Supplementary Materials for

Heat, Health, and Infrastructure: Infant Mortality in a Warming South and Southeast Asia (SSEA)

Chunping Xie[1], Erik Berglöf[1], Elizabeth Robinson[2], Candice Howarth[2], Taiding Guo[3], Richard Tyler Simmons[3], Yuhang Pan[3*]

*Corresponding author. Email: yhpan@pku.edu.cn

[1]Asian Infrastructure Investment Bank, Beijing 100101, China.

[2]London School of Economics and Political Science, London WC2A 2AE, UK.

[3]Peking University, Beijing 100871, China.

This PDF file includes:

Materials and Methods

Supplementary Texts 1-2

Figure S1

Tables S1 to S5

Materials and Methods

Health data. Mortality data is sourced from the DHS. The DHS conducts comprehensive household and individual-level health surveys across over 90 countries, collecting information on infant and child mortality from parents and adult mortality from siblings. It has been widely used for mortality-related analyses, particularly in regions where more comprehensive data sources like those from the Centers for Disease Control and Prevention (CDC) are unavailable (*1*). While the DHS may not offer mortality records as detailed as the CDC's, it remains a valuable and feasible alternative for studying mortality patterns in many low- and middle-income countries.

For each individual level death incidence, the dataset includes its location cluster and the exact timing in terms of year and month. Table S1 summarizes the population size, period coverage, and number of location clusters involved for each country sampled. The analysis includes data on 3,360,451 individuals from 64,606 clusters, spanning the years 1963 to 2022 across the eight countries (Philippines, Pakistan, Myanmar, Indonesia, India, Cambodia, Bangladesh, and Timor-Leste) in South and Southeast Asia. We only use the DHS samples which provide corresponding geographical information for each cluster.

Climate data. Climate data is obtained from the ERA5, which is produced by the Copernicus Climate Change Service at the European Centre for Medium-Range Weather Forecasts. The ERA5 offers a global atmospheric reanalysis, covering climate data from 1940 onward. The raw ERA5 data provides hourly estimates of climate variables at a 0.25°x0.25° horizontal resolution. The single-level atmospheric product of ERA5 is used to generate the cluster-by-day climate factors. For example, the temperature variable derived from single level ERA5 represents the temperature measured 2 meters above the land's surface. Reanalysis data offers the advantage of uniform availability across time and space, minimizing measurement error related to cluster-level characteristics. Due to these benefits, reanalysis data has been increasingly utilized in economic research (*2*).

Access to medical services and electricity. Access to electricity and medical services is self-reported by respondents in the Demographic and Health Surveys (DHS). In each cluster, individuals report whether their household has access to electricity and whether they face barriers to accessing medical care. These responses are aggregated to the cluster level to construct measures of basic infrastructure access.

Transportation infrastructure. Transportation infrastructure is measured using road length data derived from OpenStreetMap (OSM), sourced via the Geofabrik project. OpenStreetMap is a collaborative, open-source geospatial database that provides detailed information on global transportation networks and infrastructure. The dataset includes annual snapshots from 2014 to 2024, though coverage varies by year and region. For this analysis, we use OSM data from Bangladesh, Cambodia, India, Indonesia, Timor Leste, Myanmar, Pakistan, and the Philippines. Due to limitations in community reporting, data are not consistently available for every year in all subnational regions.

Green space. Green space is proxied using the Leaf Area Index (LAI), a globally consistent remote sensing–based measure of vegetative cover. LAI captures the amount of leaf surface area per unit of ground area and serves as a reliable indicator of greenness and natural shading. This dataset includes complete geospatial coverage for all eight countries included in this study, allowing for consistent cross-country comparisons of environmental greenness as a form of natural heat mitigation.

