Renewable Energy Reduces Infant Mortality in the Developing World

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From Wind and Sun to Fewer Funerals: How Renewable Energy Reduces Infant Mortality in the Developing World

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Abstract

This paper estimates the effect of renewable energy growth on infant mortality by exploiting variation in renewable energy penetration driven by global technological progress and heterogeneous regional potential for renewables. Using data covering seven million births across 427 subnational regions in 54 developing countries, we find that a 10-percentage-point increase in the share of renewables in electricity generation reduces infant mortality by 1.99 deaths per 1,000 live births. Our results imply that the growth of renewable energy in these countries averted 1.2 million infant deaths from 1990 to 2020, corresponding to 8.23% of the total decline in infant mortality. The mortality decline is disproportionately concentrated among disadvantaged subpopulations and thus reduces inequality in infant mortality. Mechanism analysis indicates that air pollution abatement and local income growth serve as key channels.

Keywords: renewable energy, infant mortality, air pollution, inequality, developing country
JEL: I18, Q42, O13, Q53

1 Introduction

High infant mortality rates have persisted as a defining characteristic of many developing economies, significantly constraining human capital formation in these regions. As of 2020, annual neonatal mortality in developing countries still remained alarmingly high at 20‰ (WHO, 2022). The advancement of renewable energy (RE) technologies—particularly solar and wind power—presents a potentially transformative opportunity to address this critical development challenge (Rauner *et al.*, 2020). Owing to favorable geographical and environmental conditions, many developing nations possess substantial RE endowments (Shahsavari & Akbari, 2018). From 2010 to 2020, the share of RE in total electricity generation in developing countries rose from 27.4% to 37.7%. RE growth may reduce infant mortality by mitigating exposure to harmful air pollutants and by stimulating local economic development. However, empirical research examining the effect of RE adoption on infant mortality in developing country contexts remains scarce.

This study estimates the effect of RE adoption on infant mortality using data covering seven million births across 427 subnational regions in 54 developing countries from 1990 to 2020, which are derived from Demographic and Health Surveys (DHS). These 54 sample countries account for 44.5% of the total population in the developing world. We estimate the causal effect using two instrumental variables (IVs) for regional RE share constructed from plausibly exogenous shocks to local RE share. The first IV is constructed from the commissioning year of the first RE project (with capacity above a threshold) in each region. The second IV is constructed from local RE potential and global trends in RE technological improvements. The estimates derived from these two IVs are highly comparable.

We find that a 10 percentage point increase in the RE share reduces the infant mortality rate by 1.99 deaths per 1,000 live births. The growth of RE can explain 8.23 percent of the observed total decline in infant mortality in the developing world from 1990 to 2020. We roughly calculate that RE growth helps avoid 1.2 million infant deaths from 1990 to 2020 in the 54 sample developing countries. We estimate that, when combined with the costs of RE projects, spending an extra $272,000 on renewable energy projects helps save one infant life in these countries. We also find that the mortality reduction effect of RE is larger for population groups and regions that have traditionally experienced higher infant mortality, suggesting that RE adoption tends to reduce inequality in infant mortality. Mechanism analysis indicates that air pollution abatement and local income growth serve as key channels through which RE adoption reduces infant mortality.

This study contributes to the large literature that evaluates the impact of RE. Many studies have examined the effect of RE on various issues such as carbon emissions (Wang *et al.*, 2023; Lei *et al.*, 2023), economic outcomes (Fabra *et al.*, 2024; Gilbert *et al.*, 2024), biodiversity (Sonter *et al.*, 2020; Niebuhr *et al.*, 2022), air pollution (Siler-Evans *et al.*, 2013; Jacobson *et al.*, 2015), and health outcomes (Siler-Evans *et al.*, 2013; Jacobson *et al.*, 2015). However, most existing studies are based on data from developed countries. To the best of our knowledge, this study is the first to focus on the effect of RE on infant mortality in developing countries using a large sample of micro-level data.

This study highlights RE as an important policy tool for developing countries to address their health challenges. Developing countries are facing a persistent and structural health crisis, with the dual burden of communicable and non-communicable diseases (Vos *et al.*, 2020; Vollset *et al.*, 2024). The infant mortality rate is one of the most important indicators of population health in developing countries (Reidpath & Allotey, 2003). Studies have shown that the high infant mortality rate in developing countries is mainly caused by factors such as poverty and malnutrition (Baird *et al.*, 2011; Benshaul-Tolonen, 2019; Kammerlander & Schulze, 2023), environmental pollution (Gutierrez, 2015; Cesur *et al.*, 2017; Landrigan *et al.*, 2018), regulatory policies (Foster *et al.*, 2009; Tanaka, 2015), and industrial shocks (Benshaul-Tolonen, 2019). Existing studies on reducing infant mortality in developing countries mainly focus on maternal and child health services (Bhutta *et al.*, 2010), health education (Gertler, 2004), subsidies to increase preventive product use (Cohen *et al.*, 2015), improving healthcare infrastructure (Kruk *et al.*, 2018), agricultural technology upgrading (Von Der Goltz *et al.*, 2020; Bharadwaj *et al.*, 2020), and environmental regulation (Greenstone & Hanna, 2014). This study finds that increasing the use of RE could be an important tool for reducing infant mortality in developing countries.

The remainder of the study proceeds as follows. Section 2 provides the background of this study, Section 3 describes the data and the empirical strategy, Section 4 presents the main results, Section 5 examines the mechanisms of the effect, Section 6 discusses the welfare effects of the RE-induced decline in infant mortality, and Section 7 concludes.

2 Background

2.1 Renewable Energy in developing countries

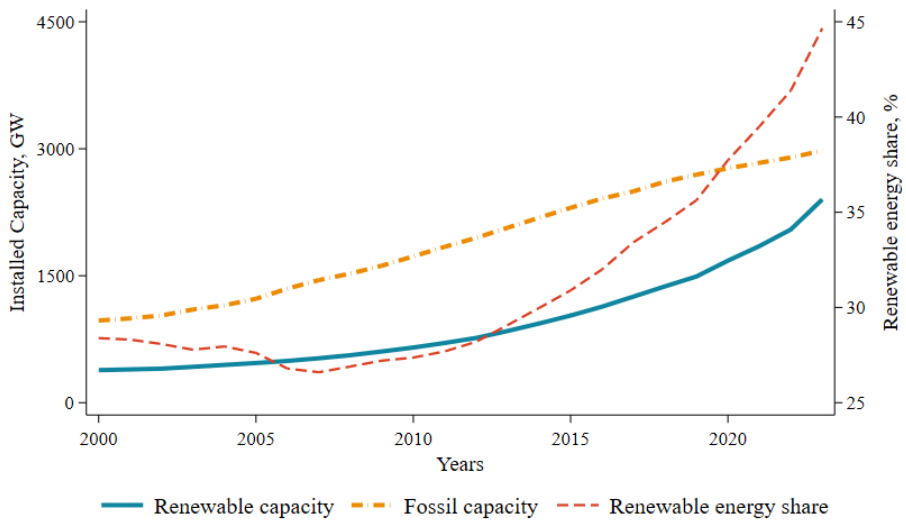

Figure 1: Electricity capacity from fossil and RE in developing countries, respectively

Notes: This graph shows the electricity capacity from fossil fuel and renewable energy (RE) sources (including hydro, wind, solar, biomass, and geothermal sources) of all developing countries. Specifically, we follow the United Nations' classification criteria to define developing countries. The data are obtained from IRENA (2024a).

As Figure 1 shows, during the past two decades, the growth of renewable energy (RE) in developing countries has accelerated. The annual growth rate of RE in developing countries was 6.9% from 2000 to 2010 and 20.7% from 2010 to 2023. The RE share (i.e., the percentage of renewable energy capacity in the total installed capacity (renewable + fossil) increased from 28.4% in 2000 to 44.7% in 2023. Figure 2 shows the installed capacity and electricity generation of five major RE sources in developing countries: solar, wind, hydropower, biomass, and geothermal. While hydropower dominates the RE capacity, the growth of RE over the past 15 years has been driven mainly by the expansion of solar and wind power. The total energy capacity from other renewable sources surpassed that from hydropower after 2020.

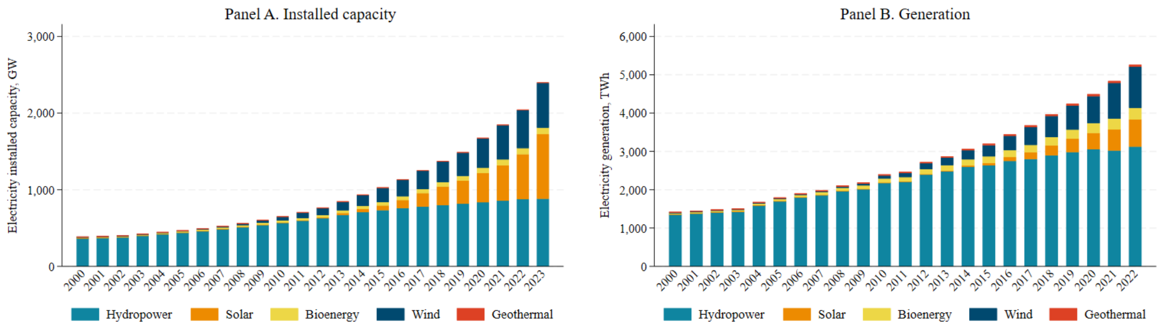

Figure 2: Installed capacity and electricity generation from each type of RE in developing countries

Notes: This figure shows the installed capacity and electricity generation for five major renewable energy (RE) sources: hydropower, wind, solar, biomass, and geothermal. We follow the United Nations' classification of developing countries. The data are obtained from IRENA (2024a).

The growth of RE in developing countries has been primarily driven by exogenous technological advancements. Amid rising concerns about climate change, energy security, and the depletion of fossil fuel reserves, substantial investments have been made to develop new energy technologies, with the aim of reducing the cost of RE generation (Ashraf *et al.*, 2024). These investments have been led primarily by developed countries and China (IEA, 2023; World Bank, 2022). As a result of these advancements, the global costs of solar and wind power declined by 89% and 70% from 2010 to 2020, respectively (IRENA, 2021). Solar energy deployment has soared, propelled by falling photovoltaic costs and its scalability for both large-scale and small-scale setups (Green *et al.*, 2019). Wind energy has also expanded rapidly, driven by the deployment of onshore turbines in plains and offshore systems in coastal zones (Veers *et al.*, 2019).

