Noonan 2004), which may reduce children's social trust in the long run (Furstenberg 2005). Third, social capital is formed during the generation of human capital (Valdivieso and Villena-Roldan 2014), and PHSE can hinder various aspects of human capital formation (Hu and Li 2019). As a result, negative prenatal shocks from extreme weather may reduce individuals' later-life PWB by hindering their social capital formation.

We measure social capital formation on the basis of social trust and social support, in line with existing studies on social capital (Ziersch et al. 2005; Kim et al. 2011; Mehbub Anwar, Astell-Burt, and Feng 2019). Specifically, to gauge social support, we measure social trust by using a 5-point Likert scale for the following questions: “Do you trust the neighborhood and other residents in your community/village?” (1 = completely untrustworthy, 2 = relatively untrustworthy, 3 = fairly trustworthy, 4 = relatively trustworthy, 5 = completely trustworthy) and “How many close friends/acquaintances do you have from whom you can obtain support and help in your local place of residence?” (in logarithm). The descriptive statistics of the above mechanism variables are reported in table 1.

Empirical strategy and results. We further quantify the effects of PHSE by separately calculating the effects on the different mechanisms. We replicate equation (1)for each mechanism j by replacing $Y_{i,y}$ with the potential mechanism indexes $M^j_{i,p,y,bc,bm,by}$:

$$\begin{aligned} M^j_{i,p,y,bc,bm,by} = {} & \alpha^j_0 + \alpha^j_1 HighTemp_{bc,bm,by} + \varphi^j_{bc,by} + \varphi^j_{bc,bm} + \varphi^j_{by,bm} \\ & + \varphi^j_{p,y} + \varepsilon^j_{i,p,y,bc,bm,by}. \end{aligned} \tag{2}$$

Table 4 presents the regression outcomes for equation (2). In columns 1 and 2, we examine the potential effects of PHSE on human capital indicators. The results imply that prenatal exposure to high-temperature conditions is negatively associated with human capital formation. One additional 10-day increase in PHSE improves the standard deviation and the mean of diagnosed hospitalization rate in adulthood by 9.21% and 26.13% ($b = 0.029$, 95% CI: [0.010, 0.048]), respectively. Similarly, one additional 10-day increase in PHSE reduces the standard deviation and the mean of hourly income by 7.02% and 5.54% ($b = -0.127$, 95% CI: [-0.241, -0.013]), respectively. For social capital indicators, adverse prenatal heat stress effects are outlined in columns 3 and 4.

TABLE 4
EFFECTS OF PHSE ON MECHANISM INDEXES

	Physical Illness (1)	Hourly Income (2)	Social Trust (3)	Social Support (4)
High-temperature days				
(maximum > 90°F, 10s)	.029***	−.127**	−.067***	−.141***
	(.010)	(.058)	(.023)	(.053)
Observations	11,913	11,913	11,913	11,913
R^2	.744	.766	.808	.849
Mean of dependent variable	.111	2.293	3.443	1.908
SD of dependent variable	.315	1.809	1.070	1.462
SD of high-temperature days	3.702	3.702	3.702	3.702

Note. OLS estimates include multiple fixed effects (birth city by birth year, birth city by birth month, birth year by birth month, and province by year). High-temperature days are defined as the number of days (10s, or in units of 10 days) with daily temperature (maximum or mean) exceeding a certain threshold during pregnancy. Robust standard errors in parentheses are clustered at the birth-city level. Conversion equation for temperature: °F = °C × 1.8 + 32.
** $p < .05$.
*** $p < .01$.

One additional 10-day increase in PHSE reduces the standard deviation of social trust and social support among adults by 6.26% ($b = -0.067$, 95% CI: [-0.112, -0.023]) and 9.64% ($b = -0.141$, 95% CI: [-0.246, -0.035]), respectively. Additionally, it reduces the mean of social trust and social support among adults by 1.95% and 7.39%, respectively. Our findings suggest that PHSE may negatively affect an individual's PWB through undermining the procedure of human and social capital formation.[12]

VI. Conclusions

This study highlights the negative effects of exposure to extremely high temperatures during pregnancy on PWB outcomes in adulthood. Using a nationally representative data from China, we find that members of the adult labor force who experience prenatal exposure to extremely hot weather suffer significantly from a rise in unhappiness and life unsatisfaction as well as an increase in depressive symptoms. Specifically, individuals with an additional 10-day increase in PHSE (with maximum temperature > 90°F) are predicted to experience a rise in unhappiness ($b = 0.055$; 95% CI: [0.014, 0.097]), life unsatisfaction ($b = 0.072$; 95% CI: [0.020, 0.124]), and depression ($b = 0.049$; 95% CI: [0.016, 0.082]) by 5.93%, 7.56%, and 8.35% of the standard deviation (or 2.48%, 3.10%, and 10.79% of the mean), respectively.[13] In addition, the effects seem to be concentrated in the second and third trimesters, which may demonstrate the biological effects of PHSE on later-life mental health. Nonlinear regressions suggest that only high-temperature bins result in larger and more significant negative consequences. Moreover, we document that the PHSE-PWB