Temperature Bin Model

We rely on the following fixed effects regression to identify the impact of temperature exposure on infant mortality (*3–6*):

$$MT_{icym} = \alpha + f(T_{cym}) + \gamma \mathbf{X}_{cym} + \eta \mathbf{M}_{icym} + \pi_c + \rho_y m + \varepsilon_{icym} \quad \text{(S1)}$$

where MT_{icym} is a dummy variable, indicating the mortality status of individual i living in cluster c during year y and month m. It takes the value 1 if the individual died in cluster c during year y and month m according to the survey and 0 otherwise. $\mathbf{X}_{cym}$ represents a set of control variables at the cluster-by-year-month level, such as precipitation in previous months and other time-variant characteristics of the cluster. MT_{icym} refers to a set of individual-level control variables. When analyzing the infant temperature-mortality model separately, the analysis includes covariates such as maternal age, parental education, gender of child, multiple birth indicators and family size.

In the model, π_c and ρ_{ym} represent cluster fixed effects and year-month fixed effects, respectively. Including cluster fixed effects can help control for time-invariant characteristics within each cluster, which can confound the temperature-health relationship, such as culture factors, geolocation, elevation and many other long-term factors of the cluster. Year-month fixed effects control for all time-variant common shocks affecting all clusters. In some specifications, the analysis further controls for fixed effects using cluster-by-quarter birth dummies, denoted by $\lambda_c yq$, which eliminates confounding factors that vary at the cluster-by-quarter level.

The temperature response function is represented by $f(T_{cym})$. For infant deaths, the model focuses on daily temperature exposure during both the in-utero period and in the month of birth, using linear models, higher-order polynomials and splines. Since the Demographic and Health Surveys (DHS) data does not report the exact date of the mother's last menstrual period to estimate the date of conception, the analysis considers the nine months preceding the child's birth as the in-utero period. A widely used function form of $f(T_{cym})$ is the binned model, expressed as:

$$f(T_{cym}) = \sum_k \beta_k T_{cym}^k \tag{S2}$$

where $T_{cym}^{k=1}$ indicates the number of days in a given location, month, and year (cym) where the average daily temperature fell below 0 degrees, $T_{cym}^{k=2}$ represents the number of days with average daily temperature in the (0, 3] interval, $T_{cym}^{k=3}$ for temperature in the (3, 6] interval, and so on. The 12-15 degrees temperature bin is the reference group, so the obtained coefficients of interest can be interpreted as the effect on monthly health outcomes of an additional day spent in bin k, relative to a day spent in the (12 °C, 15 °C] bin.

Cumulative Degree Days (CDD) Model

To specifically assess the impact of high temperatures, we use the Cumulative Degree Days (CDD) model (*7, 8*):

$$MT_{icym} = \alpha + \beta T_{30C} + \gamma \mathbf{X}_{cym} + \eta \mathbf{M}_{icym} + \pi_c + \rho_y m + \varepsilon_{icym} \tag{S3}$$

where T_{30C} measures the Cumulative Degree Days (CDD) greater than 30°C. T_{30C} can be illustrated by the following example: in Delhi in July 2005, if there were two days when the temperature exceeded 30°C, with one day reaching 35°C and another 40°C, the cumulative degree days over 30°C would be calculated as:

$$\text{CDD} = (35 - 30) + (40 - 30) = 15$$

Back-of-the-envelope Calculation

We estimate excess infant deaths attributable to elevated temperatures during the period 2001–2020, using average temperatures from 1960–2000 as the reference baseline. Throughout this period, most countries in South and Southeast Asia (SSEA) included in our study experienced higher annual temperatures relative to the baseline (Table S5). To quantify the regional burden of temperature-related infant mortality, we compare estimated infant mortality rates in the eight SSEA countries under two scenarios: observed temperature conditions and a counterfactual scenario in which temperatures remained at baseline levels, assuming no warming since 1960–2000. These estimates are based on the following equations (*9*):

$$\Delta IMR_{ny} = \overline{MT}_{ny} - \overline{MT}^{b}_{ny} = \sum_{ny} \sum_{k} (T^{k}_{cym} - T^{k,b}_{cym}) * \beta_k \tag{S4}$$