Local RE endowments and international aid are also major determinants of RE adoption in developing countries. Given similar technology and economic conditions, developing countries with more abundant RE resources are more likely to develop RE. Figure 3 presents subnational-level RE potential from wind, solar, and hydropower in Panels B–D, and the combined potential in Panel A. It shows that many developing countries in Asia and Africa possess abundant RE endowments. As the construction of RE projects is expensive, international aid has also played an important role in the development of RE in poorer developing countries (IRENA, 2021; Burke *et al.*, 2017).

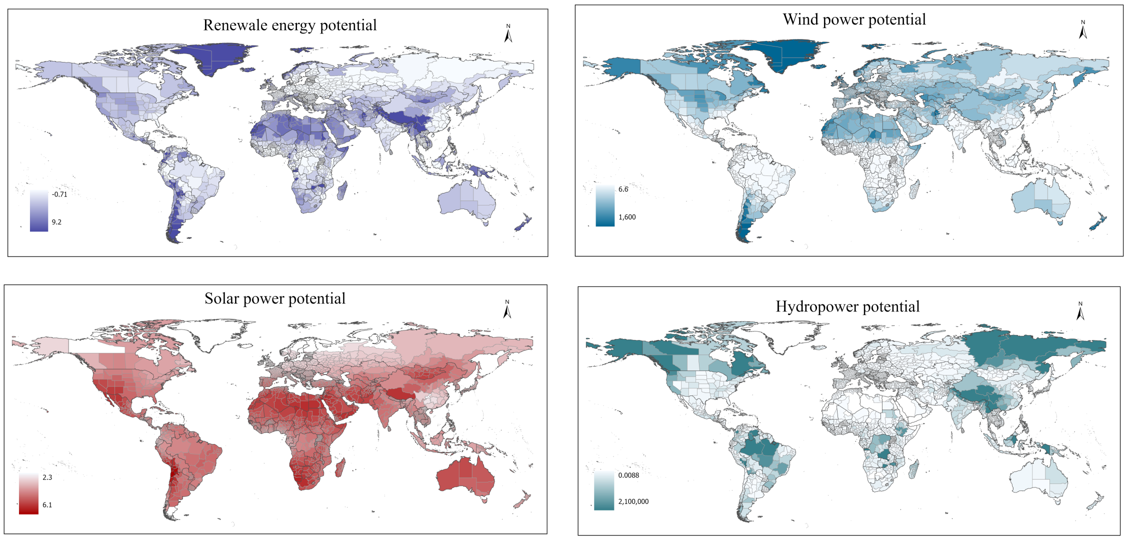

Figure 3: Sub-country level potential of major RE sources

Notes: This figure presents the power potential for wind, solar, and hydropower individually, as well as their combined potential, at the subnational level, calculated using raster data from Solargis s.r.o. and World Bank Group (2023), Davis *et al.* (2023), and Hoes (2014).

2.2 Infant mortality

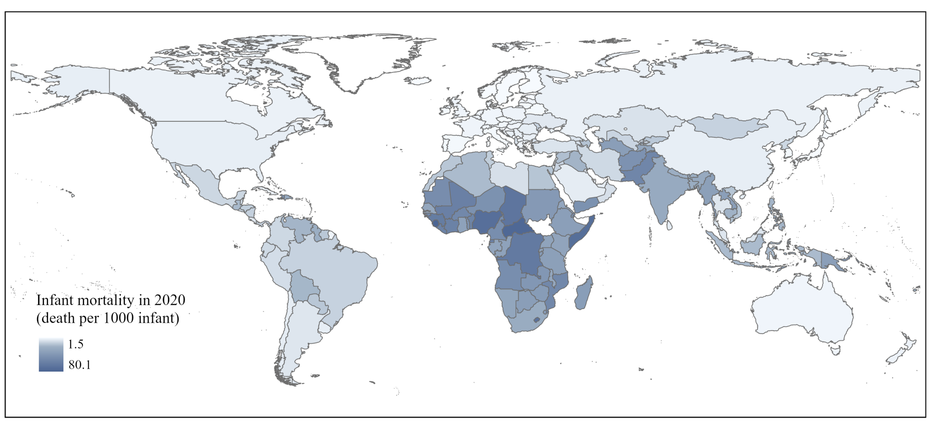

Figure 4: Infant mortality rate in 2020

Notes: This figure presents the country-level average infant mortality rate in 2020, using United Nations data to classify developing countries.

Figure 4 presents the global distribution of infant mortality rates in 2020. It shows that infant mortality rates are generally very low in developed countries. In sharp contrast, infant mortality rates are very high in many developing countries. Figure 5 presents the trends in infant mortality rates for developed and developing countries separately.

In developed countries, infant mortality rates remain consistently low and show only a slight decline from 2000 to 2020. In contrast, a substantial declining trend is observed in developing countries, dropping by 22.3 deaths per 1,000 live births over the two decades. The concurrent decline in infant mortality and increase in RE share (Figure 1) in developing countries suggests a negative relationship between these two factors. This study aims to examine whether this association reflects a causal effect of RE on infant mortality.

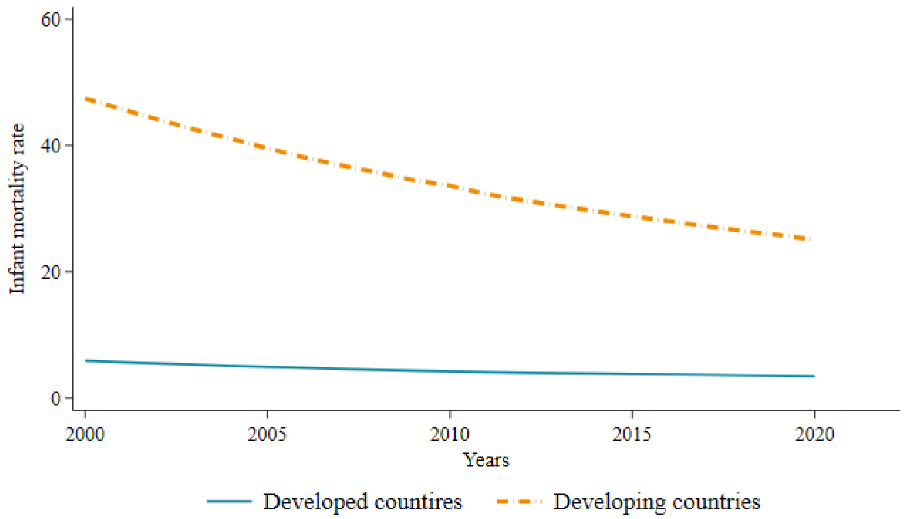

Figure 5: Infant mortality rate trends

Notes: This figure presents the trends in infant mortality rates in developed and developing countries, using the data from the United Nations to classify developing countries.

3 Data and Empirical Strategy

3.1 Data

3.1.1 Demographic and Health Surveys

We use micro data from the Demographic and Health Surveys (DHS), renowned for their reliability, geographic granularity, and global comparability among household surveys in developing countries (Von Der Goltz *et al.*, 2020). The DHS provides comprehensive individual-level health data, focusing on women aged 15–49 and their children, including variables on health, fertility, and education. DHS data have been widely used in the literature to study child health and infant mortality due to its standardized and nationally representative design (Heft-Neal *et al.*, 2018; Bharadwaj *et al.*, 2020; Baird *et al.*, 2011). As a repeated cross-sectional dataset, it captures diverse populations without tracking individuals over time. The detailed geographic information from DHS enables us to match the micro data with regional RE data.

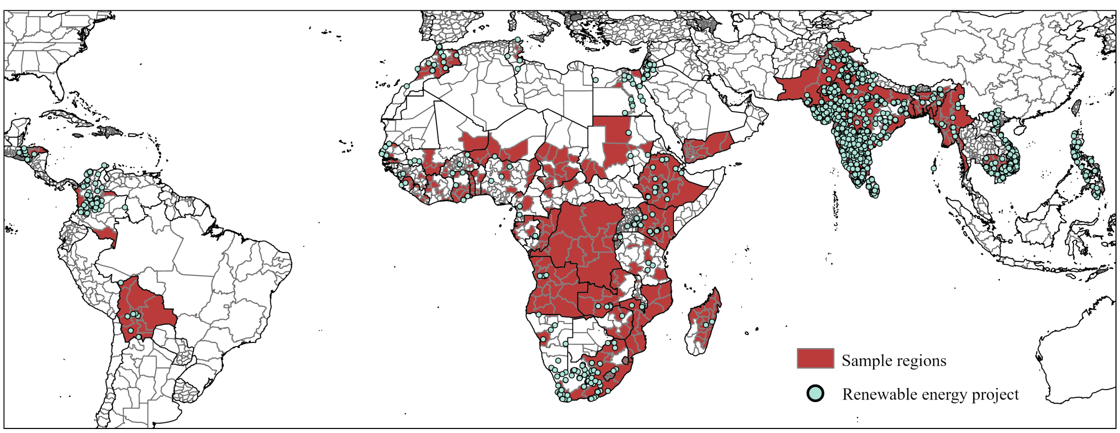

Figure 6: Distribution of DHS regions and the RE projects within these regions

Notes: This figure shows the DHS sample regions and the distribution of RE projects across these regions.

This study utilizes DHS data from all countries with available surveys conducted between 1990 and 2020. The dataset includes 427 regions across 54 developing countries, covering regions in Africa, Asia, the Indian Ocean, South America, and Central America. These sample countries account for 44.5% of the total population in the developing world, although some large developing countries, such as China, are not covered by the surveys. The sample period aligns with the RE dataset. The sample includes 7 million children born between 1990 and 2020. Appendix Table A1 provides a list of the 54 sample countries. Figure 6 presents the distribution of the 427 DHS sample regions at the sub-country level. And Appendix Figure A2 shows the distribution of child birth years in the sample.

The primary outcome variable of this study, infant mortality rate, is a binary indicator indicating whether a child died before reaching 12 months of age, following the definition in the literature (Von Der Goltz *et al.*, 2020; Bharadwaj *et al.*, 2020). It takes the value 1 if the child died within the first 12 months of birth and 0 otherwise. To avoid bias due to incomplete mortality records, we exclude children born in the survey year. We also exclude individuals identified as visitors rather than usual residents. We construct this variable based on women's birth history data, including birth date, survival status, and death date (if applicable). The average infant mortality rate in our sample is 58.72‰, with a standard deviation of 235.10‰. Figure 7 presents the subcountry-level average infant mortality rate calculated based on the DHS data. And Appendix Figure A3 shows the infant mortality rate trend.

