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The Effect of Nature's Wealth on Economic Development: Evidence from Renewable Resources

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Abstract

We study the causal effect of short-run variations in nature's wealth on human and economic development. We focus on the ocean as a naturally occurring source of food and study early-life exposure to exogenous variation in the wealth of marine life near human settlements. Analyzing data on 36 low- and middle-income countries between 1972 and 2018, we estimate impacts by analyzing 0.5 million adult women and 1.5 million births. Negative shocks have a significant effect on mortality early in life, and long-lasting negative impacts on human capital and economic well-being. These effects operate through mild nutritional deprivation, in absence of contemporaneous changes in individual behavior and aggregate income. Both short- and long-run effects are amplified by overexploitation of marine resources, highlighting the role of nature's wealth in insuring against short-run shocks. Aggregate estimates reveal that persistent negative shocks lead to considerable life loss in the long run. (*JEL* I15, Q20, Q54, O10)

Keywords: Child; Climate Change; Economic development; Health; Mortality; Natural resource; Ocean; Renewable resource.

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The availability of abundant wildlife was a catalyzer of early development and remains a factor of economic success (Barrett et al., 2011; Dalgaard et al., 2020). It is unclear whether its effect results from the exogenous presence of large amounts of these renewable natural resources, i.e., nature's wealth, or from the ability of countries to sustainably use them as a source of food, energy or inputs of production. A large body of literature, at least since Malthus (1872), has focused on the latter, highlighting the determinants of overexploitation but ignoring the contribution of nature. This is the case of well-known issues like deforestation (Burgess et al., 2012; Jayachandran, 2013), overfishing (Stavins, 2011; Huang and Smith, 2014; Noussair et al., 2015), and poaching (Kremer and Morcom, 2000).[1]

We disentangle both channels by studying the consequences for economic development of short-run variations in nature's wealth. We provide evidence of causal effects on mortality, human capital, and economic well-being by focusing on the ocean as a naturally occurring source of food. To this day, fish continues to provide nutrients that are both accessible in nature and essential for human health, in particular for maternal and child health (United Nations, 2021; Victora et al., 2021).[2] Worldwide more than 3 billion people, who mostly reside in low- and middle-income countries (L&MICs), depend on the consumption of fish for their survival (FAO, 2020b).[3]

We quantify causal effects by studying early-in-life exposure to natural resource wealth in the ocean. We proxy this wealth at the local level using variation in the ocean's acidity or basicity of its waters, as measured by pH. At lower levels of pH (indicating acidity), the availability of minerals needed by marine life to develop is reduced, and the nutritional content of commonly-harvested species is negatively impacted (Maire et al.,

[1]Models of wildlife preservation were introduced by Smith (1969); Clark (1973). Relatedly, a large literature studies nature as one of the inputs to agriculture (Auffhammer, 2018).

[2]Fish is a primary source of proteins and of several micronutrients that are crucial for maternal health and child development (FAO, 2020a): *iron* and *iodine* support brain development and help prevent stillbirth; *zinc* and *vitamin A* support childhood survival and promote growth; *calcium* and *vitamin D* prevent preterm delivery; *vitamin B12* contributes to a healthy nervous system and brain development; and *essential fatty acids* prevent preeclampsia, preterm delivery, and low birth weight.

[3]Twenty-six percent of all animal protein that is consumed in L&MICs is derived from fish, with peaks of 50% or more in countries like Bangladesh, Cambodia, the Gambia, Ghana, Indonesia, Sierra Leone, and Sri Lanka. The global average is 17% (FAO, 2020b). In L&MICs, fish is also an important contributor of micronutrient intake (Hicks et al., 2019).

2021).[4] We exploit the natural cycle of this chemical property: in a given area, pH varies in the short run as random draws from the long-run distribution, which climate change has altered with spatially-heterogeneous increases in acidity, a process known as *ocean acidification*. Therefore, in the short run, the ocean's water near a specific coastal community can be relatively more (or less) acidic than its normal level, resulting in reduced (or increased) mineral availability for marine life. This plausibly random short-run variation, which we exploit for identification, is similar to that of rainfall or temperature, which have been widely used in the literature (see, e.g., Corno et al., 2020).

This phenomenon is novel in the economic literature and cannot be read under the lens of available knowledge about early-in-life shocks (see, e.g., Almond et al., 2018). Shocks to ocean's resources are not only understudied in the literature (Colt and Knapp, 2016), but due to the rivalrous and non-excludable essence of marine resources, they are also not comparable to the well-known effects of shocks to agricultural or subsoil extractive activities (Collier, 2010; Van der Ploeg, 2011). In addition, they present features that are unique in the literature: the ocean's pH is not directly observed or felt by individuals, it has no direct effect on health, and public awareness about its changing nature is highly limited (Gelcich et al., 2014).[5] Because short-run shocks to open-access resources have small impacts on income and prices (Kroodsma et al., 2018; Bianchi et al., 2021), a finding that we confirm in the paper, the most plausible channel of the effect is the consumption of fish.

Focusing on L&MICs, we study both short- and long-run effects using a unique historical and geographical coverage: for the period 1972–2018, we analyze half a million adult women and 1.5 million live births in 36 countries across Africa, Asia, and Latin America. We compute early-in-life exposure to resource wealth by matching each individual's geolocation and date of birth with data on water's pH at a high spatial and

[4]Water acidity limits the ability of fish to calcify bones during development and raises their metabolic cost of life (Doney et al., 2020). We discuss the effect of variables that have direct effect on fish survival, and thus fish stocks, in Appendix B.2.

[5]The literature covers a wide variety of events that are either observable (directly or indirectly through market mediators) or have direct effects on health, such as atmospheric events (Heft-Neal et al., 2018; Geruso and Spears, 2018a; Adhvaryu et al., 2020), conflict (Wagner et al., 2018), macroeconomic fluctuations (Baird et al., 2011; Paxson and Schady, 2005; Bhalotra, 2010), political institutions (Kudamatsu, 2012), environmental contamination (Chay and Greenstone, 2003; Arceo et al., 2016; Isen et al., 2017; Geruso and Spears, 2018b), and radioactive exposure (Black et al., 2019).

temporal resolution. For identification, we define *shocks to resource wealth* as short-run deviations in pH levels from the spatially-specific (and seasonally-adjusted) long-run trend, an approach that makes relatively few identifying assumptions and allows unusually strong causative interpretation (Dell et al., 2014). Deviations are obtained by capturing residual unobserved heterogeneity in the estimating equation using a multi-way fixed effects (FEs) model. Identifying assumptions are supported by several checks.

We show that resource wealth has a significant effect on mortality early in life. This effect is specific to larger deviations in acidity (negative shocks) experienced *in utero*, highlighting the role played by natural resource scarcity, rather than abundance, and by maternal health. A negative one standard deviation shock raises neonatal mortality –the probability of dying during the first month of life– by approximately 0.5 deaths per 1,000 live births in communities located near the ocean's shore. The effect gradually converges to zero by the first year of life.

Beyond the effect on mortality, resource wealth has important consequences for human capital accumulation. Anthropometric measurements show that, on average, mortality is more prevalent among the weakest children because those who are alive past the first month, on average, have slightly better health. However, among female children, we observe a scarring effect, with a significant increase in stunting. The magnitude of the effect is small, and plausibly not directly observable by parents. However, negative consequences persist among adult women, whose economic well-being is also adversely affected.

We document how a negative shock operates through mild nutritional deprivation. First, we exclude changes in income. We observe no effect on satellite-based nightlight luminosity, a proxy for economic productivity and human development (Henderson et al., 2012; Bruederle and Hodler, 2018). For negative shocks to agriculture, we observe a significant reduction in luminosity that operates independently from shocks in the ocean, reinforcing the difference between the two channels. Main estimates are also unaffected by including controls capturing income processes in coastal areas at the time in which resource wealth is measured.

Second, we exclude behavioral changes contemporaneous to the shock, which further confirms its mild nature. Parental investments on child health are unaffected, while the effect on early-life mortality is homogeneous by wealth and education of the household. Results also exclude important correlates of neonatal death, such as differential access to medical care and nutrient supplementation (Black et al., 2013), behavioral changes that can occur after observing a child's health, and maternal stress, which has been found to play a role in more traumatic events (Berthelon et al., 2021).[6]

Third, we provide evidence against adjustments in consumption and nutrition patterns. Focusing on the Philippines, one of the most fish-dependent country in the world, we show that short-run shocks in local fish prices contribute to mortality. However, resource wealth operates independently, reinforcing the finding that maternal nutrition is affected only in a mild way. This is in line with the medical literature highlighting that fetal growth restrictions–the main cause of neonatal deaths and an important determinant of future child development–are closely associated with micronutrient deficiencies (Black et al., 2013), hard to observe without adequate access to health services. The largest impacts are in fact recorded where fish is an essential source of nutrients, while consumption patterns in a larger sample of countries at the time of the interview show no effect on the probability to consume fish or proteins from other sources.

We reconcile our findings with the literature on natural resource exploitation and highlight how overexploitation amplifies the effects of short-run negative shocks. We build two geographically granular measures for the intensity of fishing: one capturing an extractive form of fishing, which depletes fish stocks without generating economic benefits for local communities in the form of consumption or income; and an arguably more inclusive form of fishing, which does not necessarily imply overexploitation and can potentially redistribute benefits among local populations. Short- and long-run effects of negative shocks are amplified only in areas with higher intensity of extractive fishing. On the contrary, in areas with higher intensity of inclusive forms of fishing, negative shocks are compensated. This finding emphasizes how human-driven overexploitation

[6]Absence of parental adaptation is contrary to available evidence on observable deprivation, for example, during famines and fasting (Razzaque et al., 1990; Almond and Mazumder, 2011; Majid, 2015), or after the supplementation of nutrients (Adhvaryu and Nyshadham, 2016).

acts as a limiting force to nature's ability to act as insurance against short-run shocks.

These results provide novel evidence on the role of natural resources for human development, further contributing to the nascent literature on the relationship between biodiversity and poverty. While a large literature studies non-renewable resources, evidence on the exploitation of renewable natural assets remains limited (Dasgupta, 2021). As the ocean's chemical composition is impacted by climate change, providing novel results on the relationship between renewable resources and human development also deepens our understanding of the potential effects of climate change on household behavior. In line with evidence on the sizable effects of varying temperature and rainfall (Barreca et al., 2016; Burke and Emerick, 2016), our counterfactual analysis shows that, in the absence of adaptation, short-run shocks can translate into large long-run aggregate effects of ocean acidification.