where $\overline{MT}_{ny}$ denotes the observed infant mortality rate in country n in year y, and $\overline{MT}^{b}_{ny}$ denotes the infant mortality rate if the mean temperature has remained unchanged compared to 1960 to 2020. To estimate $\overline{MT}^{b}_{ny}$, we subtract the country-specific annual temperature anomaly (relative to the 1960–2000 average) from the observed temperature for each year. This yields a counterfactual temperature series in which no warming occurs. We then recalculate mortality rates using these counterfactual temperatures, $T^{k,b}_{cym}$. ΔIMR_{ny}, therefore, it refers to country-by-year level change in infant mortliaty rate due to change in temperature.

Because DHS data are not available for all country-year combinations, we apply a linear interpolation strategy. For countries with partial data, we interpolate within country and model ΔIMR_{ny} as a function of temperature variation, ΔT_{ny}. For countries not included in the baseline analysis, we impute missing values using the regional average across South and Southeast Asia. Specifically, we estimate:

$$\Delta IMR_{ny} = \gamma_1 \Delta T_{ny} + \gamma_2 \eta_y + \gamma_3 \Delta T_{ny} * \eta_y + \varepsilon_{ny} \tag{S5}$$

where ΔT_{ny} denotes the temperature deviation in country n and year y from its baseline average, η_y indexes year, and ε_{ny} is the error term.

After interpolating country-specific values of ΔIMR_{ny}, we compute total excess infant deaths across the South and Southeast Asia (SSEA) region — 19 countries: Afghanistan, Bangladesh, Bhutan, Brunei Darussalam, Cambodia, India, Indonesia, Lao People's Democratic Republic, Malaysia, Maldives, Myanmar, Nepal, Pakistan, Philippines, Singapore, Sri Lanka, Thailand, Timor-Leste, and Viet Nam — as follows:

$$EID_y = \sum_n Births_{ny} * \Delta IMR_{ny} \tag{S6}$$

Supplementary Text 1: Literature Review

As global temperatures continue to rise due to anthropogenic climate change, understanding the nature and health consequences of extreme heat has become increasingly urgent. This escalating trend not only exacerbates existing vulnerabilities but also introduces complex new challenges for public health. The physiological effects of heat on the human body are both profound and multifaceted. Much like the Earth's climate system, the human body depends on maintaining a precise thermal equilibrium. Thermoregulation is achieved when heat gain is balanced by heat loss, with core body temperature tightly regulated around 37°C (*10*). However, exposure to extreme heat disrupts this balance, placing increased strain on the cardiovascular and renal systems. Peripheral vasodilation may lead to a drop in blood pressure, requiring the heart to work harder to maintain circulation, while excessive sweating can result in dehydration, electrolyte imbalances (such as hyperkalemia), and reduced plasma volume. These physiological stresses can induce oxidative stress, increase intestinal permeability, and in severe cases, lead to systemic inflammation and multi-organ failure.

The health consequences of heatwaves extend far beyond heatstroke. A growing body of evidence links extreme heat to increased mortality and morbidity across a wide spectrum of conditions (*11, 12*). The interplay between rising average temperatures and air quality is increasingly critical as higher temperatures and sunnier conditions intensify atmospheric chemical reactions, leading to elevated concentrations of ground-level ozone—a pollutant with significant health impacts. Ground-level ozone exacerbates respiratory and cardiovascular NCDs, placing those with chronic obstructive pulmonary disease (COPD) at greater risk (*13*).

Epidemiological studies document a U-shaped relationship between temperature and health, where both extreme cold and heat are associated with elevated health risks (*14, 15*). However, extreme heat has particularly severe and immediate impacts on mortality across age groups (*11, 16, 17*). Vulnerable groups, including the elderly, pregnant women, children, outdoor workers and individuals with pre-existing health conditions, are disproportionately affected (*17, 18*).