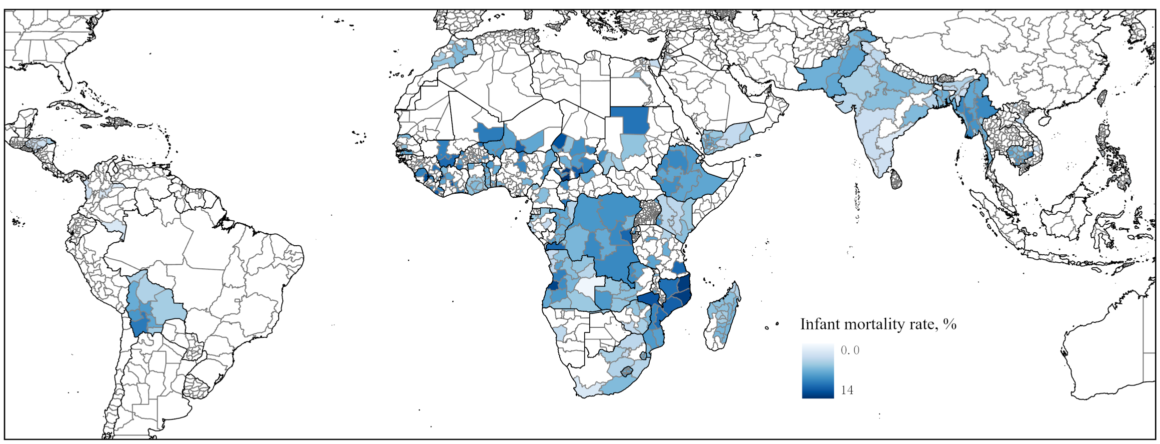

Figure 7: Infant mortality rate at the sub-country level

Notes: This figure presents the average infant mortality rate from 1990 to 2020 for each subnational region, calculated using DHS data.

Our analysis incorporates a range of additional variables derived from the DHS. We use maternal-level variables, including age at birth, educational attainment, employment status and household wealth. At the child level, we consider birth month, gender and birth weight. Furthermore, we utilize additional DHS-derived health variables for women, including anemia status, heart disease, diabetes, and indicators for being underweight or overweight. Since we mainly focuses on infant mortality, the impact on these aspects of women's health can be seen in the Appendix Table A4. Summary statistics for these variables are presented in Appendix Table A2.

3.1.2 Renewable energy

We source RE data from the Global Energy Monitor (GEM), which maintains specialized trackers for major types of RE, including hydropower, solar, geothermal, wind, and bioenergy. GEM also includes trackers for fossil fuel and nuclear power, which are also used in our analysis. These trackers provide data for each type of energy at the power-plant level worldwide, including commissioning dates, geographic coordinates, and installed capacities. The data cover all power plants above certain capacity thresholds.[1] GEM data are widely recognized for their granularity and reliability, enabling precise spatial and temporal analysis of energy infrastructure. Appendix Figure A1shows the distribution of the specific different RE project.

The primary explanatory variable, RE share, is defined as the share of RE (i.e., solar, wind, hydropower, geothermal, and bioenergy) of total electricity generation capacity in each region and year. This measure is calculated by summing the capacities of active RE facilities in each subcountry area and dividing by the area's total energy capacity (including fossil and nuclear). Each energy facility is matched to a subcountry area based on its coordinates and standard administrative boundaries. Figure 8 presents the RE share in each of our sample areas (i.e., the DHS sample areas), calculated as the 1990–2000 average RE share for each sub-country region containing DHS data.

[1]For example, the thresholds are 30 MW for geothermal, 75 MW for hydropower, and 10 MW for wind power.

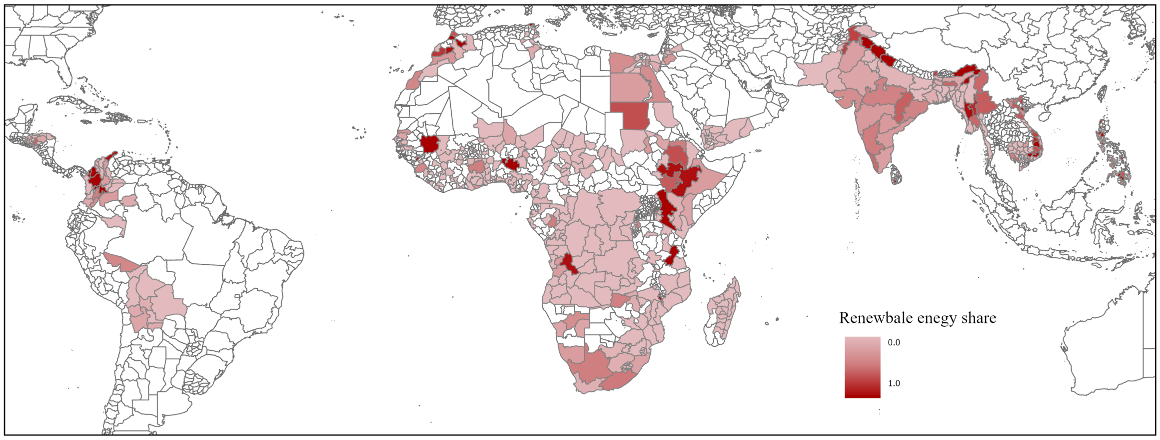

Figure 8: RE share at the sub-country level

Notes: This figure presents the average RE share from 1990 to 2000 for each subcountry area that contains DHS data.

Our analysis also uses information on the commissioning date of RE facilities, defined as the date when the first RE facility (above the threshold) became operational in each subcountry area. Figure 9 presents the cumulative distribution of RE project commissioning years at the subcountry level. This variable provides plausibly exogenous variation in RE availability. We use this exogenous variation to construct instrumental variables (IVs) for local RE share to address concerns about endogenous RE adoption.

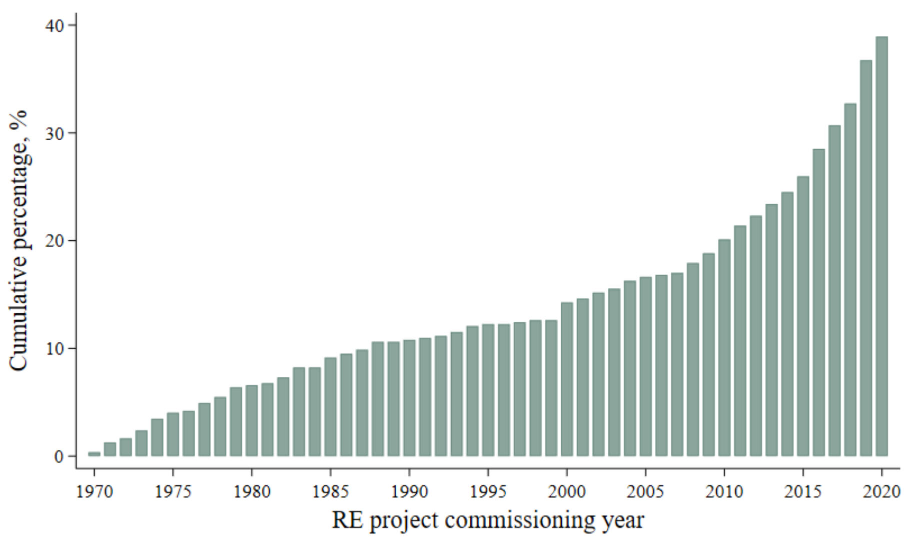

Figure 9: Distribution of the RE project commissioning year across regions

Notes: The figure shows the cumulative distribution of RE project commissioning years across subcountry regions. The commissioning date is defined as the date when the first RE facility (above the threshold scale) became operational in each subcountry region.

3.1.3 Auxiliary data

In our robustness checks and supplementary analyses, we also incorporate data from various additional sources. Country-level GDP and population data are obtained from the World Bank. Nighttime light data are sourced from the DMSP-OLS (1992–2013) and NPP-VIIRS (2012–present) datasets, which have been harmonized through cross-sensor calibration to construct a consistent global time series from 2000 to 2018 (Chen *et al.*, 2021). Air pollutant data are drawn from the Emissions Database for Global Atmospheric Research (EDGAR).[2] Specifically, we use data on ozone precursor gases (carbon monoxide and non-methane volatile organic compounds), primary particulate matter (PM_{10} and $PM_{2.5}$), and their carbonaceous components (organic carbon). Summary statistics for these variables are provided in Appendix Table A2.

3.2 Empirical Strategy

We estimate the effect of RE on infant mortality by comparing mortality rates across regions with varying RE shares based on the following regression model:

$$y_{ivrct} = \alpha + \beta_1 Share_{rct} + \mu_v + \lambda_t + \omega_s + X_{it}\theta + \varepsilon_{ivrct} \tag{1}$$

where y_{ivrct} is the mortality dummy of infant i born in community v, region r, country c, and year t. The key explanatory variable, $Share_{rct}$, is the RE share in region r, country c, and year t. Recall that the infant mortality dummy equals 1 if death occurred within the first 12 months of birth, and 0 otherwise. RE share refers to the subnational share of RE capacity. RE includes hydropower, solar, wind, geothermal, and bioenergy. In robustness checks, we also examine the effect of each RE type separately.

The model includes community-fixed effects (μ_v) to account for all time-invariant community-specific factors affecting infant mortality,[3] cohort-fixed effects (λ_t) to account for annual shocks common to all births, and survey year fixed effects (ω_s) to adjust for differences across surveys. The baseline model also controls for child gender, birth month, and birth order (X_{it}). Finally, ε_{ivrct} denotes the error term. Standard errors are clustered at the region-year level to address potential bias from spatial correlation

[2] We use version 8.1 of the EDGAR database, available at `https://edgar.jrc.ec.europa.eu/dataset_ap81`. This database provides comprehensive global emission inventories for a range of air pollutants and greenhouse gases, with a spatial resolution of 0.1° × 0.1°.

[3] In DHS surveys, the sampling clusters are usually villages in rural areas and city blocks in urban areas. We refer to the villages and city blocks as communities for simplicity.

and autocorrelation.

If the RE share were randomly assigned, the ordinary least squares (OLS) estimate of β_1 from model (1) would capture the causal effect of RE on infant mortality. However, the RE share in a region is most likely endogenous. For example, a region with a more developed economy is more likely to adopt RE, since RE project construction is costly. The potential bias arising from endogenous RE share cannot be fully addressed by the community and year fixed effects included in the model. This is because there may be community-specific time-varying omitted factors that could bias the OLS estimate. The following proposes different approaches to address the potential bias from endogenous RE share.