Finally, we provide new evidence on the roots of development in settings of relative deprivation. Short-run negative shocks at the time of gestation can explain future differences in mortality rates, development, and long-term economic outcomes that are in part due to chance, as parents do not compensate for unobserved or mild shocks. These results are particularly important in light of the centrality of parental investments for early childhood development (Attanasio et al., 2020).

1 Data

We collate a wide variety of data sources that we describe in this section. Appendix A.1 provides further details of the variables used and data sources.

Mortality, human capital and adaptative behavior. We collate and homogenize 95 household surveys from 36 countries collected by the Demographic and Health Surveys (DHS) Program between 1990–2018. Individual surveys provide nationally representative data on health and population in L&MICs, with a particular focus on maternal and child health, and have been widely used to build mortality rates among children thanks to its detailed and accurate birth histories. The dataset is supplemented with objective measurements of child development and nutrition, such as height and weight. The program surveys women aged 15–49 and includes information about their demographics, including wealth and human capital accumulation. Each surveyed woman's birth history is recorded and includes information on the children's year and month of birth, sex, birth order, whether they are twins, and the date of death when it applies.[7]

The primary sampling unit is a cluster, which represents the community (a village or a neighborhood). Our dataset includes all available surveys with geocoordinates and only considers countries with direct access to the ocean. Appendix A.1 provides the full list of countries and surveys included in the study. We use all available surveys and re-weight observations to correct for oversampling of countries with multiple surveys.[8]

Geolocation of communities allows for restricting the sample to households living in coastal areas; by definition, these are the ones with the highest dependence on the ocean. Following the United Nations (2003), a *coastal area* is defined as the buffer extending landward from the ocean's shore up to a distance of 100 km. Distances from the shore are computed as the minimum straight distance from the community to the shoreline (see Appendix A.2 for details about the procedure). Figure 1 shows the geographical coverage of the study area, and Table 1 presents descriptive statistics for the sample. While individual characteristics tend to be comparable in magnitude between communities in the coastal and inland areas, households in proximity with the ocean are slightly richer and present lower mortality rates (Appendix Table A4). Appendix B.1 discusses alternative approaches to the definition of coastal area.

Resource wealth. We proxy resource wealth by focusing on variation in the natural habitat of marine life, measured by the ocean's chemical composition. We focus on water pH at the surface, i.e., a logarithmic scale indicating the acidity or basicity of an aqueous solution. Lower values indicate higher acidity. For seawater, pH typically ranges between 7.5 and 8.4. Chemical features of the ocean in open waters are obtained from the Hadley Global Environment Model 2 - Earth System provided by the Euro-

[7]While stillbirths are not recorded, we assume measurement error is minimal because the death of a child is a tragic event. Appendix B.7 shows evidence against recall bias.

[8]Results are robust to different selection criteria (Appendix Table A3). For questions that are omitted in certain survey rounds, we re-compute the weight to account for this selection.

pean Space Agency (ESA) Pathfinders-OA project (Sabia et al., 2015).[9] The produced series from the model matches available information from observational data (Totterdell, 2019).[10] Data are provided as monthly global raster data at the $1^{\circ}\times 1^{\circ}$ resolution for the period 1972–2018. We match this information with DHS data using a proximity criteria: each community is matched with a data point in the ocean using the shortest straight-line distance.

We supplement data with other variables that could affect resource wealth in the ocean and inland in the coastal area. First, using the HadGEM2-ES model, we gather information about other chemical features of the ocean at the same resolution used to measure of pH. Second, using the ERA5 database, we supplement data with other meteorological features in the same ocean's location where pH is measured, including temperature and wind speed. Third, to control for weather characteristics inland, we include yearly rainfall and temperature data at the community level from the PRIO-GRID database. Appendix B.2 provides descriptive statistics for these variables.

Ocean's exploitation. We use geographically-granular data about the intensity and the type of natural resource exploitation. First, we consider a form of *extractive fishing* by focusing on industrial fishing. In L&MICs, this practice is largely responsible for the greater biodiversity declines in these areas, but with limited economic benefits for local communities as a positive trade balance for seafood correlates with undernourishment (Golden et al., 2016; Sala et al., 2021). We measure it using the Global Fishing Watch dataset, which provides data on the hours industrial fishing vessels spend at specific geolocations. Because data are available only for the period 2012–2016, we build a global grid at the $1^{\circ}\times 1^{\circ}$ resolution summing fishing hours within each cell over the available period. Because industrial fishing patterns have low sensitivity to economic and environmental variation and are highly stable over time (Kroodsma et al., 2018), time-invariant heterogeneity is likely capturing suitability for industrial fishing, rather than

[9]Chemical features are measured in open waters rather than coastal waters to avoid the confounding effects of pollution. Excluding areas near estuaries–the main source of pollution for the ocean–has no effect on estimates (Appendix B.1).

[10]Any measurement error is uncorrelated with unobservable determinants of local development because the model is exclusively determined on climatology. For the use of re-analysis climatology datasets in economics, refer to Dell et al. (2014).

short-run responses to changes in the ocean's health. Dependency on fish for nutrition is also highly stable over time (Appendix B.3).

Second, we also measure fishing activities characterized by a lower degree of extractive exploitation. We focus on *night-time fishing* using the Automatic Boat Identification System for VIIRS Low Light Imaging Data (Elvidge et al., 2015), which provides the time and geolocation of boats detected using nightlight measured from satellite imaging. Because only 16% of fishing detected with this algorithm is also captured by industrial fishing (Kroodsma et al., 2018), night-time fishing tends to capture boats operating on a smaller and on a local scale, thus potentially contributing to the local economy. Similar to the measure of extractive fishing, we build a global grid at the $1^\circ \times 1^\circ$ resolution with the sum of all detected boats for the period in which data are available (2017–2019). We normalize intensity from both activities to be between 0 (no presence) and 1 (high intensity). Appendix Figure B14 shows an example of the geographical distribution.

Aggregate income. We complement data with the average night-time light emission from the calibrated DMSP-OLS Night-time Lights Time Series 4. Yearly data are available for the period 1992–2012. We normalize luminosity by population in the grid cell using the PRIO-GRID database, performing the analysis using nightlight luminosity per 100,000 inhabitants in a gridded dataset at the $0.5^\circ \times 0.5^\circ$ resolution, selecting only grid cells where DHS clusters used in the main analysis are present.

2 Empirical strategy

The ocean's chemical composition varies over time and space in a similar fashion to weather systems (Feely et al., 2008). Globally and locally, it is affected by winds, temperature, sea ice, precipitation, runoff, and ocean circulation. Similar to other chemical properties of the ocean, water's pH presents a short-term component, that we exploit for causal identification. The short-term component is randomly drawn from the long-run distribution, which has been altered by climate change as the ocean's absorption of anthropogenic CO_2 has led to an increase in the global average of water acidity by 26% since the Industrial Revolution (Doney et al., 2020). Because acidification is determined at a global scale, but with spatially-heterogeneous effects, it introduces further exogenous variation in short-run shocks: some regions exhibit steeper trends and/or more amplified within-year variation than others.

In our sample, variation in pH originates from both the time and geographic dimensions with comparable contributions of its between and within components (Appendix B.4). Summary statistics for matched raster points confirms its similarity with weather systems: short-run variation in pH occurs around a global trend with within-year seasonality, just like air temperature or rainfall (Appendix B.2). The peak in average pH is reached in January (8.10) and the minimum is around September (8.09), with a median within-year variation of 0.01 units of pH. Average *in-utero* exposure to pH decreased from 8.08 to 8.02 in the considered time frame.

For identification, we follow a standard approach in the literature on the effects of weather shocks (see, e.g., Dell et al., 2014), and define a *shock* as the short-run deviation in water pH levels from the spatially-specific long run trend (corrected for seasonality) at the location of birth. We denote as $R_{vc,mt}$ the open water's pH of the ocean in the nearest point from the community v of macro-region c measured in the month m of year t. We multiply $R_{vc,mt}$ by 100 to relate coefficients to an increase of 0.01 units in pH (approximately three standard deviations in the main identifying sample). Individual exposure is computed by matching individual information about children and adult women with $R_{vc,mt}$ using their date and location of birth.[11] When exposure is computed over multiple months, we average pH over that period. For instance, exposure *in utero* is the average $R_{vc,mt}$ during the 9 months preceding the date of birth.

This approach relies on the inclusion of a set of fixed effects (FEs) in the estimating equation. First, we remove spatially-specific trends and seasonality in both the ocean's chemical composition and in outcome variables by including macro-region by birth month FEs, $\mu_{c,m}$. Second, we remove spatially-specific trends by including community FEs, θ_{vc}, which capture time-invariant (observed or unobserved) spatial characteristics, and macro-region by birth year FEs, $\phi_{c,t}$, which captures unobserved variation in trends

[11]We assume that the location of surveying correspond to the location of birth. We do not highlight potential issues associated with selective migration (Appendix B.7).

among areas affected by faster or slower rates of acidification. Finally, time FEs, η_{mt}, remove unobserved characteristics of the date of birth by controlling for year by month of birth indicators. Appendix Figure B4 shows the evolution of the average shock in the sample over time, reinforcing the nature of abnormal deviation in pH of our main independent variable.

For children and adult women's outcomes, the causal effect of a shock in resource wealth, β, is therefore estimated in deviations using the following specification:

$$y_{ikvc,mt} = \beta\, R_{vc,mt} + \mathbf{X}_{ikvc,mt}\gamma + \Omega_{vc,mt} + \epsilon_{ikvc,mt} \tag{1}$$

where y_{ikvym} is the outcome of interest for individual i born from mother k in month m of year t in community v of macro-region c, $\mathbf{X}_{ikvc,mt}$ is a vector of control variables, and $\epsilon_{ikvc,mt}$ are idiosyncratic errors assumed to be clustered at the ocean raster data point.[12] For FEs $\Omega_{vc,mt}$, we consider two main alternatives: in the *benchmark* specification, the set of FEs is defined by $\Omega_{vc,mt} = \eta_{mt} + \theta_{vc} + \phi_{c,t} + \mu_{c,m}$, while in the *within-sibling* specification, we replace community FEs with mother-specific FEs, τ_k. The latter strategy restricts the analysis to siblings and allows controlling for mothers and households' time-invariant characteristics.