Infants, in particular, are highly sensitive to temperature extremes due to their immature thermoregulatory systems and much narrower optimal body temperature range compared to adults (*19*). A case-crossover study conducted over 30 years in Montreal, Canada, examined the relationship between ambient heat and Sudden Infant Death Syndrome (SIDS). The study found that daily maximum temperatures exceeding 29°C were associated with a 2.78 times higher likelihood of SIDS compared to temperatures of 20°C (*20*). Both elevated and low ambient temperatures pose serious risks to neonatal health, as indicated by a study that analyzed data from 29 low- and middle-income countries between 2001 and 2019. The study found that 4.3 percent of neonatal deaths were associated with non-optimal temperatures, with 32 percent of these deaths attributable to climate change (*21*).

The evidence linking heat exposure to adverse birth outcomes and infant mortality is growing. In India, (*22*) found that exposure to high temperatures during pregnancy leads to an additional two infant deaths per 1,000 births. Similarly, in a study conducted in Philadelphia, (*23*) reported a 22.4 percent increase in infant mortality risk for every 1°C rise in minimum daily temperature above 23.9°C. Research conducted in Sweden found that an increase in temperature from 14.5°C to 20°C was associated with a 25 percent rise in neonatal mortality, suggesting that even moderate temperature increases can significantly impact infant health (*24*). These findings, covering diverse geographic and socioeconomic settings, highlight the critical need to consider temperature extremes when evaluating and safeguarding infant health outcomes globally.

Despite its vulnerability, the South and Southeast Asia (SSEA) region remains understudied in this literature. While country-specific studies have been conducted in India, Pakistan, Thailand, Bangladesh, the Philippines, and Viet Nam (*12, 18, 25–28*) , most of these studies focus on a single country or a few cities. The lack of comprehensive analysis across the entire SSEA region leaves a significant gap in understanding the regional-scale health impacts of extreme heat, as well as the broader social and economic implications of inaction.

Historically, medical and public health interventions have focused primarily on individuals, their biology and behaviors. However, research increasingly shows that this approach is often ineffective, as people's choices are heavily influenced by their surrounding environments and contexts. For example, infrastructure is crucial across many sectors, yet infrastructure interventions remain an understudied area with significant potential to mitigate health risks from climate-related hazards (*29*). In response to the growing threat of extreme heat, developing sophisticated infrastructure and adaptation strategies is essential. Effective interventions include adopting advanced cooling technologies and building cooling centers, ensuring a reliable power grid for uninterrupted electricity supply, increasing accessibility to healthcare services, improving public transportation and enhancing urban green infrastructure (*30–33*).

Green infrastructure, which involves integrating nature-based solutions into urban planning and built environments to deliver environmental, social and economic benefits, such as strategic networks of green spaces, contributes significantly to ecosystem-based adaptation. For example, forms of urban agriculture can reduce physiological equivalent temperature by 10 to 13 percent (*34*). These adaptation strategies not only aim to protect human health and well-being but also contribute to the overall resilience of urban and rural environments in the face of escalating climate challenges.

Supplementary Text 2

CDD model results on the relationship between in utero temperature exposure and infant mortality – Robustness Checks by alternative fixed effects choices. Table S2 provides robust evidence of a significant positive relationship between in utero exposure to high temperatures and infant mortality using the Cumulative Degree Days (CDD) model. Across all five model specifications, the coefficient for CDD exceeding 30°C remains positive and statistically significant, ranging from 0.025 to 0.029. The inclusion of various control variables, such as individual, family, and fixed effects (including cluster and birth year-month fixed effects), reinforces the robustness of the results. These consistent findings across different model specifications suggest a causal link between high-temperature exposure during pregnancy and increased infant mortality risk.

References and Notes

1. A. Deribew, *et al.*, Trends, causes, and risk factors of mortality among children under 5 in Ethiopia, 1990–2013: findings from the Global Burden of Disease Study 2013. *Population Health Metrics* **14**, 42 (2016).

2. R. Burgess, O. Deschenes, D. Donaldson, M. Greenstone, The Unequal Effects of Weather and Climate Change: Evidence from Mortality in India (2013), working Paper.