3.2.1 Instrument variables

We adopt two instrumental variables (IVs) to address the potential endogeneity bias. The first IV is constructed using plausibly exogenous variation in the commissioning year of RE facilities (with capacity above a threshold) in each region. If regions that adopted RE earlier did not differ in their pre-existing trends in infant mortality, then differences in RE commissioning year represent an exogenous shock to local RE intensity. The exclusion restriction is that the commissioning year of RE is not affected by community-specific time-varying determinants of infant mortality; recall that time-invariant determinants of both RE commissioning and infant mortality have been accounted for by the community-fixed effects. See Figure 9 for the distribution of regional RE commissioning years. Evidence from the event-study estimates presented in Figure 10 supports the exogeneity of RE commissioning year.

The second IV is a Bartik IV constructed from local RE potential and global trends in RE technological improvements. The local RE potential is a composite index created by normalizing and weighting the potentials of hydropower (sourced from Hoes (2014)), solar (sourced from Solargis s.r.o. and World Bank Group (2023)), and wind (sourced from Davis *et al.* (2023)), with the global share of each RE as the weight.[4] These three major RE sources account for more than 95% of the RE capacity in the developing world (see Figure 2). The regional potential of each RE and the composite potential index are presented in Figure 3. We proxy the global trend of RE technological improvements by the one-year lagged global RE capacity. Specifically, the Bartik IV is constructed as

[4]Specifically, the share of hydropower is 40%, wind is 35%, and solar is 25%.

(Goldsmith-Pinkham *et al.*, 2020; **?**):

$$IV_{rct}^{B} = \text{Capacity}_{t-1} \times \text{Potential}_{rc} \ , \tag{2}$$

where Capacity_{t-1} is the global RE capacity lagged by one year, and Potential_{rc} is the composite potential index of RE in region r and country c. This IV is relevant because, all else equal, regions with higher RE potential are more likely to adopt RE when global RE development accelerates. The exogeneity of the IV sourced from the fact that global RE trends are exogenous to local RE shares. Although local RE potential is likely correlated with local-specific determinants of infant mortality, these factors should be accounted for by the fixed effects included in the model.

With the IVs in hand, the first stage regression of the two-stage least squares (2SLS) estimation is:

$$Share_{rct} = \delta + \beta_2 IV_{rct} + \mu_v + \lambda_t + \omega_s + X_{it}\theta + \eta_{rct} \ , \tag{3}$$

where IV_{rct} denotes the IV, δ is the constant term, η_{rct} is the error term, and all other variables are as previously defined. The second stage of the 2SLS regression corresponds to equation (1). The first-stage estimates presented in Appendix Table A3 indicate that both IVs are positively and strongly correlated with the local RE share.

3.2.2 Staggered DID estimation

As a robustness check, we also estimate the dynamic effects of local RE construction on infant mortality based on the following event-study model:

$$y_{ivrct} = \alpha + \sum_{j=2}^{J} \gamma_j Lag_{rct}^{j} + \sum_{k=0}^{K} \beta_k Lead_{rct}^{k} + \mu_v + \lambda_t + \omega_s + X_{it}\theta + \varepsilon_{ivrct} \tag{4}$$

where Lag_{rct}^{j} and $Lead_{rct}^{k}$ represent the j-year lags and k-year leads relative to the RE project commissioning year in region r and country c, and all other variables are as previously defined. The first lag ($j = 1$) is used as the base year and thus excluded from the model.

The identification assumption is that, conditional on the fixed effects, regions that introduced RE projects early and those that introduced them later have no preexisting differential trends in infant mortality rates. This assumption is supported if the lag estimates γ_j are all close to zero and statistically insignificant. As presented in Figure 10, the event-study estimates provide no evidence of preexisting differential trends. This finding is not surprising since, as detailed in subsection 2.1, the timing of RE project commissioning in developing countries is driven by exogenous technological improvements and local RE potential, and is unlikely to be affected by infant mortality rates. Even if there are time-invariant factors that could affect both the timing of RE commissioning and infant mortality, these factors should have been accounted for by the community fixed effects. Based on this identification assumption, the dynamic effects of RE construction are captured by the estimates of β_k.

To estimate the average effect of RE project construction, we also adopt the following staggered DID model:

$$y_{ivrct} = \alpha + \tau Treat_{rct} + \mu_v + \lambda_t + \omega_s + X_{it}\theta + \varepsilon_{ivrct} \tag{5}$$

where $Treat_{rct}$ is a dummy variable equal to 1 for years after the commissioning of the RE project in region r and country c, and all other variables are defined as before. The coefficient τ captures the average effect of the RE project construction.

4 Main Results

4.1 Baseline estimates

Table 1 presents the estimated effect of RE intensity on the infant mortality rate, based on model (1). Recall that the infant mortality rate is a binary indicator measuring whether a child died before reaching 12 months of age. We multiply the estimated coefficient of the mortality dummy by 1,000 so that the coefficient can be interpreted as the effect on deaths per 1,000 live births, in line with the conventional definition of the infant mortality rate in macro-level studies. The RE intensity is defined as the share of total energy capacity from renewable sources (i.e., solar, wind, hydropower, geothermal, and bioenergy). All estimations control for birth-year fixed effects, community fixed effects, survey-year fixed effects, and infant characteristics. Standard errors reported in square brackets are clustered at the community level. The first stage of the 2SLS estimations is reported in Appendix Table A3.

Table 1: Effects of RE intensity on the infant mortality rate

Independent variable	*RE share*			RE capacity per capita	RE capacity per GDP
	OLS	IV (baseline)	Bartik IV	IV (baseline)	
	(1)	(2)	(3)	(4)	(5)
RE share	-5.30*** [0.65]	-19.90*** [1.77]	-24.26*** [5.41]	-643.02*** [63.51]	-71.12*** [6.55]
Infant controls	Yes	Yes	Yes	Yes	Yes
Birth year FE	Yes	Yes	Yes	Yes	Yes
community FE	Yes	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes	Yes
Independent variable mean	0.33	0.33	0.33	0.03	0.16
Observations	7,085,028	7,085,028	7,085,028	7,085,028	7,039,854

Notes: This table presents the effect of RE intensity on the infant mortality rate, estimated based on Model (1). The key explanatory variable is RE share in columns 1–3, RE capacity per capita in column 4, and RE capacity per GDP in column 5. The dependent variable, infant mortality rate, is a binary indicator measuring whether a child died before reaching 12 months of age. We multiply the estimated effect by 1,000 so that the estimate can be interpreted as the effect on deaths per 1,000 live births. Column 1 presents the OLS estimate, while the remaining columns present the 2SLS estimates. Column 3 uses the Bartik IV, while the other 2SLS estimations use the baseline IV (i.e., RE commissioning year). Standard errors reported in square brackets are clustered at the community level. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

The OLS estimate presented in Column 1 suggests that a 10 percentage point increase in the RE share would reduce the infant mortality rate by 0.53 deaths per 1,000 live births, and this effect is statistically significant at the 1% level. However, the

OLS estimate could be biased, given that the RE share may be correlated with omitted community-specific time-varying determinants of the infant mortality rate. To address this concern, Column 2 presents the 2SLS estimates using the local RE commissioning year as the IV. The 2SLS estimate confirms that RE significantly reduces the infant mortality rate. The 2SLS estimate is larger than the OLS estimate, suggesting that the OLS estimate is downward biased. Column 3 presents the 2SLS estimate based on the Bartik IV constructed in equation (2). The two IV estimates are comparable and show no statistically significant difference. We use the RE commissioning year as our baseline IV because we can verify its validity based on parallel trends tests in event studies (Figure 10).

The baseline 2SLS estimate suggests that a 10 percentage point increase in the RE share would reduce the infant mortality rate by 1.99. This effect is economically large. Given that the mean infant mortality rate in our sample regions is 58.7, this estimate suggests that a 10 percentage point increase in the RE share would reduce the infant mortality rate by 3.39 percent. As presented in Figure 1, the RE share in developing countries increased by 9.34 percentage points from 2000 to 2020. Therefore, this estimate suggests that the increased RE adoption during this period led to a 1.86 decline in the infant mortality rate. This effect accounts for 8.23 percent of the observed total decline in the infant mortality rate during this period in developing countries, which is 22.6. More discussions on the welfare effects of the resulting infant mortality decline will be presented in subsection 6.

4.2 Alternative RE intensity measures

Our baseline analysis measures RE intensity by the share of RE capacity. As robustness checks, we adopt two alternative measures of RE intensity: RE capacity per capita and RE capacity per unit of GDP per capita. Due to the lack of real GDP data at the subcountry level for a significant share of our sample areas, we use nighttime light data derived from the World Bank as a proxy for GDP. The per capita values are calculated by dividing by the annual population in each region. As presented in columns 4 and 5 of Table 1, we still find a significantly negative effect of RE on infant mortality when using these alternative measures of RE intensity. Note that the effect sizes are not directly comparable to the baseline estimate when using different intensity measures with different units.

4.3 Dynamic effect estimates

Figure 10 examines the dynamic effects of RE projects on infant mortality, estimated based on the event-study model (4). As presented in Panel A, all estimates before the RE project construction are close to zero and statistically insignificant, supporting the exogeneity of the RE commissioning year. In addition, the estimates suggest that RE construction significantly reduces the infant mortality rate; the reduction effect increases over time and levels off after 8 years. Panel B addresses the potential spillover effects of RE projects by excluding DHS samples from non-RE regions connected to regions with RE facilities. The resulting estimates are comparable. Appendix Figure A4 addresses the potential bias from heterogeneous treatment effects by adopting the estimation methods proposed by Sun & Abraham (2021) and Cengiz *et al.* (2019), and finds comparable estimates.