We support the validity of the identifying assumption with a variety of tests. First, we check the exogeneity of the resource shock to observed heterogeneity by estimating equation (1) without controls and with mothers and communities' observable characteristics as dependent variables. Balance on observables is confirmed as characteristics are not statistically different in areas with different shocks (Appendix B.5).

Second, we present estimates using alternative identifying assumptions, varying the set of FEs in equation (1), thus altering the definition of a shock. We control for alter-

[12] Including control variables has limited impact on the main estimates (Figure 2). When included in child-level regressions, *demographic controls* include the child's gender and birth order, the number of twins born with the child, mother's age at birth (including a square term), mother's age at the time of the interview (including a square term), mother's years of education, the household head's gender and age, and household size. For adult-level regressions, controls are limited to mother and household head's characteristics. *Weather controls* include the community's average temperature and rainfall (and their interaction) in the year of birth, and another chemical feature of the ocean that relates with ocean temperature, oxygen concentration (Appendix B.2 provides further details about this control variable).

native sets of control variables, including the exclusion of $\mathbf{X}_{ikvc,mt}$, and for different time FEs, including year and month indicators separately. Further, we vary the definition of macro-regions, considering administrative indicators, such as the country or the district of the community, which is a standard approach in the literature, and global grids at different resolutions, which dissuade concerns about the potential endogeneity of administrative bounds. In the latter, the macro-region is defined by the grid cell that contains the community v. To guarantee sufficient variation in ocean's pH, we use as main reference a global grid with a latitude–longitude resolution of $5° \times 5°$ per grid cell.

Third, we address issues related to non-random selection driven by FEs. In our setting, this can occur from the loss of groups with only one observation and can lead estimates to differ from the population-wise average effect if impacts are heterogeneous (Cameron et al., 2011). For example, the within-sibling identifying assumptions require restricting the sample to mothers with at least two live births, who are generally older, have fewer years of education, were younger at the time of their first birth, and live in poorer households and communities (Appendix B.4). Threats from this form of selection are limited by a shock being not only continuous, but also presenting a high degree of variation (the within-community variance in the identifying sample used by the benchmark specification is always positive). Nevertheless, in all results tables, we report the number of observations used in the estimation (*identifying observations*), and the number of observations that are dropped due to the identifying restrictions (*singleton observations*). In addition, Appendix B.4 provides estimates using the Miller et al. (2021) re-weighting procedure, and estimating the benchmark specification with the within-sibling identifying sample (see, e.g., Alesina et al., 2021).

Finally, we present results using alternative assumptions related to statistical inference. We show robustness to alternative assumptions about standard errors, and to permutation-based inference by artificially varying the shock (Appendix B.6).

3 Results

3.1 Mortality and human capital accumulation

We begin by focusing on the effect of a resource wealth on neonatal mortality. Table 2 presents estimates of the effect on the Neonatal Mortality Rate (NMR)–the number of deaths in the first month of life per 1,000 live births. To isolate a channel operating through maternal health, we begin by studying exposure to resource wealth while *in utero*. Panel A uses the benchmark specification, while Panel B uses the within-sibling specification. Columns (1)–(3) remove seasonality at the country level, while columns (3)–(6) remove seasonality at the grid cell level. Columns (1) and (4) do not include any control variables, columns (2) and (5) add weather controls, and columns (3) and (6) further add demographic controls.

Shocks experienced *in utero* have a substantial impact. A 0.01 decrease in pH significantly increases NMR by 1.42–2.12 deaths per 1,000 live births in our benchmark specification (Panel A). Estimates using the within-sibling specification are not dissimilar (Panel B of Table 2), suggesting that family-specific unobserved heterogeneity is not driving identification. In terms of standardized effects, a one-standard-deviation negative shock leads to an increase in NMR by 0.53–0.60 deaths per 1,000 live births in the benchmark specification and 0.53-0.67 deaths per 1,000 live births in the within-sibling specification (Appendix Table B2). Adding control variables has a limited effect on the estimates of the effect, providing further evidence in support of the exogeneity of a shock. Significant effects are also found when varying the definition of coastal area.[13]

Results are robust to a wide variety of checks. First, the effect on neonatal mortality is robust to alternative specifications (Figure 2). While we expect some degree of variation in the estimates, because changing the set of FEs alters our identifying assumptions and our measure of shock, we highlight a high stability of the estimates. At standard confidence levels, estimates are always negative and significantly different from zero.[14]

[13]The most affected communities live within 40 km from the shore. Restricting coastal areas to altitudes below 100 meters or excluding estuaries have limited effect on estimates (Appendix B.1). Estimates are also robust to potential sources of measurement error associated with distances (Appendix B.5).

[14]Results are also robust to including interactions between the birth year and the birth month of the

Second, results are not driven by selection into identification. Estimating the effect using the reweighting procedure proposed by Miller et al. (2021) and the benchmark specification restricting the sample to the within-sibling identifying sample highlight similar estimates and conclusions. Third, statistical inference is robust to alternative assumptions about standard errors in equation (1) and to permutation-based inference, which artificially varies the exposure in both space and time to the shock. For all specifications in Table 2 and all tests, using permutation-based inference we reject the null hypothesis of a nil effect at a 5% significance level for all estimates (Appendix B.6).

Figure 3 shows that the effect of resource wealth is specific to negative shocks experienced while *in utero*. Similar to Deschênes and Greenstone (2011), we implement an analysis based of binned variation of pH rather than continuous. Panel A shows estimates of equation (1) replacing the ocean's pH while *in utero* with the share of time children were exposed to values of the ocean's pH within a specific range during their gestation period. After controlling for the set of fixed effects, the effect on neonatal mortality is driven by exposure to lower levels of pH. This suggests that the effect is driven by scarcity shocks rather than abundance shocks, in line with the process of ocean acidification. To understand whether exposure of shocks in periods in proximity to gestation can also explain mortality, Panel B shows estimates of equation (1) by adding exposure one month before conception (10 months before birth), the month of birth, and 1–4 months after birth (a placebo period because it is posterior to the period considered for the death). Impacts are driven by the specific exposure to shocks during the gestation, reinforcing the role of maternal health during pregnancy and excluding channels operating through direct effects on children.

We then look at how resource wealth experienced *in utero* impacts mortality up to age 5. We focus on the probability of death at the monthly level to avoid potential issues related to the heaping of self-reported date of death.[15] We estimate the probability of

child with the time-invariant average across the study period of the following variables: intensity of extractive and night-time fishing; the gross cell product, the population living in the cell, and the average nightlight luminosity. Results available upon request.

[15] The heaping of deaths at 1 year is common, while mortality rates at ages 2, 3, 4 and 5 are hardly affected by heaping (Croft et al., 2018). In Figure 4, we indicate these points by vertical lines. We do not observe any effect on the estimates due to these potential issues. For comparison, Appendix B.8 presents estimates of the effect on mortality rates at standard times.

death at age x (in months) using equation (1) and restricting the sample to children who, at the time of the interview, are born at least x months before (independently from being alive). We select the sample based on time from birth, rather than age, to avoid selecting children alive and younger than x. We repeat the same specification for x ranging from 1 month to 60 months. The dependent variable, updated in every iteration, is an indicator variable equal to one if the child is not alive at time x from birth, and 0 otherwise, and is multiplied by 1,000 to relate coefficients to changes in deaths per 1,000 live births. Figure 4 plots the coefficients.

The effect peaks in the first month of life, which corresponds to the effect on neonatal mortality, and remains significant for the very first months of life. A smaller net effect is observed beyond the first month of life, with convergence to zero within the first year of life. Because, short-run effects slowly disappear as the initial increase in mortality is offset by later decreases, the pattern is consistent with a displacement of mortality that is hastened by experiencing worse conditions.[16]

Turning to human capital accumulation, Table 3 shows the effects of resource wealth experienced *in utero* on physical development built upon anthropometry, whose relation with long-term human capital accumulation is well established in the literature (McGovern et al., 2017). Panels A and B focus on short-run effects by analyzing measurements for children, while Panel C presents long-run effects among adult women.

In column (1), we define *physical development* as the average z-score of available anthropometric measures. We include weight-for-height (w/h), which captures insufficient food intake or a high incidence of infectious diseases in temporal proximity with the measurement, and height-for-age (h/a), which captures past or cumulative effects of under-nutrition and infectious diseases since conception.[17] Estimates of the effect on these individual indicators are reported in columns (2)–(3). Estimates in columns (4)–(5) focus instead on indicator variables for abnormally low values of weight-for-height (*wasting*), and of height-for-age (*stunting*). All measures rely on objective measure-

[16]This mechanism is known in the literature as *death harvesting*. For weather-related shocks, evidence is mixed (Deschênes and Moretti, 2009; Heutel et al., 2017; Geruso and Spears, 2018a).

[17]For adults older than 18 years old, z-scores refer to standard reference curves at age 18, when physical development is assumed to be complete.

ments performed by the enumerators on a random subset of children and adults. These measures are conditional on the individual being alive at the moment of the interview, and therefore need to be interpreted in light of the results on mortality.

Panel A in Table 3 highlights that a negative shock induces *mortality selection* among children. Living children that experienced a negative shock tend to have slightly better indicators (Panel A). A 0.01 decrease in pH increases physical development by 1.8 percentage points, mainly driven by an increase in weight-for-height and a reduction in wasting. Importantly, these differences in anthropometrics are not associated with contemporaneous nutrition.[18] This findings highlights that the effect on neonatal mortality is primarily affecting the weakest children, in line with the overall negative relationship between mortality and anthropometrics for L&MICs (Deaton, 2007).