3. S. Agarwal, Y. Qin, L. Shi, G. Wei, H. Zhu, Impact of Temperature on Morbidity: New Evidence from China. *Journal of Environmental Economics and Management* **109**, 102495 (2021).

4. O. Deschênes, M. Greenstone, Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US. *American Economic Journal: Applied Economics* **3** (4), 152–185 (2011).

5. C. White, The Dynamic Relationship between Temperature and Morbidity. *Journal of the Association of Environmental and Resource Economists* **4** (4), 1155–1198 (2017).

6. F. Cohen, A. Dechezleprêtre, Mortality, Temperature, and Public Health Provision: Evidence from Mexico. *American Economic Journal: Economic Policy* **14** (2), 161–192 (2022).

7. N. D. Miranda, *et al.*, Change in cooling degree days with global mean temperature rise increasing from 1.5°C to 2.0°C. *Nature Sustainability* **6** (11), 1326–1330 (2023), doi:10.1038/s41893-023-01155-z.

8. Y. Petri, K. Caldeira, Impacts of global warming on residential heating and cooling degree-days in the United States. *Scientific Reports* **5** (1), 12427 (2015), doi:10.1038/srep12427.

9. G. He, Y. Pan, T. Tanaka, Air pollution and the airborne diseases: Evidence from China and Japan. *Journal of Environmental Economics and Management* **130**, 103117 (2025).

10. Institute for Quality and Efficiency in Health Care (IQWiG), *General Methods: Version 6.1*, Tech. rep., Institute for Quality and Efficiency in Health Care, Cologne, Germany (2022).

11. H. Green, J. Bailey, L. Schwarz, J. Vanos, K. Ebi, Impact of heat on mortality and morbidity in low and middle income countries: a review of the epidemiological evidence and considerations for future research. *Environmental Research* **171**, 80–91 (2019).

12. C. Huang, *et al.*, The impact of heatwaves on mortality and emergency hospital admissions: a systematic review and meta-analysis. *Epidemiology* **22** (5), 632–645 (2011).

13. T. Münzel, *et al.*, Environmental risk factors and cardiovascular diseases: a comprehensive review. *Cardiovascular Research* **118** (14), 2880–2902 (2022).

14. G. Heutel, N. H. Miller, D. Molitor, J. Reif, Temperature, Mortality, and Health: Evidence from the United States. *Journal of Public Economics* **197**, 104408 (2021).

15. Y. Guo, *et al.*, Global Variation in the Effects of Ambient Temperature on Mortality: A Systematic Evaluation. *Epidemiology* **25** (6), 781–789 (2014).

16. T. Li, R. M. Horton, P. L. Kinney, Projections of Seasonal Patterns in Temperature-Related Deaths for Manhattan, New York. *Nature Climate Change* **3**, 717–721 (2013).

17. W. Ma, R. Chen, H. Kan, Temperature-Related Mortality in 17 Large Chinese Cities: How Many Deaths Could Be Attributed to High and Low Temperatures? *Environmental Research* **137**, 171–177 (2015).

18. V. Ingole, *et al.*, Socioenvironmental Factors Associated with Heat and Cold-Related Mortality in Vadu HDSS, Western India: A Population-Based Case-Crossover Study. *International Journal of Biometeorology* **61**, 1797–1804 (2017).

19. K. Lunze, D. H. Hamer, Thermal protection of the newborn in resource-limited environments. *Journal of Perinatology* **32**, 317–324 (2012).

20. N. Auger, *et al.*, Ambient Heat and Sudden Infant Death: A Case-Crossover Study Spanning 30 Years in Montreal, Canada. *Environmental Health Perspectives* **123**, 712–716 (2015).

21. A. Dimitrova, *et al.*, Temperature-related neonatal deaths attributable to climate change in 29 low- and middle-income countries. *Nature Communications* **15**, 49890 (2024).

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

23. L. H. Schinasi, N. DeFelice, M. J. Strickland, K. M. Williams, High ambient temperature and infant mortality in Philadelphia, Pennsylvania: A case-crossover study. *American Journal of Public Health* **110** (2), 189–195 (2020).