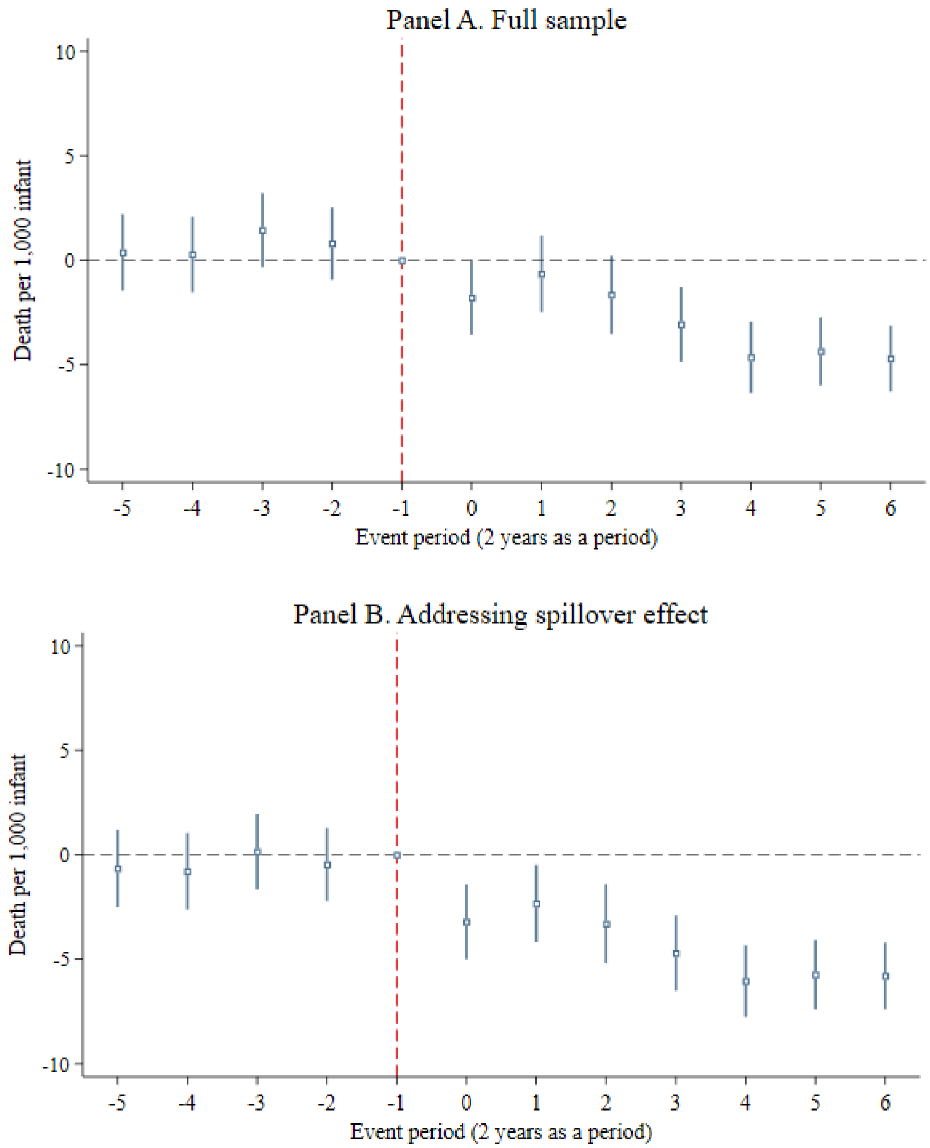

Figure 10: Dynamic effects of the RE project construction on infant mortality rate

Notes: This figure presents the dynamic effects of RE project construction on infant mortality rate, estimated based on model (4). Panel A uses the full sample, while Panel B excludes DHS samples from non-RE regions in countries within RE facilities. The vertical lines represent the 95% confidence intervals.

4.4 DID estimates and additional robustness checks

Table 2 presents the DID estimates based on model (5). The DID estimation uses the commissioning of the first RE project as the treatment and thus can be seen as a simplified form of the baseline 2SLS estimation presented in column 2 of Table 1. The advantage of the DID model is that it facilitates robustness checks and heterogeneous effect analyses. As presented in column 1 of Table 2, the DID estimate suggests that RE project construction reduces infant mortality rate by 6.15 deaths per 1,000 live births.

We conduct a series of robustness checks based on the DID model. Column 2 addresses the potential spillover effects of RE project construction by excluding DHS samples from non-RE regions in countries within RE facilities. Column 3 excludes regions that experienced war during the sample period. Column 4 presents the weighted estimate using the DHS sample weights. Column 5 excludes the infant-level control variables. All resulting estimates are comparable to the baseline DID estimate. Appendix Table A5 further confirms the robustness of our findings by presenting results based on country-level data and provides additional evidence on the impact of RE on infant mortality.

Table 2: DID estimates of the effect of RE on the infant mortality rate

	(1) Baseline	(2) Exclude spillover effects	(3) Exclude country in war	(4) Adjust sample weight	(5) Exclude controls
$Treat_{irct}$	-6.145***	-9.679***	-6.721***	-4.007***	-6.602***
	[0.459]	[0.510]	[0.494]	[0.616]	[0.463]
Birth year FE	Yes	Yes	Yes	Yes	Yes
community FE	Yes	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes	Yes
Infant controls	Yes	Yes	Yes	Yes	No
Observations	9,087,046	7,319,305	8,378,915	8,316,914	9,087,046
R-squared	0.023	0.024	0.024	0.024	0.022

Notes: This table presents the DID estimates of the effects of the commissioning of RE projects on the infant mortality rate, based on Model (5). Column 1 presents the baseline estimate; Column 2 excludes DHS samples from non-RE regions in countries within RE facilities; Column 3 excludes regions that experienced war during the sample period; Column 4 presents the weighted estimate (using DHS sample weights); and Column 5 excludes the infant-level control variables. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

4.5 Heterogeneity

We examine the heterogeneity of the effect across infant gender, maternal education, and local economic conditions. The heterogeneous effects are analyzed using an extension of the DID model (5):

$$y_{ivrct} = \alpha + \beta_1 Treat_{rct} + \beta_2 Treat_{rct} \times Dummy_i + \mu_v + \lambda_t + \omega_s + \varepsilon_{ivrct} \ , \qquad (6)$$

where $Dummy_i$ is an indicator for each moderating variable, and all other variables are defined as in model (5). Effect heterogeneity is inferred by comparing the estimates of β_1 and $\beta_1 + \beta_2$.

As presented in Figure 11, we find that the mortality reduction effect is larger for male infants than for female infants and greater for children of mothers with lower education levels. In addition, the effects are more pronounced in regions with lower GDP per capita and lower levels of industrial development. These findings suggest that the adoption of RE tends to reduce inequality in infant mortality. Traditionally, higher infant mortality rates are observed among mothers with lower education and in areas with lower levels of economic development. The larger reductions in infant mortality among these disadvantaged groups could help reduce inequality. We will discuss this further in Section 6, which examines the welfare implications of RE adoption.

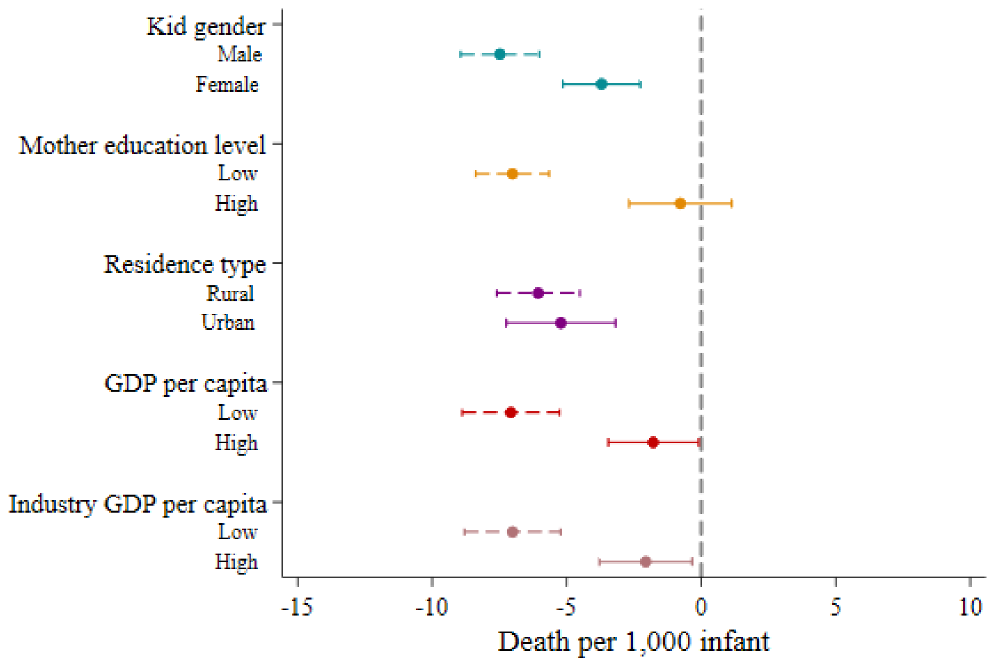

Figure 11: Heterogeneity of the effect of RE energy on infant mortality rate

Notes: This figure presents the heterogeneity in the effect of RE on infant mortality rate, estimated based on model (6). The 95% confidence intervals (horizontal lines) are computed using standard errors clustered at the community level.

Table 3 presents the effect of each type of energy on infant mortality. As we do not have good IVs for each type of energy, here we only present the OLS estimates. The estimations are still based on model (1), but the key explanatory variables are the log of added capacity for each type of energy in each region. See Figure 2 for the trends of each type of energy. Column 1 shows that fossil energy has a positive effect on infant mortality, while columns 2–5 show that each type of renewable energy has a negative effect on infant mortality. This finding is consistent with our baseline estimate that increasing RE share reduces infant mortality. The marginal effect of renewable energy varies across energy types, with the largest effects found for wind power and bioenergy. However, as these estimations do not address the potential bias from endogenous renewable energy adoption, the marginal effects should be interpreted with caution.

Table 3: Effects of different type of energy on infant mortality rate

Dependent variable	Infant mortality rate				
Independent variable	Fossil energy	Wind power	Solar power	Hydropower	Bioenergy
	(1)	(2)	(3)	(4)	(5)
Log added energy capacity	4.699***	-7.998***	-2.555***	-2.970***	-11.279***
	[0.832]	[0.902]	[0.922]	[0.520]	[3.180]
Birth year FE	Yes	Yes	Yes	Yes	Yes
community FE	Yes	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes	Yes
Observations	2,633,252	1,809,987	642,204	2,587,869	1,038,674
R-squared	0.041	0.051	0.101	0.042	0.072

Notes: The effects are estimated based on a modified version of model (1), which uses the log of added capacity for each type of energy as the key explanatory variable. Standard errors, reported in square brackets, are clustered at the community level. Significance levels are *** p < 0.01, ** p < 0.05, and * p < 0.1.

5 Mechanisms

5.1 Reducing air pollution

An intuitive channel through which RE reduces infant mortality is by reducing air pollution. Abundant evidence suggests that higher levels of air pollution increase infant mortality (e.g., Chay & Greenstone, 2003; Foster *et al.*, 2009; Gutierrez, 2015; Ebenstein *et al.*, 2017; Heft-Neal *et al.*, 2018). If we find that RE reduces air pollution, we can conclude that lower air pollution is a channel through which RE reduces infant mortality. As presented in Table 4, we estimate the effect of RE intensity on five frequently used measures of air pollution: CO (carbon monoxide), NMVOC (non-methane volatile organic compounds), OC (carbonaceous components of organic carbon), PM_{10}, and $PM_{2.5}$. We find significantly negative effects of RE intensity on each of these air pollution measures, regardless of whether we use the OLS estimation (Panel A) or the 2SLS estimation (Panel B). Appendix Table A6 shows the effects of RE commissioning on infant mortality with different levels of air pollution.