While mortality selection is the prevalent mechanisms among children, we observe that this channel is driven primarily by male children. While male children experience only a slightly larger and not statistically different mortality as compared to female children (Appendix B.10), when looking at physical development among female children, we highlight the prevalence of a scarring effect (Panel B). While we do not observe any significant effect on variables associated with weight, we record a significant effect on stunting. A 0.01 negative shock increases the probability of the child to be stunted by 1.3 percentage points, corresponding to an impact of 5.7% relative to the sample mean. Importantly, this effect is persistent in the long-run. In Panel C, we observe a significant effect on physical development among adult women. A 0.01 negative shock decreases significantly physical development by 0.9 percentage points, driven primarily by increases in height-for-age and stunting. Adaptation at later ages could play a role as the magnitude of the effect, corresponding to an impact of 2.3% relative to the sample mean, is smaller among adults as compared to children.

Overall, the magnitude of the effects on physical development remains relatively small, making it likely that these small differences would remain unobserved by parents. To

[18] A negative shock leads to a reduction in the probability of being underweight the first months of life, indicating differences in birth weight (Appendix Figure B12). We do not observe any significant effect on morbidity and on an objective measurement of micronutritional deficiency (i.e., anemia) among children at the time of the interview (Appendix B.9).

further understand how these effects translate into long-run impacts on the economic well-being of women, Table 4 focuses on economic outcomes. In column (1), we proxy economic well-being in adult life with a measure of wealth, computed as an asset-based index and known to be capturing households' longer-run economic well-being (Jean et al., 2016). Columns (2)–(6) focus instead on correlates of well-being, such as fertility (number of births), years of schooling, cognitive skills (determined by the ability to read a sentence), and on labor supply. Columns (1) and (6) select only women that are either a household head or their partner (labeled as *main*), while Columns (2)–(5) refer to the full sample of women aged 15–49.

Resource wealth has long-run consequences that are not limited to anthropometrics. We highlight a significant impact on economic well-being: a 0.01 decrease in pH experienced *in utero* decreases adulthood wealth by 1.6 percentage points, an effect that corresponds to 0.5% relative to the sample mean. This impact is accompanied by statistically significant decreases in the number of births per woman and in the probability to work in the sample of main women by 0.008 children and 1.6 percentage points, respectively. We do not observe any effect on schooling and cognitive skills. In line with the impacts on physical development, the effects on economic well-being are small in magnitude, but statistically detectable even in the long-run.

3.2 Mechanisms

Section 3.1 provides evidence in favor of a mechanism centered around maternal health. This section tests alternative mechanisms that could explain these results.

Income. The exploitation of the ocean is a central economic activity in L&MICs. Out of the 120 million workers employed worldwide in the marine capture sector, 116 million lives in L&MICs. Of these, more than 90% work in small-scale and artisanal fisheries, whose capture is almost entirely absorbed by local consumption (The World Bank, 2012). Dependency on the exploitation of fish can be identified purely out of distance from water bodies (FAO, 2020b). Figure 5 shows estimates of the effect of resource wealth on neonatal mortality allowing estimates to vary flexibly with distance from the ocean's shore (Panel A), and from other water bodies (Panel B).[19] The largest effect on neonatal mortality is observed at the shore, while the estimate converges to zero as distance increases. On the contrary, the effect is homogeneous with respect to distance from other water bodies. These results confirms that impacts are concentrated in communities that rely more heavily on the ocean's resources. Areas in high proximity to the ocean, are also areas with higher population densities.

While these findings highlight the importance of marine resources, they do not exclude whether a shock induces changes in aggregate income. To clarify this point, we first look at satellite-based nightlight luminosity. The objective is to compare the effect on luminosity of two negative shocks to natural resources' wealth: one in ocean's waters, similar to the resource shock studied in Section 3, and one inland, which is known to generate income shocks. For the latter, we focus on a shock to agricultural productivity measured by the presence of a *drought*. In L&MICs, rainfall is an important determinant of income due to the dependence of these economies on agriculture (Barrios et al., 2010). Following Corno et al. (2020), we define drought using an indicator variable taking value one when annual rainfall in the grid cell is below the 15th percentile of the grid cell's historical rainfall distribution. For comparability, we follow the same approach to define the shock affecting the ocean's resources and we define a *negative resource shock* with an indicator variable taking value one when the yearly average pH in the nearest open ocean's raster point is below the 15th percentile of the grid cell's historical distribution.

Using a gridded dataset at the 0.5°×0.5° spatial resolution, we build yearly panel data for the coastal area covered by DHS, matching data about nightlight luminosity and resource shocks. In our sample, these shocks are comparable: the negative resource shock in the ocean is affecting 14.6% of observations, as compared to 12.9% for the drought. However, these shocks do not take place at the same time within the same grid cell because their correlation coefficient is -0.05. For identification, we follow a similar

[19] Other water bodies include lakes, ponds in islands within lakes, and all rivers. Freshwater ecosystems are also acidifying, but proximity to these is negatively correlated with proximity to the ocean's shore. Estimates are robust to excluding areas near estuaries (Appendix B1).

approach to equation (1) and estimate the following specification:

$$nlight_{ic,t} = \beta_{coast}\, R^{coast}_{i,t} + \beta_{inland}\, R^{inland}_{i,t} + \mathbf{X}_{ic,t}\gamma + \delta_i + \eta_{c,t} + \epsilon_{ic,t} \qquad (2)$$

where $nlight_{i,ct}$ is the nightlight luminosity in the grid cell i of macro-region c at time t, $R^{coast}_{i,t}$ is the indicator variable for the presence of a drought, and $R^{inland}_{i,t}$ is the indicator variable for the present of a negative resource shock in the nearest open ocean's raster point. $\mathbf{X}_{ic,t}$ is a vector of time-varying controls, δ_i are cell-specific time-invariant unobservable characteristics, and $\eta_{c,t}$ capture local trends. $\epsilon_{ic,t}$ are idiosyncratic errors assumed to be clustered at the grid cell.

Table 5 presents estimates under different sets of control variables. Not only estimates of the effect of a negative shock in the ocean's waters is very small, but they are also never significantly different from zero. In addition, estimates of these effects are unaffected by adding the indicator variable for droughts. On the contrary, in line with the literature highlighting the economic consequences of rainfall shocks, droughts have a significant negative effect on nightlight luminosity in coastal areas. The magnitude is about ten times as large as a comparable shock in the ocean's waters. While we cannot exclude that climate change and ocean acidification influence aggregate income in the long run, these results confirm that short-run variation in the ocean's resource wealth is different from income shocks associated with agriculture and do not to induce any short-run change in income.

The absence of a change in income is supported by the results of estimating equation (1) adding (potentially-endogenous) controls capturing income processes at the time in which resource wealth is measured. We control for: the (potentially-endogenous) presence of human activity using a measure of pollution in coastal waters; the presence of conflict in coastal areas, which have been shown to respond to fishing income (Axbard, 2016); and adverse weather events such as heat and storms that could negatively impact income near the shore (Hsiang and Jina, 2014; Gröger and Zylberberg, 2016). The inclusion of the these controls does not affect our main estimates (Appendix B.2).

Behavioral adaptation. While aggregate income is unaffected by resource wealth in the ocean, it is important to study individual behavior to understand not only whether adaptation limits the magnitude of the effects, but also whether lack of adaptation confirms that shocks are mild. Columns (1)–(2) of Table 6 examine adaptation at the time of the shock using birth-level information on parental health investments on antenatal investments (attendance to health visits during pregnancy and presence of health professionals during these visits), and delivery investments (presence of health professionals during delivery and whether delivery was performed in a health center). Both variables range from 0 (no investment) to 2 (high investment). Appendix B12 provides evidence on the individual indicators composing these variables. Columns (3)–(5) focus on investments after birth: postnatal healthcare, the completion of the cycle of basic vaccinations, and whether the child has ever been breastfed, an important determinant of child development (Black et al., 2013).

For both antenatal and delivery investments, we do not observe any significant effect. The effect is also homogeneous in the birth order and gender of the child, two predictors of differential parental investments in the presence of adverse shocks (Baird et al., 2011). Because antenatal care is also a strong predictor of nutrient supplementation plans during pregnancy, we also exclude this channel. We do not observe any effect on postnatal care, which indicates that, during periods of temporal proximity to birth, parental adaptation following the observation of child health is limited.

Adjustments in consumption and nutrition. Evidence on the importance of fish-dependence to explain the effect on early-life selection, in absence of any effect on income and adaptation, supports a channel that is exclusive to the nutritional content of fish which is harvested and used for consumption. However, this does not exclude the possibility to respond to the shock in the ocean by reverting to markets, especially if the relative prices of fish or nutritious food are impacted. However, L&MICs tend to export high-quality fish caught in their waters and supplement local demand only with imports of low-quality fish (Pauly and Zeller, 2016), limiting this possibility. In line with this evidence, we highlight larger effects on neonatal mortality in countries with a positive trade balance for fish products (Appendix B.3), while cannot identify any heterogeneous effect with respect to the ability to purchase more nutritious food.[20]

To verify this channel, we look at fish markets and compare the effect of *in-utero* exposure to resource wealth with the effect of *in-utero* exposure to fish price shocks. Focusing on markets allows also testing the role of aquaculture and other local market imperfections (see, e.g., Jensen, 2007). Due to data limitations, we restrict our analysis to the Philippines, a unique setting in our context: its coastline is the 5$^{\text{th}}$ largest in the world, it is home to 9% of global coral reefs, and depends highly on fish. We gather monthly retail fish prices at the province level for the period 1990–2018 from the Philipppine Statistics Authority. Prices are spatially heterogeneous and their pattern over time is in line with the global trend (Appendix Figure B15). Using retail prices, we compute the average fish price while *in utero* for each birth using their date of birth, and matching DHS communities with the provinces where prices are recorded. Similar to the effect of resource wealth, for identification, we rely on deviations in average retail fish (log-)prices from the spatially-specific (and seasonally-adjusted) long-run trend by adding this indicator in equation (1). Table 7 presents the results.

The effect of resource wealth on NMR is significant for the Philippines: a one-standard-deviation negative shock results in approximately 0.75 deaths per 1,000 live births. At the same time, a 1 percent increase in fish prices while *in utero* leads to an increase in NMR of 0.07 per 1,000 live births. As higher prices capture the capacity of households to purchase and consume fish, a positive estimate is a clear indication of the link between fish consumption and maternal health. However, conditional on the set of FEs, the two channels operate independently on mortality, reinforcing the finding of an unobservable or mild deterioration of natural resource quality, rather than quantity.