24. J. Junkka, *et al.*, Climate vulnerability of Swedish newborns: Gender differences and time trends of temperature-related neonatal mortality, 1880–1950. *Environmental Research* **192**, 110400 (2021).

25. K. Burkart, *et al.*, The effects of season and meteorology on human mortality in tropical climates: a systematic review. *Transactions of the Royal Society of Tropical Medicine and Hygiene* **108** (7), 393–401 (2014).

26. U. Ghumman, J. Horney, Characterizing the impact of extreme heat on mortality, Karachi, Pakistan, June 2015. *Prehospital and Disaster Medicine* **31** (3), 263–266 (2016).

27. X. T. Seposo, T. N. Dang, Y. Honda, Exploring the effects of high temperature on mortality in four cities in the Philippines using various heat wave definitions in different mortality subgroups. *Global Health Action* **10** (1), 1368969 (2017).

28. D. Phung, *et al.*, Heatwave and risk of hospitalization: A multi-province study in Vietnam. *Environmental Pollution* **220**, 597–607 (2017).

29. B. Wake, Infrastructure and climate–health risks. *Nature Climate Change* **13**, 97–98 (2023).

30. M. Kiarsi, *et al.*, Heat wave adaptation paradigm and adaptation strategies of community: A qualitative phenomenological study in Iran. *Journal of Education and Health Promotion* **12**, 47 (2023).

31. L. L. Turek-Hankins, M. Keith, S. Meerow, Urban heat governance: Examining the role of urban planning. *Journal of Environmental Policy & Planning* **23** (5), 641–657 (2021).

32. A. Barreca, K. Clay, O. Deschenes, M. Greenstone, J. S. Shapiro, Adapting to Climate Change: The Remarkable Decline in the U.S. Temperature-Mortality Relationship over the 20th Century. *Journal of Political Economy* **124** (1), 105–159 (2016).

33. World Health Organization, Heatwaves: Health advice (2015), accessed: 2025-04-09.

34. T. Zolch, J. Maderspacher, C. Wamsler, S. Pauleit, Using green infrastructure for urban climate-proofing: An evaluation of heat mitigation measures at the micro-scale. *Urban Forestry & Urban Greening* **20**, 305–316 (2016).