Table 4: Effects of RE intensity on air pollution

	(1)	(2)	(3)	(4)	(5)
	Ozone precursor gases		Primary particulates		
Dependent variable	CO	NMVOC	OC	PM_{10}	$PM_{2.5}$
			Panel A. *OLS results*		
$RE\ share_{rct}$	-0.022**	-0.047***	-0.035***	-0.026**	-0.022**
	[0.010]	[0.011]	[0.010]	[0.011]	[0.010]
			Panel B. *IV results*		
$RE\ share_{rct}$	-0.053**	-0.112***	-0.083***	-0.063**	-0.053**
	[0.024]	[0.026]	[0.025]	[0.027]	[0.025]
Birth year FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes	Yes
Observations	17,119	17,119	17,119	17,119	17,119
R-squared	0.987	0.988	0.987	0.988	0.988

Notes: This table presents the OLS (Panel A) and 2SLS (Panel B) estimates of the effect of RE intensity on different air pollution measures: CO (carbon monoxide), NMVOC (non-methane volatile organic compounds), OC (carbonaceous components of organic carbon), PM_{10}, and $PM_{2.5}$. The estimation is based on modified versions of model (1), using the RE project commissioning year as the IV. Standard errors reported in square brackets are clustered at the region-year level. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

5.2 Income effect

The income effect of RE projects is another potential channel through which RE reduces infant mortality. As shown in Appendix Figure A5, families with higher wealth levels have lower infant mortality rates. Table 5 estimates the effect of RE on family wealth level, measured by the log wealth index factor score.[5] The wealth level is a categorical variable reported in the DHS survey. Columns 1 and 2 present the OLS and 2SLS estimates, respectively, of the effect of RE intensity on family wealth level, based on model (1). Column 3 presents the DID estimate based on model (5). All these estimates suggest that RE projects significantly increase family wealth. Appendix Table A7 presents additional evidence that RE projects improve macro-level economic performance, whether measured by GDP per capita or nighttime lighting. Appendix Table A8 provides a robustness check using an alternative wealth index that is calculated uniformly across urban and rural samples. Therefore, increasing income is also an important channel through which RE reduces infant mortality.

Table 5: The effect of RE on log family wealth index factor score

	Region RE share		RE project commissioning
	OLS (1)	2SLS (2)	DID (3)
$RE\ share_{rct}$	0.264*** [0.050]	0.440*** [0.060]	
$Treat_{rct}$			0.228*** [0.031]
Birth year FE	Yes	Yes	Yes
community FE	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes
Infant controls	Yes	Yes	Yes
Observations	119,074	119,074	119,074
R-squared	0.397	0.001	0.397

Notes: Columns 1 and 2, respectively, present the OLS and 2SLS estimates of the effect of RE intensity on family wealth level, based on model (1). Column 3 presents the DID estimate based on model (5). Standard errors, reported in square brackets, are clustered at the community level. Significance levels are *** p < 0.01, ** p < 0.05, and * p < 0.1.

[5]The wealth index factor score in the DHS is a standardized measure of household wealth calculated using Principal Component Analysis, and it is computed separately for urban and rural areas. This score ranges from -41.98 to 100, with higher values indicating relatively better economic status.

6 Welfare implication

6.1 Welfare gains from the reduction of infant mortality

We calculate the total infant deaths avoided by RE adoption in our sample countries by combining the 2SLS estimate presented in column 2 of Table 1 with annual data on RE share and total live births in each of the 54 sample developing countries from 1990 to 2020. We roughly estimate that increased RE adoption avoided 1.18 million infant deaths in these countries from 1990 to 2020, which accounts for 0.49‰ of the total births in these countries during this period.[6] Country-level infant deaths avoided are presented in Figure 12. Note that we only calculate the effect for our sample countries, as the estimates may not necessarily apply to other developing countries. Recall that these 54 countries account for 44.5% of the developing world population. We extrapolate the effect to the whole country that contains the DHS sample based on the fact that DHS surveys are nationally representative.

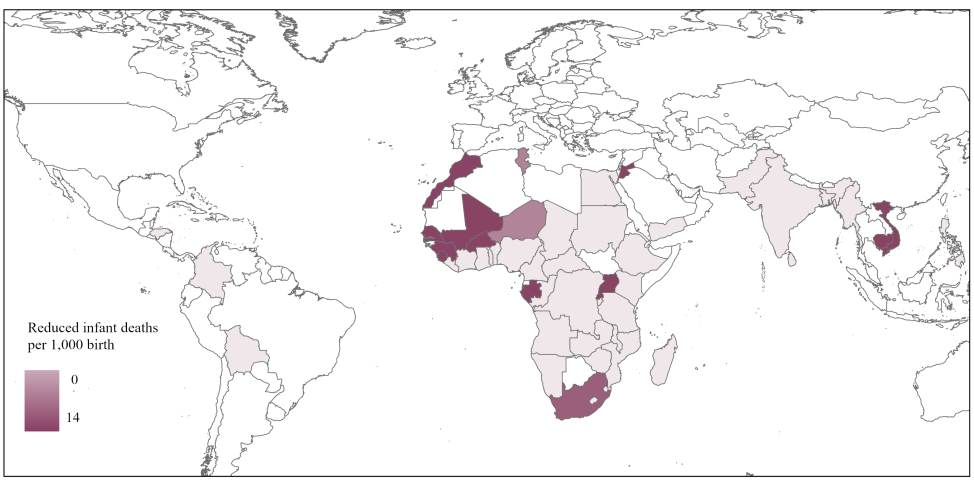

Figure 12: Reduced infant deaths caused by RE adoption in DHS countries during 2000-2020

Notes: This figure presents the total number of infant deaths avoided by RE adoption in each of the sample countries from 1990 to 2020. The values are calculated by combining the 2SLS estimate presented in column 2 of Table 1 with annual data on RE share and total live births in each of the 54 sample developing countries during this period.

To provide more intuition on the welfare effects of RE through reducing infant

[6]We multiply the estimated marginal effect of RE share on infant mortality by both the increase in RE share from the 1990 baseline and the total number of live births. We then aggregate these annual effects across countries and over time to obtain the total impact of RE adoption on infant mortality. Therefore, the calculated effect can be interpreted as the effect of RE growth.

mortality, we also compare the deaths avoided with the cost of RE project construction in the sample countries. Based on the RE project construction cost data and the RE increase data in each country during our sample period, we calculate that the total RE construction costs amounted to 320.19 billion USD in the 54 developing countries from 1990 to 2020.[7] Therefore, an additional investment of 272.1 thousand USD in renewable energy construction is associated with the prevention of one infant death in these developing countries.

6.2 Effects on the inequality of infant mortality

Our findings suggest that RE adoption could reduce inter-regional inequality in infant mortality. For the DHS sample areas, Panel A of Figure 13 and Appendix Table A10 shows that regions with higher RE potential tend to have higher infant mortality rates. Combining this fact with the findings that regions with higher RE potential adopt more RE (column 2 of Table A3) and that RE adoption reduces infant mortality, one can conclude that RE adoption could reduce inter-regional infant mortality inequality. This conclusion is consistent with the converging trends between regions with high and low RE potential also presented in the figure.

Consistently, as presented in Panel B of the figure, we find a declining trend in the Gini index of infant mortality, calculated based on the average infant mortality in each DHS region.[8] Appendix Table A11 presents additional evidence showing that increases in RE share reduce the cross-country Gini index of infant mortality and that the reducing effect of RE on infant mortality increases with RE potential. These findings are consistent with the estimates presented in the heterogeneity analysis, which show that the mortality reduction effect of RE is larger for children of mothers with lower education levels and in regions with lower GDP per capita and lower levels of industrial development.

[7] The data on RE project construction costs (per capacity) for each of the five major RE sources are available from 2010 to 2023 from the International Renewable Energy Agency (presented in Appendix Table A9). Based on the average RE cost from 2010 to 2023, we calculate the weighted cost of RE construction in each country during our sample period, using the share of each RE type in the country as the weight.

[8] We only present the trends before 2010, as the number of DHS regions reduced substantially after that, which makes inter-region comparison infeasible. This fact does not affect our main analysis, as we can obtain a full panel of infant mortality for each DHS region based on the birth history data of each mother.

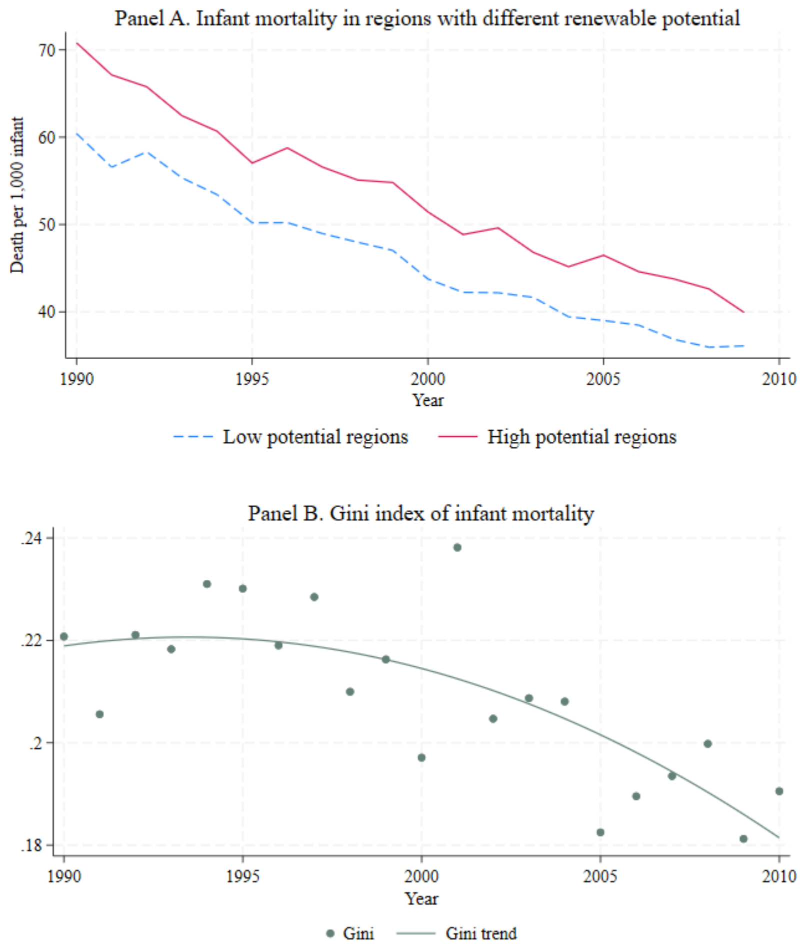

Figure 13: Trends of inter-region inequality in infant mortality

Notes: Panel A presents the trends in the difference in infant mortality between DHS regions with RE potential above (red line) and below (blue dashed line) the median. Panel B calculates the Gini index of infant mortality across DHS regions for each year. We first calculate the mean infant mortality in each region for each year, and then use these values to calculate the Gini index annually. We exclude samples after 2010 because the number of DHS regions was substantially reduced after that (see Footnote 8 for more details).