The mechanism recorded for the Philippines is further supported by evidence of larger effects in areas with overall greater dependency on fish for nutrition: where fish represent a higher percentage of total animal proteins consumed, and where artisanal fisheries are a central activity, such as in proximity to reefs (Appendix B.3). In addition, while recorded information about maternal nutrition during each pregnancy is not available,

[20] The effect is homogeneous across a wide array of individual characteristics (Appendix B.10). Higher (but not statistically significant) vulnerability is observed among male children, and children born from younger and less educated mothers living in poorer households.

in periods with negative shocks in the ocean's resource wealth, women's probability of consuming fish is unaffected, further supporting this channel (Appendix B12). These results are in line with the medical literature highlighting that a reduced intake of nutrients derived from fish can result in malnutrition and have long-run consequences, especially in places where knowledge about appropriate food choices is limited (McGovern et al., 2017). The effect of a negative shock in resource wealth is also independent from other shocks that have more direct effects on fish stocks, such as water temperature or pollution (Appendix B.2).

3.3 Resource exploitation

In L&MICs, studying the consequences of a resource shock in the ocean requires considerations over the magnitude of overexploitation, i.e.,overfishing. In L&MICs' coastal waters, only half of the total catch is made by small-scale and artisanal fisheries, while the other half is predominantly characterized by extractive forms of fishing. In the face of more stringent regulations, the demand for fish in richer countries has been satisfied by an increase of industrial fishing in the waters of L&MICs, also taking advantage of a worse natural resource governance.[21]

To understand how the natural wealth of renewable resources interacts with their exploitation, we turn our attention to heterogeneity with respect to the type and intensity of fishing activities defined in Section 1. For comparability, we quantify the effect of a *scarcity shock*, which we define as a one-standard-deviation decrease in resource wealth (or increase in water acidity) experienced while *in utero*, and we report estimates in terms of percentage change with respect to the sample mean. Figure 6 plots estimated effects of such shock at different intensities of night-time fishing (left-hand-side figures), and extractive fishing (right-hand-side figures).

Panel A focuses on short-run effects, showing impacts on neonatal mortality and on physical development among children. In terms of night-time fishing, both the effect on

[21] Marine capture fishery production in richer countries is about half its 1980s level, while in L&MICs has increased steadily since the 1950s (Ye and Gutierrez, 2017). For anecdotal evidence, see, e.g., The Guardian's *UK steps in to help West Africa in fight to overturn EU fishing abuses* (18/03/2012).

neonatal mortality and the effect on physical development are homogeneous along the fishing intensity. In terms of extractive fishing, we observe instead heterogeneous effects. Areas characterized by high intensity of extractive fishing present a significantly larger effect on neonatal mortality as compared to areas where extractive fishing is absent. A scarcity shock leads to a 1.4% increase in mortality in areas where extractive fishing is absent, and to a 5.0% increase in areas where extractive fishing is largest. The mortality selection induced by these effects is captured in the heterogeneity of the impact on physical development among children. A scarcity shock leads to an improvement in physical development among children that survive beyond the first month of life by 0.7% in areas where extractive fishing is absent and by 4.3% in areas where extractive fishing is largest.

The scarring effect among women, highlighted in Section 3.1, is evident in Panel B of Figure 6, which focuses on long-run impacts on economic well-being and physical development among adult women. Impacts on economic well-being are homogeneous with respect to night-time fishing, while their magnitude decreases significantly at higher intensities of extractive fishing. The effect varies between -0.2% and -0.1% depending on the intensity of night-time fishing, and it decreases from -0.1% at low levels of extractive fishing to -1.5% in areas where extractive fishing is highest. In terms of physical development, we observe a negative effect only at low intensities of night-time fishing, while the effect converges to zero at higher levels, indicating that higher intensities can compensate for the negative consequences of a shock experienced *in utero*. Instead, in presence of higher intensities of extractive fishing, shocks are significantly amplified. In absence of extractive fishing, a scarcity shock leads to a decrease of 0.3% in development, while in areas where extractive exploitation is highest, the reduction reaches 1.8% relative to the sample mean.

Overall, these results highlight how extractive fishing, an activity that is known to deplete marine resources through overexploitation, reduces significantly the ability to counteract short-run shocks. In fact, it amplifies their impacts. Night-time fishing, by potentially generating consumption and/or income for local communities, tends to compensate these effects in the long run, but has no effect in the short run, in line with the lack of parental adaptation (Section 3.2). Formal tests of heterogeneous impacts confirm these results (Appendix B.11).

4 The aggregate effect of ocean acidification

Resource wealth in the ocean is also affected in the long-run by climate change, in particular through the process of ocean acidification. While we cannot identify the causal effect of ocean acidification directly, Appendix C provides evidence using counterfactual estimates and focusing on long-run adaptation.

We produce counterfactual estimates of NMR under the assumption that children in our sample were exposed *in utero* to the ocean's conditions in 1975. NMR attributed to the change in the ocean's chemical composition is computed as the community-level average difference between the predicted NMR under real conditions and its counterfactual prediction. In all selected countries, acidification is responsible for an increase in neonatal deaths. In coastal areas, NMR attributed to acidification ranges, in aggregate term, from 3.0 deaths per 1,000 births in the DR of Congo to 9.0 in the Philippines and 11.9 in the Comoros Islands. This result highlights considerable heterogeneity, as the average NMR in the corresponding period is 49.4 in the coastal area of the DR of Congo, 14.8 in the Philippines and 26.8 in the Comoros Islands. Relative to average NMR, contributions of acidification are larger in countries that are more dependent on the ocean's resources.

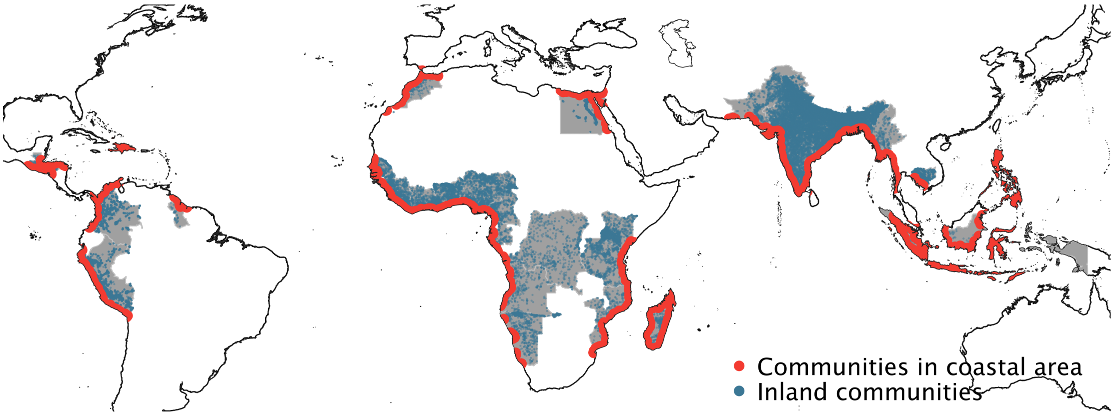
Following Dell et al. (2014), we also estimate equation (1) interacting the ocean's pH while *in utero* with the spatially-specific initial conditions, proxied by the 1972–1975 (standardized) average pH in the correspondent ocean's raster point. The effect of resource wealth on NMR is systematically larger in locations that have been historically exposed to more acidic waters. Because it is exactly these areas that would have had more time to adjust to acidification shocks, these differences further support lack of adaptation in the long-run.

5 Conclusions

Animal species are under severe pressure from human overexploitation and climate change. We show that the nature's wealth is an important source of insurance for human development, highlighting the need to prioritize the conservation of wildlife and biodiversity. Our results show that this is particularly important for communities that are more dependent on renewable natural resources for survival, and therefore more vulnerable to variation in nature's wealth. United Nations (2012) highlight as priorities to "regulate the industrial fishing sector to protect the access rights of traditional fishing communities" and "introduce exclusive artisanal fishing zones and user rights for small-scale and subsistence fisheries." However, weak natural resource governance in L&MICs complicates the feasibility of these goals.

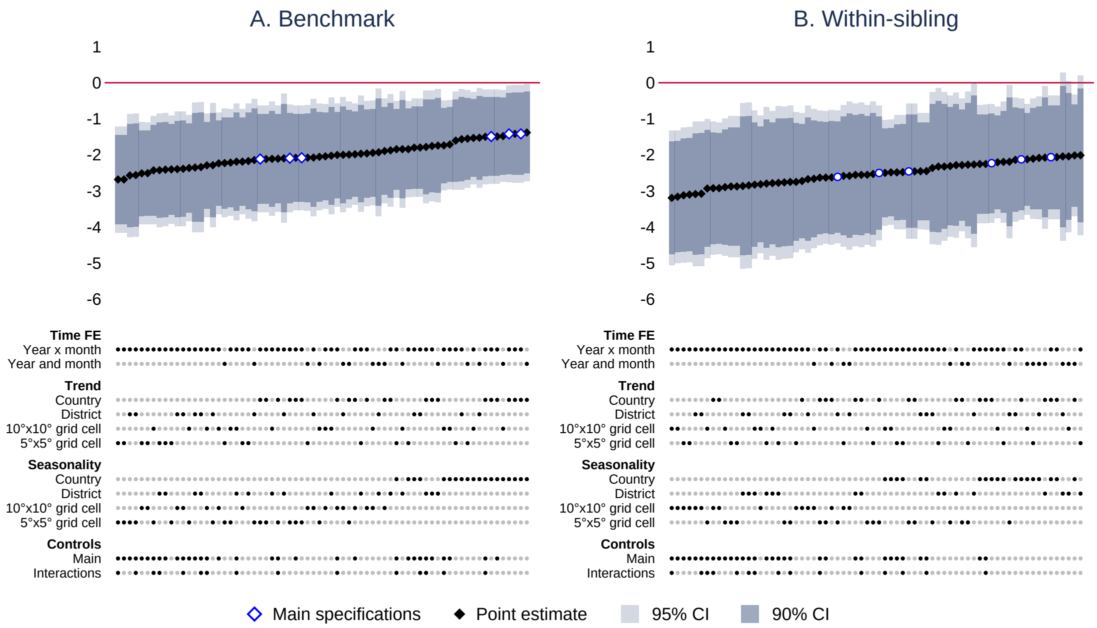
In absence of effective mechanisms to incentivize conservation, policymakers need to channel resources efficiently to the communities that need mitigation support the most. By showing that negative shocks to nature's wealth behave as exogenous reductions in the availability of nutrients that can be consumed, our results provide a rationale for investing in targeted nutritional interventions early in life. These interventions have shown to mitigate not only the short-run consequences of malnutrition, but also its long-term effects (Hoddinott et al., 2013; Gertler et al., 2014). Ocean acidification will impact commercial and subsistence fishing, with negative consequences beyond the short-run effects highlighted in this paper. As the IPCC (2013) predicts a decrease in average ocean's pH at surface of 0.32 units by 2100, we should be wary of large effects, even in the face of improved mitigation capacity.