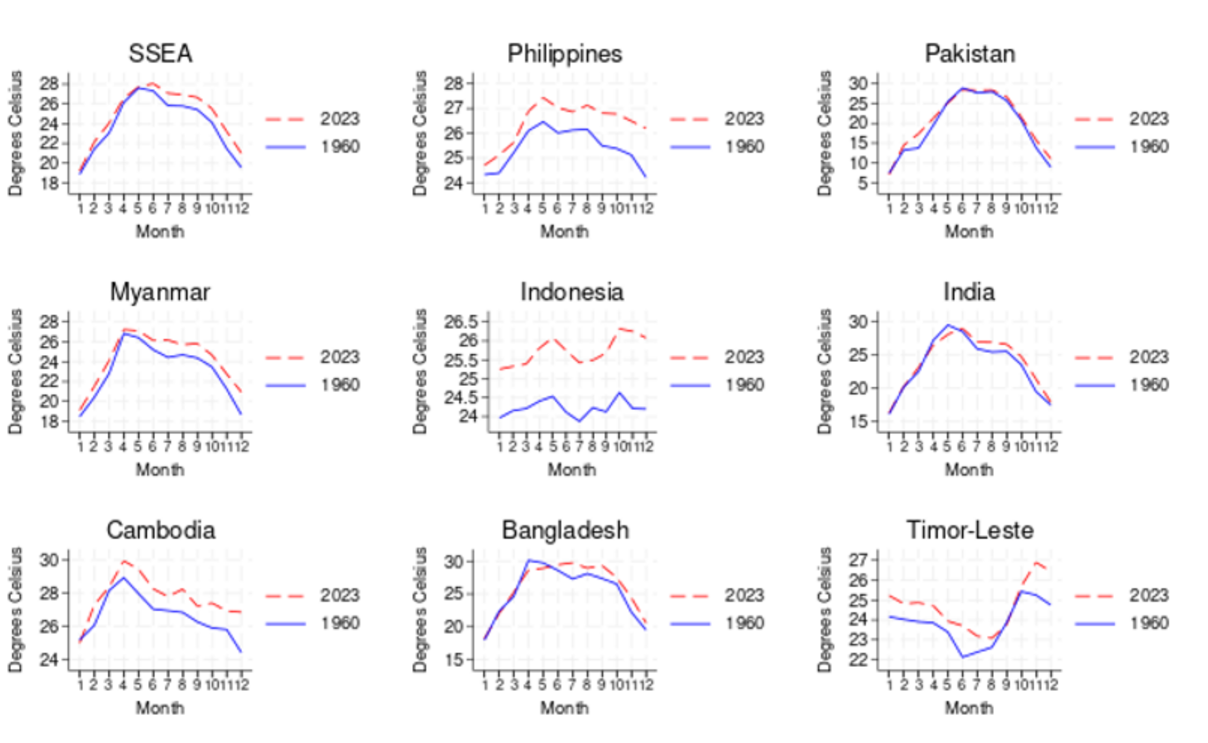

Figure S1: Climate Change in SSEA: Average Temperature in 1960 vs. 2023

Table S1: Summary Statistics for Selected SSEA Countries

Country	Population	Period Coverage	Number of Clusters	Urban Clusters
Panel A. South Asia				
India	2,579,752	1970–2021	57,389	44.9%
Pakistan	88,970	1970–2018	1,246	43.7%
Bangladesh	233,294	1963–2018	1,129	44.4%
Panel B. Southeast Asia				
Burma (Myanmar)	22,989	1980–2016	441	27.7%
Cambodia	185,642	1965–2021	1,147	42.6%
Timor-Leste	64,620	1974–2016	552	31.0%
Indonesia	35,238	1965–2003	572	44.4%
Philippines	149,946	1968–2022	2,130	45.8%

Notes: Authors' calculations based on data from the DHS. Only DHS samples with available corresponding geographical information are included in the analysis.

Table S2: Effects of In Utero Temperature Exposure on Infant Mortality — Robustness Checks by Alternative Fixed Effects Choices

	(1)	(2)	(3)	(4)	(5)
CDD Exceeding 30℃	0.018**	0.019**	0.019**	0.018**	0.021**
	(0.009)	(0.008)	(0.007)	(0.009)	(0.010)
R-Squared	0.701	0.737	0.813	0.840	0.861
Observations	3,360,451	3,360,451	3,360,451	3,360,451	3,360,451
Number of Clusters	64,606	64,606	64,606	64,606	64,606
Individual Controls	No	Yes	Yes	Yes	Yes
Family Controls	No	No	Yes	No	Yes
Control for Air Pollution	No	No	No	Yes	Yes
Control for Humidity	No	No	No	No	Yes
Birth Year-Cluster Fixed Effects	Yes	Yes	Yes	Yes	Yes
Birth Month Fixed Effects	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the effects of in utero temperature exposure on infant mortality, with robustness checks using different fixed effects specifications. Coefficients represent the impact estimates; standard errors are in parentheses. Significance levels are denoted as: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table S3: Impact of In Utero Temperature Exposure on Infant Mortality (CDD model with alternative temperature thresholds)

	(1)	(2)
Cumulative Degree Days (CDD) > 33℃	0.030***	0.032***
	(0.010)	(0.008)
Cumulative Degree Days (CDD) > 27℃	0.018**	0.017**
	(0.007)	(0.007)
Cumulative Degree Days (CDD) > 24℃	0.012*	0.010
	(0.006)	(0.008)
Cumulative Degree Days (CDD) > 21℃	0.007	0.008
	(0.005)	(0.007)
Cumulative Degree Days (CDD) > 18℃	0.002	0.003
	(0.007)	(0.007)
Observations	3,360,451	3,360,451
Number of Clusters	64,606	64,606
Individual Controls	Yes	Yes
Family Controls	Yes	Yes
Cluster FE	Yes	No
Birth Year-Month FE	Yes	No
Birth Year-Cluster FE	No	Yes
Birth Month FE	No	Yes