7 Concluding Remarks

Elevated infant mortality rates have persisted as a defining characteristic of many developing economies. The advancement of RE technologies presents a potentially transformative opportunity to address this critical development challenge in developing nations that possess substantial RE endowments. Based on data covering seven million births across 427 subnational regions in 54 developing countries from 1990 to 2020, we find that a 10 percentage point increase in the RE share would reduce infant mortality rate by 1.99 deaths per 1,000 live births, and the growth of RE can explain 8.23 percent of the observed total decline in infant mortality in the developing world from 1990 to 2020. We show that air pollution abatement and local income growth serve as key channels. We also find that RE also tends to reduce inequality in infant mortality across population groups and geographic. The findings of this study have important implications for developing countries to reduce infant mortality by accelerating the adoption of RE.

We conclude this study by highlighting two key limitations. First, due to data constraints, this study primarily examines the effect of RE on infant mortality—only one of many critical health indicators in developing countries. We posit that, through similar mechanisms, RE may also influence other health outcomes for infants, children, and adults. Second, our analysis focuses on 54 developing countries, representing just 44.5% of the developing world's population. Notably, China—a leader in RE adoption over the past two decades—is excluded due to the absence of DHS data. Given the substantial heterogeneity among developing nations, our findings may not generalize to countries outside our sample. Future research incorporating broader health metrics and additional countries could further elucidate RE's health impacts in developing economies.

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A Appendix for Online Publication

A.1 Figure

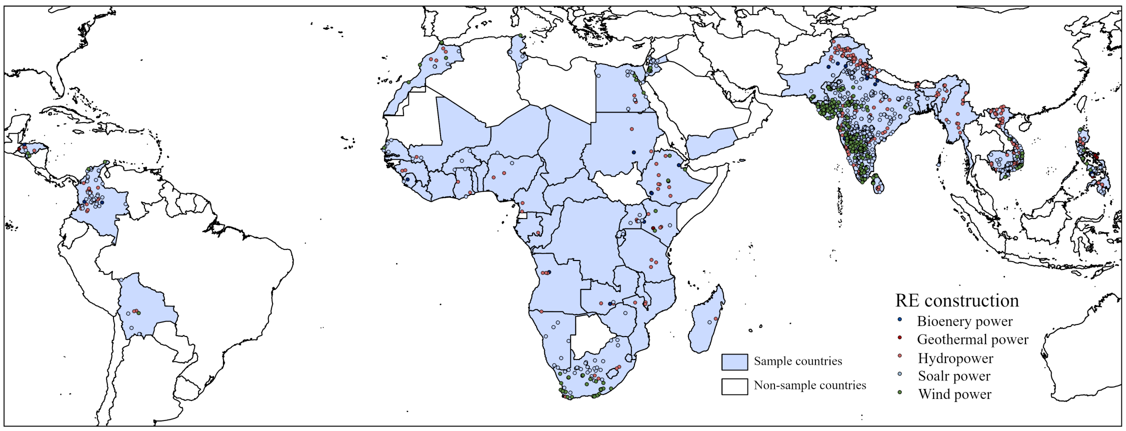

Figure A1: Distribution of DHS countries in the sample and locations of RE project

Notes: The figure shows all DHS sample countries included in our analysis, along with the locations of RE projects within these countries.

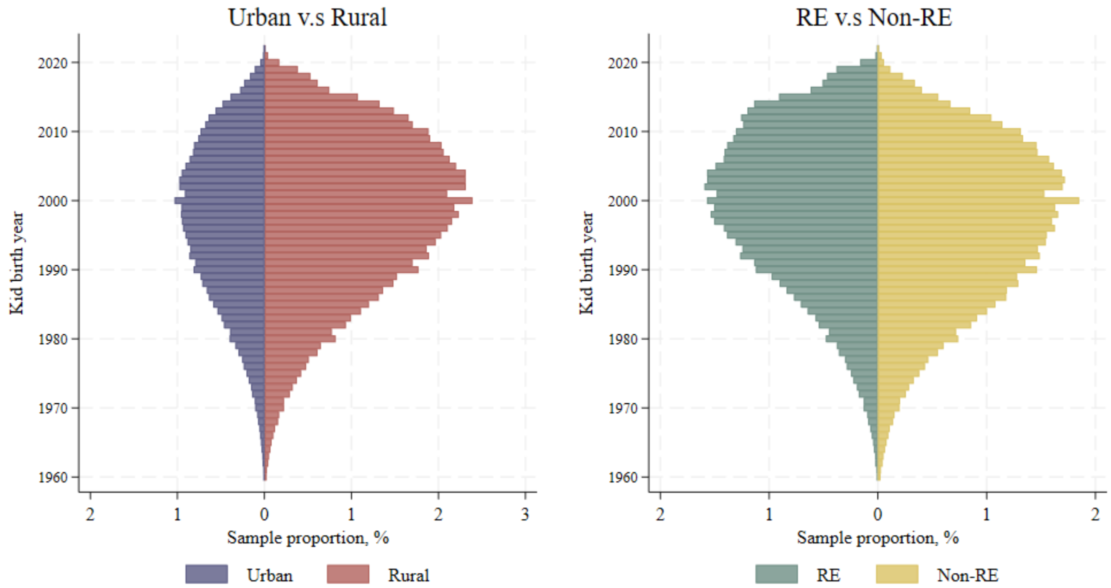

Figure A2: Distribution of child birth years in the sample

Notes: This figure shows distribution situation of child birth years in the sample. The sample is restricted to DHS mothers who are usual residents. The sample proportion refers to the percentage of individuals in a given group relative to the total number of individuals in the full sample.

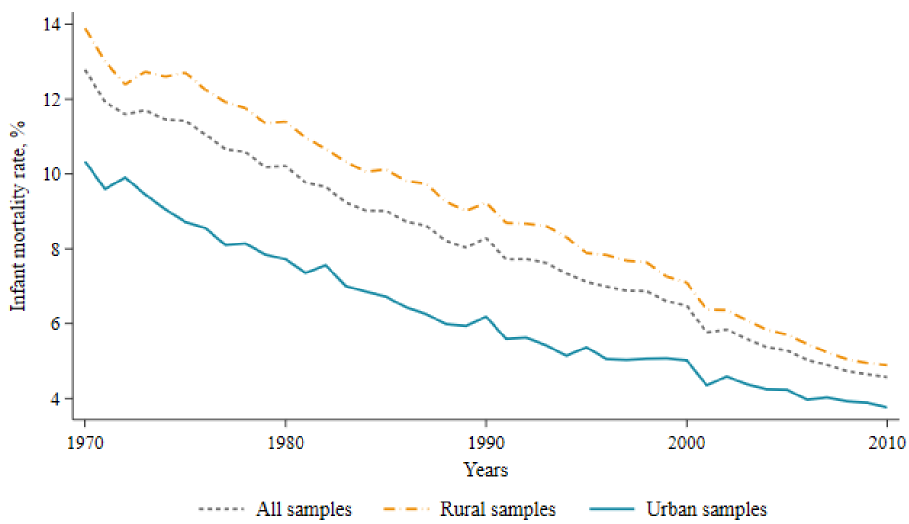

Figure A3: Infant mortality rate trend in the DHS countries

*Notes:*This figure presents the trend in infant mortality rates for rural and urban samples in the DHS countries. The sample includes only countries with data available through 2015. This approach is taken to avoid potential changes in the average IMR that could arise from countries exiting the sample, which may lead to trends that do not accurately reflect the overall sample.

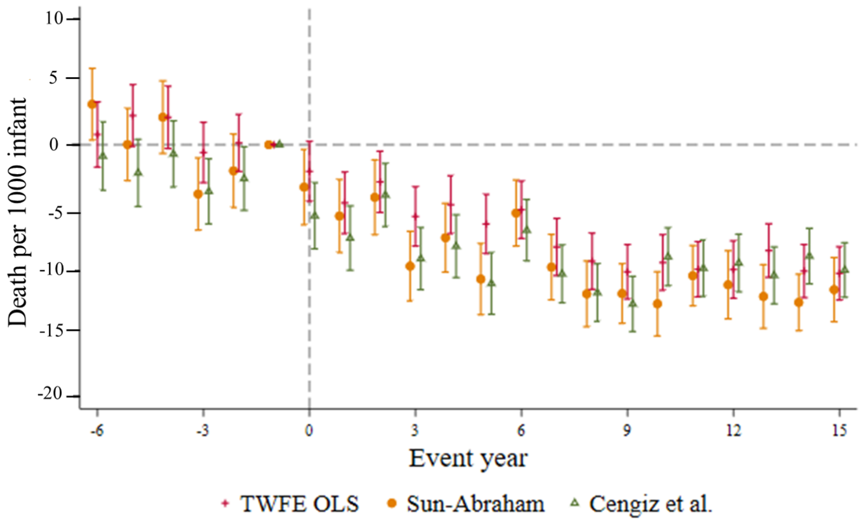

Figure A4: Dynamic effects of RE project commissioning considering heterogeneous treatment effects

Notes: This figure presents the dynamic effects of RE project commissioning on the countries' infant mortality rate. We compare the baseline event-study estimates with those that account for heterogeneous treatment effects, using the methods of Sun & Abraham (2021) and Cengiz *et al.* (2019), respectively.

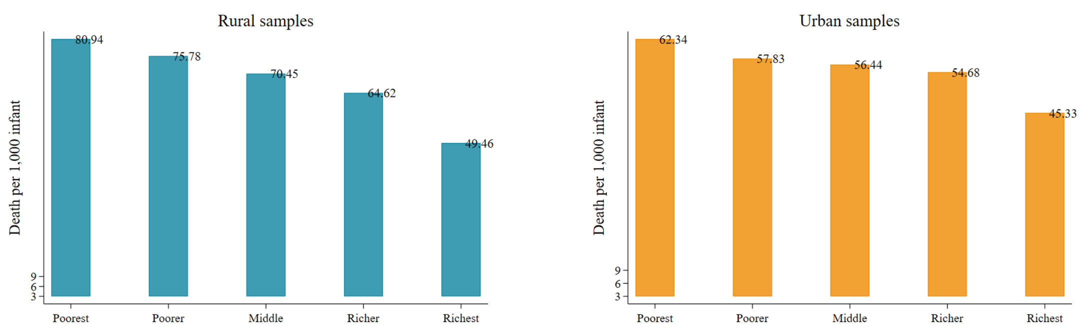

Figure A5: Infant mortality rate of different wealth level group

*Notes:*This figure presents the average infant mortality rate (IMR) for samples from rural and urban areas with different wealth levels. The classification of wealth levels is based on the quantile-based division used in the DHS data.