Figure 1: Selected coastal area



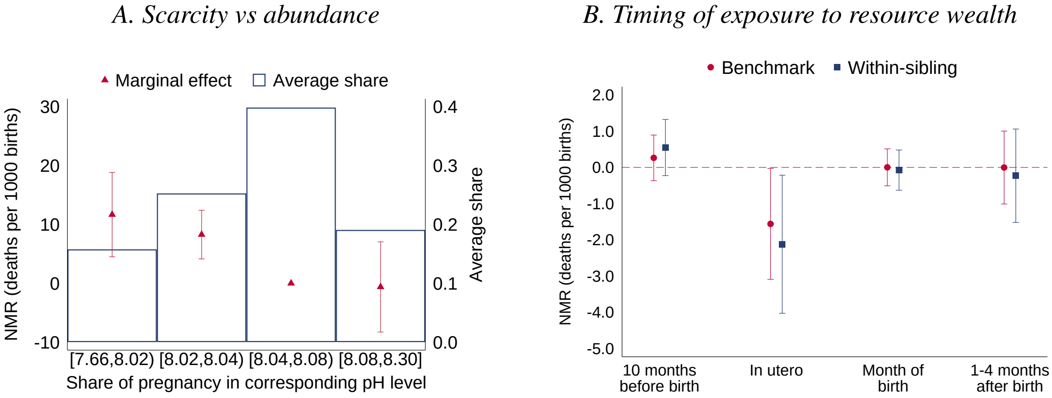
Note. Geographical distribution of selected communities in coastal areas. The shaded area represents all countries surveyed by the DHS with access to the ocean (the full list is reported in Appendix A.1). *Communities in coastal area* are villages and neighborhoods within 100 km from the ocean's shore. *Inland communities* are villages and neighborhoods further than 100 km from the ocean's shore. Appendix A.2 details the procedure followed to compute distance from shore.

Figure 2: The effect on neonatal mortality – alternative specifications



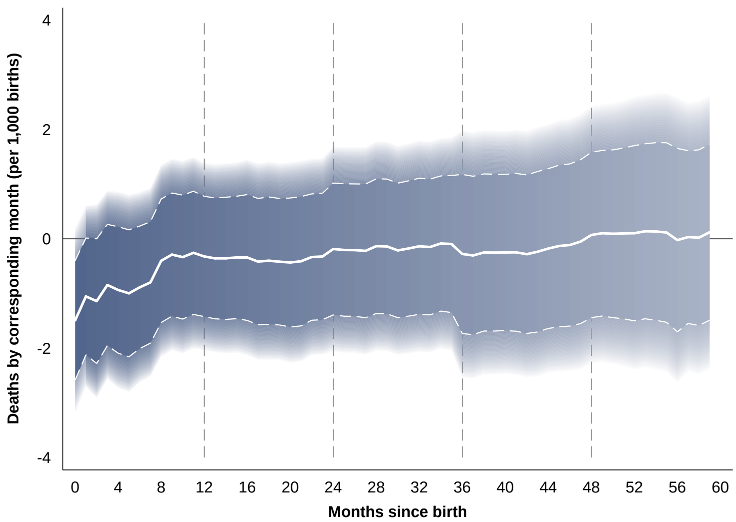
Note. Marginal effect of resource wealth under alternative sets of FEs in the benchmark specification (*Panel A*), and in the within-sibling specification (*Panel B*). The dependent variable is a dummy variable equal to 1 if the child died within the first month of life and 0 if the child survived, multiplied by 1,000. *Resource wealth* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. Marginal effects are estimated using equation (1) with the set of FEs and controls reported in the bottom panel. *Main specifications* are the ones used in Table 2. The sample is restricted to coastal areas (see Section 1). Standard errors are clustered at the ocean raster data point. Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures. *Main controls* are the weather and demographic controls (see Section 2). *Interactions* are interaction terms between the birth month and indicator variables for different oceans.

Figure 3: Resource wealth and neonatal mortality: type and timing of exposure



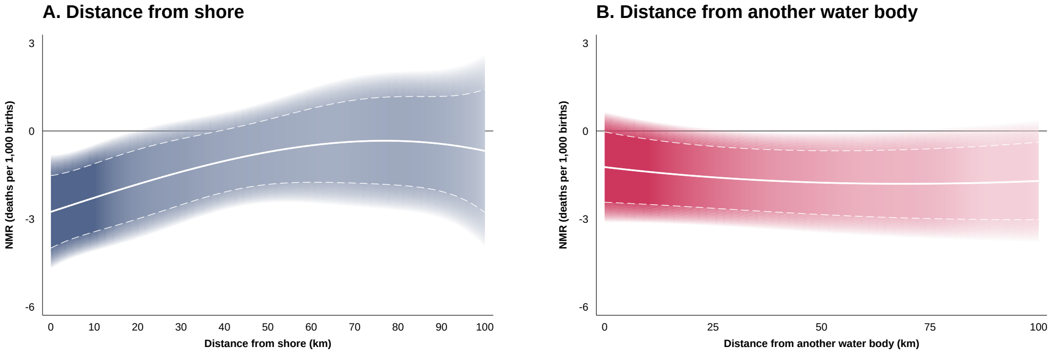
Note. Marginal effects of resource wealth by type of shock (*Panel A*), and by timing of exposure (*Panel B*). In *Panel A*, estimates are based on equation (1) where resource wealth is substituted by the share of time children were exposed *in utero* to different levels of the ocean's pH. We classify values in four bins, with the third including the historical median and mean of pH in sampled areas. The lowest and highest values in the range are the historical minimum and maximum in the sample. For each bin, the right vertical axis presents the average share of pregnancy in the corresponding bin. In *Panel B*, estimates are based on equation (1), in which *resource wealth* at different points in time, is the pH (multiplied by a factor of 100) in the ocean's cell closest to the individual's community in the corresponding period relative to birth; when the period refers to multiple months, the value is averaged. In both panels, the dependent variable is *NMR*, a dummy variable equal to 1 if the child died within the first month of life and 0 if the child survived, multiplied by 1,000. Estimates are based on the benchmark specification (see Section 2). The sample is restricted to the coastal area (see Section 1). Confidence intervals at 90% level. Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

Figure 4: The effect on mortality early in life



Note. Marginal effect of resource wealth experienced *in utero* on the probability to die. The dependent variable is a dummy variable equal to one if the child is dead at time x from birth, and zero if the child is alive, and it is multiplied by 1,000. The 90% confidence interval is indicated by dotted lines, beyond which the intervals are progressively shaded up to the 99% level. Within confidence bounds, darker colors indicate a larger number of observations (see Appendix A.3). Estimates are based on equation (1) including community FEs, birth month by birth year FEs, country by birth year FEs, country by birth month FEs, and control variables (see Section 2). Standard errors are clustered at the ocean raster data point. Appendix A.1 provides further information on the variables and for the list of surveys included in the study.

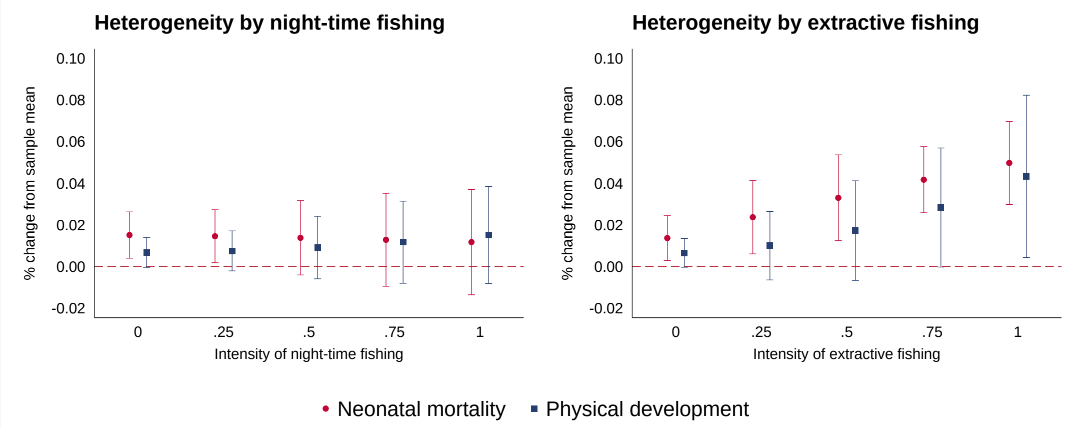
Figure 5: Early-life mortality and dependence on water bodies