Notes: Each cell represents a separate regression. Standard errors clustered at the DHS level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table S4: Effects of In Utero Temperature Exposure on Infant Mortality: by Country Estimation

	India	Pakistan	Bangladesh	Burma	Cambodia	Timor-Leste	Indonesia	Philippines
10% Percentile Days	0.110**	0.130*	0.095**	0.170**	0.120*	0.140**	0.115*	0.125**
	(0.055)	(0.075)	(0.048)	(0.068)	(0.062)	(0.070)	(0.060)	(0.060)
10% Percentile Temperature	30.2	29.0	29.2	27.3	30.8	31.7	28.1	28.5
Observations	2,579,752	88,970	233,294	22,989	22,989	64,620	35,238	149,946
Number of Clusters	57,389	1,246	1,129	441	441	552	572	2,130
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Family Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each column represents a separate country-level estimation. Standard errors clustered at the DHS cluster level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table S5: Annual Temperature Anomalies Relative to 1960–2000 Baseline (°C)

Year	SSEA	Indonesia	India	Cambodia	Myanmar	Pakistan	Philippines	Bangladesh	Timor-Leste
1960–2000 (Reference)	24.2	24.5	23.9	26.7	23.0	20.1	25.4	25.0	24.3
2001	0.4	0.5	0.2	0.7	0.4	0.9	0.4	0.2	0.1
2002	0.7	0.6	0.6	1.1	0.4	1.1	0.5	0.2	0.3
2003	0.5	0.6	0.3	0.8	0.5	0.5	0.4	0.2	0.4
2004	0.5	0.6	0.3	0.8	0.2	1.2	0.4	0.3	0.2
2005	0.6	0.6	0.3	0.7	0.9	0.1	0.6	0.6	0.6
2006	0.6	0.6	0.5	0.8	0.5	1.1	0.7	0.8	-0.1
2007	0.5	0.6	0.4	0.5	0.3	0.7	0.7	0.3	0.3
2008	0.3	0.4	0.2	0.2	0.3	0.5	0.4	0.4	0.3
2009	0.6	0.8	0.9	0.3	0.9	0.9	0.5	0.9	0.4
2010	1.0	0.9	0.8	1.2	1.1	1.1	0.9	1.0	0.7
2011	0.3	0.6	0.2	0.5	0.3	0.7	0.4	0.2	0.1
2012	0.6	0.7	0.3	1.1	0.7	0.1	0.6	0.3	0.1
2013	0.6	0.8	0.1	0.8	0.7	0.6	0.7	0.3	0.5
2014	0.6	0.9	0.4	0.8	0.9	0.3	0.5	0.4	0.3
2015	0.8	1.0	0.6	1.4	0.7	0.5	0.8	0.4	0.3
2016	1.2	1.3	1.0	1.4	0.9	1.4	1.1	0.9	1.2
2017	0.8	1.0	0.9	0.9	0.8	1.2	0.7	0.5	0.7
2018	0.8	1.0	0.7	1.0	0.5	1.3	0.9	0.3	0.7
2019	0.9	1.1	0.6	1.4	1.0	0.5	1.0	0.7	0.5
2020	0.9	1.2	0.3	1.0	1.0	0.4	1.0	0.4	0.9

Notes: This table reports annual average temperature anomalies (in °C) for South and Southeast Asia (SSEA) and selected countries from 2000 to 2020, relative to the 1960–2000 climatological baseline. For each country, the anomaly is calculated as the difference between the annual average temperature and the corresponding 1960–2000 mean. The 1960–2000 and 2000 values represent baseline and transition levels, while values from 2001 onward indicate annual deviations from the baseline.