A.2 Table

Table A1: List of sample countries

Country	Country	Country	Country
Angola	Bangladesh	Benin	Bolivia
Burkina Faso	Burundi	Cambodia	Cameroon
Central African Republic	Chad	Colombia	Comoros
Congo	Cote d'Ivoire	Democratic Republic of Congo	Egypt
Ethiopia	Gabon	Gambia	Ghana
Guinea	Honduras	India	Jordan
Kenya	Lesotho	Liberia	Madagascar
Malawi	Mali	Morocco	Mozambique
Myanmar	Namibia	Niger	Nigeria
Pakistan	Philippines	Rwanda	Sao Tome and Principe
Senegal	Sierra Leone	South Africa	Sri Lanka
Sudan	Swaziland	Tanzania	Togo
Tunisia	Uganda	Vietnam	Yemen
Zambia	Zimbabwe		

Notes: This table lists the 54 DHS sample countries.

Table A2: Summary statistics

	Mean	sd	Min	Max	N
			Main variables		
Infant mortality (death per 1000 infant)	58.720	235.101	0.000	1000.000	7085205
RE share	0.066	0.195	0.000	1.000	7091623
Treat	0.320	0.467	0.000	1.000	7091623
RE capacity per economic unit	0.190	0.513	0.000	5.351	7040031
RE capacity per capita	0.026	0.153	0.000	3.834	7085205
			Infant control variables		
Kid birth month	6.346	3.403	1.000	12.000	7085205
Kid gender	1.485	0.500	1.000	2.000	7085205
Kid birth order	2.942	2.057	1.000	21.000	7085205
			Woman level variables		
Anemia level	0.720	0.810	0.000	3.000	1356460
Heart disease	0.019	0.136	0.000	1.000	966078
Diabetes	0.041	0.198	0.000	1.000	1138926
Underweight	0.175	0.380	0.000	1.000	2448590
Overweight	0.221	0.415	0.000	1.000	2448590

Notes: This table shows the summary statistics of main variables from 1990-2020.

Table A3: First stage result

	(1)	(2)	(3)	(4)
Dependent variable	RE commissioning $Treat_{rct}$	Bartik IV Z_{rct}	RE commissioning $Treat_{rct}$	
Independent variable	RE share		RE capacity per capita	RE capacity per economic unit
Dependent variable	0.281***	0.207***	0.009***	0.077***
	[0.003]	[0.006]	[0.000]	[0.001]
Year FE	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes
community FE	Yes	Yes	Yes	Yes
Observations	7,085,028	7,085,028	7,085,028	7,039,854
R-squared	0.572	0.490	0.327	0.900

Notes: This table presents the first stage result based on Model (2). Standard errors reported in square brackets are clustered at the community level. Significance levels are *** p < 0.01, ** p < 0.05, and * p < 0.1.

Table A4: Health effects of women

Dependent variable	(1) Anemia level	(2) Heart disease	(3) Diabetes	(4) Underweight	(5) Overweight
$RE\ share_{rct}$	-0.084***	-0.017	-0.134***	0.077***	-0.195***
	[0.011]	[0.024]	[0.010]	[0.008]	[0.007]
community FE	Yes	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes	Yes
Observations	1,356,033	966,053	1,138,846	2,448,468	2,448,468

Notes: This table presents the health effects of women using IV method. Standard errors reported in square brackets are clustered at the community level. Significance levels are *** p < 0.01, ** p < 0.05, and * p < 0.1.

Table A5: Effects of RE on infant mortality and mortality at country level

Dependent variable	Log infant mortality rate			Log mortality rate		
	Total (1)	Female (2)	Male (3)	Total (4)	Female (5)	Male (6)
$Treat_{ct}$	-0.0683***	-0.0690***	-0.0683***	-0.0552***	-0.0837***	-0.0597***
	[0.0120]	[0.0123]	[0.0120]	[0.0124]	[0.0107]	[0.0097]
Birth year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,474	1,474	1,474	1,515	1,515	1,515
R-squared	0.939	0.940	0.939	0.871	0.815	0.807

Notes: This table presents the effects of RE on infant and overall mortality at the country level. Standard errors, reported in square brackets, are clustered at the country-year level. Significance levels are *** p < 0.01, ** p < 0.05, and * p < 0.1.

Table A6: Effects on the infant mortality rate from RE project commissioning

Index	(1) OC	(2) PM_{10}	(3) $PM_{2.5}$	(4) CO	(5) NMVOC
$Treat_{ct} \times Indicator_{ct}^{pollution}$	-0.008***	-0.010***	-0.012***	-0.007***	-0.014***
	[0.002]	[0.002]	[0.003]	[0.002]	[0.002]
$Treat_{ct}$	-0.011***	-0.012***	-0.012***	-0.011***	-0.013***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
$Indicator_{ct}^{pollution}$	0.009***	0.012***	0.013***	0.009***	0.015***
	[0.002]	[0.002]	[0.003]	[0.002]	[0.002]
Birth year FE	Yes	Yes	Yes	Yes	Yes
community FE	Yes	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes	Yes
Observations	3,138,922	3,138,922	3,138,922	3,138,922	3,138,922
R-squared	0.018	0.018	0.018	0.018	0.018

Notes: This table presents the effects of RE commissioning on infant mortality across countries with different levels of air pollution. We examine how the impacts vary by interacting RE with different pollution indicators. Columns 1 to 5, respectively, explore different air pollution measures: CO (carbon monoxide), NMVOC (non-methane volatile organic compounds), OC (carbonaceous components of organic carbon), PM_{10}, and $PM_{2.5}$. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A7: Effects on economic level

Dependent variable	(1) Light mean	(2) GDP per capita
$Treat$	0.256***	0.691***
	[0.017]	[0.048]
Birth year FE	Yes	Yes
community FE	Yes	Yes
Survey year FE	Yes	Yes
Observations	3,103,334	269,311
R-squared	0.320	0.837

Notes: This table presents the effects of country economic level. Standard errors reported in square brackets are clustered at the community level. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table A8: The effect of RE on log family wealth index factor score (different wealth index)

	Region RE share		RE project commissioning
	OLS	2SLS	DID
	(1)	(2)	(3)
$RE\ share_{rct}$	0.005***	0.006***	
	[0.001]	[0.001]	
$Treat_{rct}$			0.002***
			[0.000]
Birth year FE	Yes	Yes	Yes
community FE	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes
Infant controls	Yes	Yes	Yes
Observations	1,515,351	1,515,351	1,515,351
R-squared	0.063	0.001	0.063

Notes: Columns 1 and 2, respectively, presents the OLS and 2SLS estimates of the effect of RE intensity on family wealth level, based on model (1). Column 3 presents the DID estimate based on model (5). Standard errors reported in square brackets are clustered at the community level. Significance levels are *** p < 0.01, ** p < 0.05, and * p < 0.1.

Table A9: Total installed costs (2020 USD/kW)

Year	Onshore wind	Offshore wind	Solar	Hydropower	Bioenergy	Geothermal
2010	2077.29	4945.45	4854.93	1333.96	2752.04	2752.96
2011	2054.43	5664.09	4162.81	1314.76	2645.98	4170.58
2012	1932.83	5012.19	3168.96	1405.28	1850.54	5588.20
2013	1995.92	5297.45	2781.30	1589.05	3220.16	4022.01
2014	1923.69	5578.14	2513.41	1456.48	3167.14	3796.17
2015	1747.23	5594.60	1910.89	1600.94	2752.96	3717.54
2016	1750.88	4405.10	1738.08	1897.17	2313.18	3904.98
2017	1752.71	4975.62	1503.11	1947.46	3081.19	4071.38
2018	1663.11	4866.82	1284.59	1525.97	1801.17	4383.15
2019	1577.17	3899.49	1061.50	1877.06	2351.58	4218.58
2020	1418.99	3301.54	931.67	1967.57	2672.50	3834.57
2021	1344.94	2893.76	868.59	2162.32	2387.24	4075.95
2022	1208.70	3179.94	830.18	2791.36	2049.86	3296.97
2023	1060.59	2560.04	693.04	2565.53	2496.04	4195.72

Notes: Data source: (IRENA, 2021), (IRENA, 2024b). We adjust the installed costs of these energy sources to 2020 USD.

Table A10: Evidence of health inequality

Dependent variable	(1) Log generation	(2) Infant mortality rate	(3) Log GDP per capita	(4) Fossil share
Log GDP per capita	0.514***			
	[0.089]			
$Potential_c$		0.979***	-0.085*	0.130***
		[0.281]	[0.045]	[0.022]
Year FE	Yes	Yes	Yes	Yes
Observations	1,113	606	1,346	700
R-squared	0.119	0.075	0.176	0.059

Notes: This table provides descriptive evidence on country-level characteristics, including economic development, electricity generation, renewable energy potential, and energy structure. Standard errors reported in square brackets are clustered at the country level. Significance levels are *** p < 0.01, ** p < 0.05, and * p < 0.1.

Table A11: Effect of RE on the inequality of infant mortality

Dependent variable	(1) Country-level infant mortality GINI index	(2) Infant mortality	(3) Regional infant mortality
$RE\, share_{ct}$	-0.158**		
	[0.076]		
$RE\, share_{crt}$		-0.002***	
		[0.001]	
$RE\, share_{crt} \times potential_r$		-0.007***	
		[0.001]	
$Potential_r$			3.025***
			[0.572]
Year FE	Yes	/	Yes
Country FE	Yes	/	/
community FE	/	Yes	/
Survey year FE	/	Yes	/
Birth year FE	/	Yes	/
Observations	895	17,085,028	9,661

Notes: This table presents the effect of renewable energy (RE) on inequality in infant mortality. Column 1 estimates the effect of RE share on the Gini index of infant mortality at the country level for the DHS sample countries; we do not estimate the effect at the regional level as the DHS regions change over time. Column 2 estimates the interaction effect of RE potential on infant mortality by extending the baseline model (1). Column 3 estimates the effect of RE potential on regional infant mortality; this estimation does not include region fixed effects as RE potential is time-invariant. Significance levels are *** p < 0.01, ** p < 0.05, and * p < 0.1.