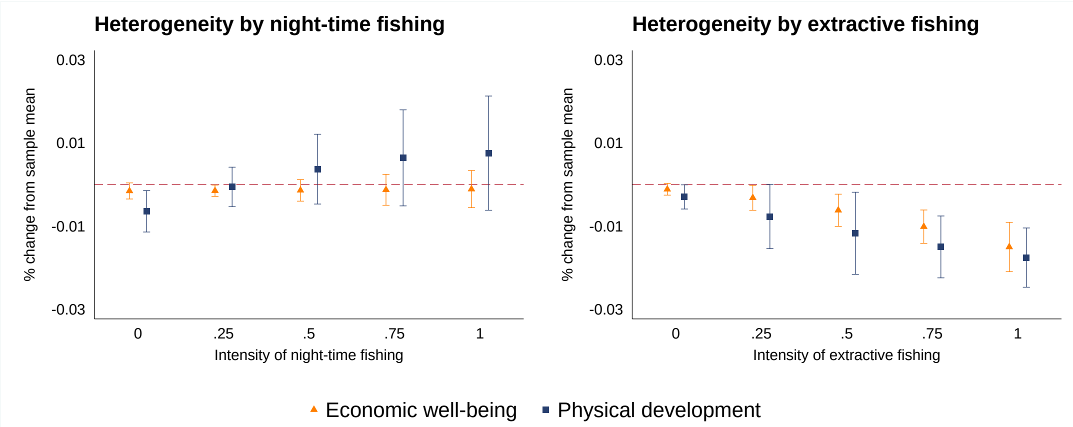
Note. Marginal effect of resource wealth on NMR as a function of distance from the shore (*Panel A*), and of distance from another water body (*Panel B*). The dependent variable is a dummy variable equal to 1 if the child died within the first month of life and 0 if the child survived, multiplied by 1,000. *Resource wealth* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. Estimates are based on equation (1) introducing interactions between the shock and a cubic polynomial in distance. The specification includes community FEs, birth month by birth year FEs, country by birth year FEs, country by birth month FEs, and control variables (see Section 2). The sample is restricted to the coastal area (see Section 1). Standard errors are clustered at the ocean raster data point. The 90% confidence interval is indicated by dotted lines, beyond which the intervals are progressively shaded up to the 99% level. Within confidence bounds, darker colors indicate a larger number of observations (see Appendix A.3). Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

Figure 6: Scarcity shocks and resource exploitation

A. Short-run effects (all children)



B. Long-run effects (female)



Note. Estimated impacts of a one-standard-deviation increase in acidity (scarcity shock) on short-run indicators (*Panel A*), and on long-run indicators (*Panel B*) as a function of intensity of fishing. Intensities range between 0 (no presence) and 1 (high). Estimates based on equation (1) introducing interaction terms between resource wealth and a quadratic polynomial in the corresponding intensity. Panel A includes the sample of all children, while Panel B includes the sample of women. *Neonatal mortality* is a dummy variable equal to 1 if the child died within the first month of life and 0 if the child survived, multiplied by 1,000. *Physical development* is the average z-score of available anthropometric measures. *Economic well-being* is a household-level asset-based index which ranges from 1 (poorest) to 5 (richest). A *scarcity shock*, i.e., a one-standard-deviation decrease in resource wealth experienced while *in utero*. *Resource wealth* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the individual's community during the 9 months before birth. The sample is restricted to coastal areas (see Section 1). Standard errors are clustered at the ocean raster data point. Confidence intervals at 90% level. All specifications include community FEs, birth year by birth month FEs, country by birth year FEs, country by birth month FEs, and control variables (see Section 2). Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures. We exclude surveys for Peru as information for the intensity of night-time fishing is not available (see Appendix A.1).

Table 1: Descriptive statistics

	Mean	Std. dev.	Percentiles			N
			1st	Median	99th	
	(1)	(2)	(3)	(4)	(5)	(6)
A. Children						
Child is alive	0.92	0.27	0.00	1.00	1.00	1,587,285
Child is female	0.48	0.50	0.00	0.00	1.00	1,587,285
Birth order	2.54	1.81	1.00	2.00	9.00	1,587,285
Number of twins born with the child	0.03	0.23	0.00	0.00	2.00	1,587,285
Years since birth	12.28	7.87	0.25	11.50	30.25	1,587,285
Mother's age at birth	24.43	5.77	14.25	23.58	40.00	1,587,285
Ocean's pH (*in utero*)	8.05	0.03	7.99	8.05	8.13	1,587,285
B. Adult women						
Age at first delivery	20.57	3.91	13.17	20.08	31.83	303,786
Current age	26.89	7.59	15.17	26.08	42.67	500,685
Years of schooling	7.66	4.69	0.00	8.00	17.00	435,839
Ocean's pH (*in utero*)	8.07	0.03	8.02	8.07	8.14	499,140
Primary education or less	0.35	0.48	0.00	0.00	1.00	500,661
Married	0.62	0.49	0.00	1.00	1.00	500,684
No children	0.38	0.48	0.00	0.00	1.00	500,685
Working	0.50	0.50	0.00	0.00	1.00	418,712
Household head is female	0.22	0.41	0.00	0.00	1.00	500,685
Household head's age	45.31	13.72	21.00	44.00	80.00	500,246
Household members	5.69	3.05	2.00	5.00	17.00	500,685
Household wealth	3.73	1.26	1.00	4.00	5.00	471,824
Living in urban area	0.53	0.50	0.00	1.00	1.00	500,685
Distance from shore	31.56	30.44	0.16	20.11	97.42	500,685
Distance from another water body	48.40	104.68	0.18	18.73	582.04	500,685
Altitude	187.77	407.29	1.00	37.00	2,234.00	500,685
Temperature (° C)	26.28	3.04	15.79	27.15	31.22	500,685
Precipitations (mm)	1,562.45	649.53	113.10	1,546.41	3,095.58	500,685
Intensity of extractive fishing	0.07	0.21	0.00	0.00	0.86	500,685
Intensity of nightlight fishing	0.08	0.18	0.00	0.02	0.53	500,685
C. Mortality rates						
Neonatal	27.51	163.55	0.00	0.00	1,000.00	1,583,731
Postneonatal	23.67	152.02	0.00	0.00	1,000.00	1,470,093
Child	21.69	145.68	0.00	0.00	1,000.00	1,141,371
Infant	50.66	219.30	0.00	0.00	1,000.00	1,516,640
Under-five	74.22	262.12	0.00	0.00	1,000.00	1,217,000

Note. The sample is restricted to coastal areas (see Section 1). Variables for antenatal and delivery care are restricted to the last birth for cross-survey comparability. Early-childhood mortality rates indicators are defined in Appendix A.1. Appendix A.2 provides further information about the computation of distances. *Years since birth* is measured at the time of the interview and is independent from the child being alive. *Mortality rates* are relative to 1,000 live births. *Ocean's pH (in utero)* is the average pH in the ocean's cell closest to an individual's community during the 9 months before birth; it refers to the date of birth of the child in Panel A and to the date of birth of the woman in Panel B. *Altitude*, *temperature*, *precipitations*, *intensity of fishing* refer to the community where the adult woman lives. Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

Table 2: The effect on neonatal mortality

Dependent variable:	**Neonatal Mortality Rate (deaths per 1,000 births)**					
	(1)	(2)	(3)	(4)	(5)	(6)
A. Benchmark specification						
Resource wealth	-1.417	-1.419	-1.491	-2.117	-2.094	-2.083
	(0.691)	(0.683)	(0.664)	(0.754)	(0.761)	(0.738)
	[0.041]	[0.038]	[0.025]	[0.005]	[0.006]	[0.005]
Mean (dep.var.)	30.473	30.473	30.474	30.474	30.474	30.475
Identifying observations	1,583,706	1,583,706	1,581,815	1,583,703	1,583,703	1,581,812
Singleton observations	25	25	25	28	28	28
Communities	31,380	31,380	31,380	31,380	31,380	31,380
Countries	36	36	36	36	36	36
Birth year range	1972–2018	1972–2018	1972–2018	1972–2018	1972–2018	1972–2018
B. Within-sibling specification						
Resource wealth	-2.065	-2.126	-2.232	-2.459	-2.502	-2.612
	(0.874)	(0.855)	(0.838)	(0.953)	(0.951)	(0.935)
	[0.019]	[0.013]	[0.008]	[0.010]	[0.009]	[0.005]
Mean (dep.var.)	31.476	31.476	31.476	31.476	31.476	31.476
Identifying observations	1,474,945	1,474,945	1,474,945	1,474,941	1,474,941	1,474,941
Singleton observations	108,786	108,786	108,786	108,790	108,790	108,790
Communities	31,356	31,356	31,356	31,356	31,356	31,356
Countries	36	36	36	36	36	36
Birth year range	1972–2018	1972–2018	1972–2018	1972–2018	1972–2018	1972–2018
Weather controls	-	Yes	Yes	-	Yes	Yes
Demographic controls	-	-	Yes	-	-	Yes
Seasonality	Country	Country	Country	Cell	Cell	Cell

Note. Estimates based on equation (1). The dependent variable is a dummy variable equal to 1 if the child died within the first month of life and 0 if the child survived, multiplied by 1,000. *Resource wealth* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. The sample is restricted to coastal areas (see Section 1). Standard errors (in parenthesis) are clustered at the ocean raster data point, p-values are reported in brackets. All specifications include community FEs, birth year by birth month FEs, country by birth year FEs. Seasonality is captured by either country by birth month FEs or 5°×5° cell by birth month FEs. The full list of controls is presented in Section 2. Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

Table 3: The short- and long-run effect on physical development

Dependent variables:	Physical development	Z-scores		Indicators	
		W/h	H/a	Wasted	Stunted
	(1)	(2)	(3)	(4)	(5)
A. Short-run effects					
Resource wealth	-0.018	-0.021	-0.012	0.006	0.004
	(0.010)	(0.016)	(0.015)	(0.003)	(0.004)
	[0.090]	[0.191]	[0.407]	[0.091]	[0.285]
Mean (dep.var.)	-0.650	-0.309	-0.984	0.080	0.234
Identifying observations	234,877	232,339	232,575	232,339	232,575
Singleton observations	1,111	1,106	1,124	1,106	1,124
Communities	25,126	24,824	25,110	24,824	25,110
Countries	33	33	33	33	33
Birth year range	1985–2018	1985–2018	1985–2018	1985–2018	1985–2018
B. Short-run effects (female)					
Resource wealth	0.006	-0.014	0.024	-0.004	-0.013
	(0.014)	(0.019)	(0.020)	(0.007)	(0.006)
	[0.688]	[0.446]	[0.227]	[0.595]	[0.037]
Mean (dep.var.)	-0.616	-0.285	-0.942	0.076	0.227
Identifying observations	112,312	111,095	111,157	111,095	111,157
Singleton observations	3,541	3,508	3,577	3,508	3,577
Communities	21,111	20,843	21,052	20,843	21,052
Countries	33	33	33	33	33
Birth year range	1985–2018	1985–2018	1985–2018	1985–2018	1985–2018
C. Long-run effects (female)					
Resource wealth	0.009	0.011	0.010	0.000	-0.007
	(0.004)	(0.007)	(0.005)	(0.001)	(0.003)
	[0.036]	[0.133]	[0.069]	[0.988]	[0.022]
Mean (dep.var.)	-0.860	-0.310	-1.386	0.082	0.301
Identifying observations	327,145	324,160	327,124	324,160	327,124
Singleton observations	683	554	683	554	683
Communities	22,848	22,635	22,848	22,635	22,848
Countries	32	32	32	32	32
Birth year range	1972–2003	1972–2003	1972–2003	1972–2003	1972–2003