[12] Our indicators should have less endogeneity and may reflect the potential explanations under the PHSE-PWB nexus because (1) indicators of human capital formation, including hospitalization and hourly income, are measured on the basis of the status of respondents in the past year, prior to the status of PWB (i.e., current unhappiness and life unsatisfaction and depressive symptoms in the past 2 weeks); (2) indicators of social capital formation, including social trust and social support, are formed gradually and remain stable over the life cycle and are less likely to be determined by the status of PWB at one specific time. However, these findings still need cautious interpretations because it is difficult to completely exclude that PWB is (or at least in part) a mediator, and the mechanisms in this section are outcomes.

[13] According to our estimates, we also project increases in high-temperature days during pregnancy under the climate scenarios from the Intergovernmental Panel on Climate Change Sixth Assessment Report. Considering that the average number of high-temperature days during pregnancy across all the cohorts in our sample is 23.05, the PHSE in 2060 on average increases by 17.39 days under the SSP5-8.5 scenario (a fossil-fuel-based development scenario that predicts the fastest global warming). Our ceteris paribus back-of-the-envelope predictions suggest that compared with those born between 1951 and 2003, PHSE will on average result in net percentage increases of 4.3% ($= 1.739 \times 0.055/2.216$), 5.4% ($= 1.739 \times 0.072/2.320$), and 18.8% ($= 1.739 \times 0.049/0.454$) for unhappiness, life unsatisfaction, and depressive symptoms of adults born in 2060 (the planned fulfillment of carbon neutrality proposed by the Chinese government) under the SSP5-8.5 scenario.

nexus becomes more substantive and significant as age increases, implying cumulative effects of in utero health shocks on individual welfare.

The adverse effects of PHSE are also more prominent among women and individuals who were born in vulnerable contexts, such as rural areas and cities with a lack of health-care resources, or those who are raised in disadvantaged family environments with parental absence, lower parental educational attainment, and lower parental occupational classes. Our results have several implications. First, prenatal shocks are predicted to exacerbate gender inequality in terms of well-being because women are generally disadvantaged in society, such as in the workplace (Petrongolo 2019). Second, improving living conditions (e.g., housing quality and the availability of cooling tools) and health-care resources for pregnant women may help to alleviate the adverse effects of hot weather on children's long-term PWB formation. Third, ambient heat stress during pregnancy may impede upward intergenerational mobility (e.g., education, occupation). Improving the family's adaptive resources might mitigate these adverse effects and improve child PWB over the life course.

Finally, the underlying mechanisms are identified from the long-term perspectives of human capital and social capital formation with regard to adults' physical health, hourly income, social trust, and social support. The results show that one additional 10-day increase in PHSE (with maximum temperature > 90°F) reduces physical health, hourly income, social trust, and social support in adulthood by 9.21%, 7.02%, 6.26%, and 9.64% of the standard deviation (or 26.13%, 5.54%, 1.95%, and 7.39% of the mean), respectively.

This study has several limitations. First, we inevitably measure the 9-month prenatal period with errors because the CLDS does not provide the exact birth date and length of pregnancy. Our estimates may suffer from measurement errors and provide a lower bound for the effects of PHSE on adult PWB outcomes. Second, owing to data limitations, we cannot provide direct evidence for biological channels that may explain whether and how PHSE affects the brain and neurologic development of the fetus. Third, although we adopt various robustness checks to exclude potential confounding factors during the long time span of data, other instances of early-life exposure as well as long-term factors after birth that we did not capture could influence PWB in adulthood.

Despite these limitations, our findings provide novel evidence for the FOH and the loss of well-being caused by environmental shocks during the prenatal period; this topic has been understudied by previous research on the negative outcomes of PHSE in developing contexts (Fishman, Carrillo, and Russ 2019; Hu and Li 2019; Chen et al. 2020; Randell, Gray, and Grace 2020). We also provide a deeper understanding of how human and social capital formation influences achievements in well-being (Lamu and Olsen 2016).

Additionally, the results have important policy implications, such as the need for early intervention for pregnant women and long-term health care for their children to ensure their well-being. Finally, taking into account the potentially positive selection for surviving individuals in our sample, our negative conclusions for the PHSE-PWB nexus might enlighten a lower bound of the true effects of climate change and appeal for long-term strategies against global warming.

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