Note. Estimates based on equation (1). Dependent variables are reported in the column's header. *Physical development* is the average z-score of available anthropometric measures. *W/h* (weight-for-height) and *h/w* (height-for-age) are z-scores from a reference scale. *Wasted* is an indicator variable equal to 1 for an for an abnormally low weight-for-height. *Wasted* is an indicator variable equal to 1 for an for an abnormally low weight-for-height. *Stunted* is an indicator variable equal to 1 for an abnormally low height-for-age, and 0 otherwise. *Resource wealth* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the individual's community during the 9 months before the birth of the child (Panels A and B) or the woman (Panel C). The sample is restricted to coastal areas (see Section 1). Standard errors (in parenthesis) are clustered at the ocean raster data point, p-values are reported in brackets. In Panels A and B, specifications include community FEs, birth year by birth month FEs, country by birth year FEs, country by birth month FEs, and control variables. In Panel C, specifications include community FEs, woman's birth year by woman's birth month FEs, country by woman's birth year FEs, country by mother's birth month FEs, and control variables (see Section 2). Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures. All panels exclude the survey(s) for Indonesia, Pakistan, and the Philippines because information is not available in the correspondent surveys. Panel C further excludes the survey for Angola for the same reasons.

Table 4: The long-run effects on economic well-being

Dependent variables:	**Economic well-being**	**Correlates of economic well-being**				
		Fertility	Schooling	Cognitive skills	Labor supply	
	(1)	(2)	(3)	(4)	(5)	(6)
Resource wealth	0.016	-0.008	0.030	0.000	0.006	0.014
	(0.009)	(0.004)	(0.034)	(0.002)	(0.004)	(0.007)
	[0.062]	[0.049]	[0.389]	[0.951]	[0.130]	[0.036]
Mean (dep.var.)	3.096	1.552	7.183	0.771	0.425	0.513
Identifying observations	212,741	497,982	433,480	414,000	429,173	190,665
Singleton observations	1,161	536	538	794	549	2,256
Communities	25,432	30,429	27,878	26,824	27,859	24,720
Countries	36	36	36	36	36	36
Birth year range	1972–2003	1972–2003	1972–2003	1972–2003	1972–2003	1972–2003
Women in the household (sample)	Main	All	All	All	All	Main

Note. Estimates based on equation (1). The dependent variables are reported in the column's header. *Economic well-being* is a household-level asset-based index which ranges from 1 (poorest) to 5 (richest). *Fertility* is the number of births per woman. *Schooling* is the number of completed years of education. *Cognitive skills* is an indicator variable equal to 1 if the respondent is able to read a whole sentence in her native language or has completed at least secondary schooling, and 0 otherwise. *Labor supply* is an indicator variable equal to 1 if the respondent is working at the time of the interview, and 0 otherwise. *Resource wealth* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the woman's community during the 9 months before her birth. The sample is restricted to coastal areas (see Section 1), and in columns (5)–(6) to women in the household that are household head or their partner. Standard errors (in parenthesis) are clustered at the ocean raster data point, p-values are reported in brackets. All specifications include community FEs, woman's birth year by woman's birth month FEs, country by woman's birth year FEs, country by woman's birth month FEs, and control variables (see Section 2). Column (2)–(4) have a reduced number of observations because, for comparability of estimates, we include only the random sub-sample of women that completed both the education and the work modules. Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

Table 5: The effect on nightlight luminosity in the coastal area

Dependent variable:	**Nightlight luminosity (per 100,000 inhabitants)**					
	(1)	(2)	(3)	(4)	(5)	(6)
Negative resource shock (ocean)	-0.001	-0.002			-0.001	-0.002
	(0.002)	(0.003)			(0.002)	(0.003)
	[0.765]	[0.468]			[0.780]	[0.447]
Drought			-0.019	-0.021	-0.019	-0.021
			(0.010)	(0.010)	(0.010)	(0.010)
			[0.055]	[0.040]	[0.055]	[0.040]
Mean (dep.var.)	0.080	0.080	0.081	0.081	0.081	0.081
Identifying observations	30,864	30,864	30,570	30,570	30,570	30,570
Singleton observations	229	229	229	229	229	229
Grid cells	1,470	1,470	1,456	1,456	1,456	1,456
Year range	1992–2012	1992–2012	1992–2012	1992–2012	1992–2012	1992–2012
Controls	-	Yes	-	Yes	-	Yes

Note. Estimates based on equation (2). The dependent variable is the satellite-based nightlight luminosity at year t in the corresponding grid cell i. Luminosity ranges between 0 (lowest) and 1 (highest), and is normalized by population in the cell. *Negative resource shock (ocean)* is an indicator variable taking value one when the yearly average pH in the nearest open ocean's waters is below the 15$^{\text{th}}$ percentile of the grid cell i's historical distribution. *Drought* is an indicator variable taking value 1 when annual rainfall in the grid cell is below the 15$^{\text{th}}$ percentile of the grid cell i's historical rainfall distribution. All specifications include grid cell FEs and $5°\times5°$ cell by year FEs. *Controls* include the levels of rainfall and temperature, oxygen concentration in the nearest coastal waters, population size and its square value. The sample includes only grid cells in coastal areas where at least one DHS community is found (see Section 1). Appendix A.1 provides further information on the variables, and the list of surveys included in the study.

Table 6: Behavioral adaptation and health investments

Dependent variables:	Antenatal investment	Delivery investment	Postnatal investment		
			Healthcare	Breastfed	Vaccinated
	(1)	(2)	(3)	(4)	(5)
Resource shock	0.004	-0.004	0.004	0.001	-0.005
	(0.007)	(0.004)	(0.009)	(0.003)	(0.005)
	[0.590]	[0.374]	[0.630]	[0.691]	[0.317]
Mean (dep.var.)	1.698	1.299	0.441	0.972	0.293
Identifying observations	263,697	256,548	101,075	206,350	210,372
Singleton observations	1,100	1,191	3,078	2,336	2,212
Communities	29,942	29,822	18,445	28,029	27,964
Countries	36	36	34	36	36
Birth year range	1985–2018	1985–2018	2002–2018	1987–2018	1987–2018

Note. Estimates based on equation (1). The dependent variables are reported in the column's header. *Antenatal investment* and *delivery investment* range from 0 (no investment) to 2 (larger investment). For postnatal investment, *healthcare* is an indicator variable equal to 1 if the mother or the child younger than 2 years old received postnatal care within 2 days of birth. *Breastfed* is an indicator variable equal to 1 if the mother reports ever breastfeeding the child, and 0 otherwise. *Vaccinated* is an indicator variable equal to 1 if the mother reports or the vaccination card shows the completion of the basic cycle of vaccinations according to the World Health Organization (WHO), and 0 otherwise. For cross-survey comparability, the sample for variables relative to antenatal and delivery investments and to postnatal healthcare is restricted to the last birth, independently from the child being alive at the time of the interview. For the remaining variables, the sample is restricted to living children under three years old and can therefore be affected by mortality selection. *Resource wealth* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. The sample is restricted to coastal areas (see Section 1). Standard errors (in parenthesis) are clustered at the ocean raster data point, p-values are reported in brackets. For cross-survey comparability, the sample in columns (1)–(3) is restricted to the last birth, independently from the child being alive, while in columns (4)–(5) is restricted to living children under three years old. All specifications include community FEs, birth year by birth month FEs, country by birth year FEs, country by birth month FEs, and control variables (see Section 2). Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures. Column (3) excludes the survey(s) for Indonesia and Morocco because information is not available in the corresponding surveys.

Table 7: Market prices and early-life mortality

Dependent variable:	Neonatal Mortality Rate (deaths per 1,000 births)				
	(1)	(2)	(3)	(4)	(5)
Resource shock	-4.887		-4.997	-4.643	-4.728
	(2.620)		(2.630)	(2.629)	(2.685)
	[0.064]		[0.059]	[0.079]	[0.080]
Fish price (*in utero*)		7.274	7.361	7.243	7.580
		(3.445)	(3.443)	(3.436)	(3.368)
		[0.036]	[0.034]	[0.036]	[0.026]
Mean (dep.var.)	15.410	15.410	15.410	15.410	15.412
Identifying observations	82,739	82,739	82,739	82,739	82,730
Singleton observations	9	9	9	9	9
Communities	2,751	2,751	2,751	2,751	2,751
Countries	1	1	1	1	1
Birth year range	1990–2017	1990–2017	1990–2017	1990–2017	1990–2017
Weather controls	-	-	-	Yes	Yes
Demographic controls	-	-	-	-	Yes

Note. Estimates based on equation (1) using the benchmark specification. The dependent variable is an indicator variable equal to 1 if the child died within the first month of life and 0 if the child survived, multiplied by 1,000. *Resource wealth* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. Fish price (*in utero*) is the average fish price (including all available prices and reported in logarithms) in the province of birth of the child during the 9 months before birth. The sample is restricted to communities in the coastal area of the Philippines (see Section 1) and to the period 1990–2018 (due to data availability; see Appendix B.11). Standard errors are reported in parenthesis and clustered at the district by ocean raster data point, p-values are reported in brackets. All specifications include community FEs, birth year by birth month FEs, district by birth year FEs, and district by birth month FEs. The full list of controls is presented in Section 2. Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

References

ADHVARYU, A., P. BHARADWAJ, J. FENSKE, ET AL. (2020): "Dust and death: evidence from the West African Harmattan," *The Economic Journal*, forthcoming.

ADHVARYU, A. AND A. NYSHADHAM (2016): "Endowments at birth and parents' investments in children," *The Economic Journal*, 126, 781–820.

ALESINA, A., S. HOHMANN, S. MICHALOPOULOS, AND E. PAPAIOANNOU (2021): "Intergenerational mobility in Africa," *Econometrica*, 89, 1–35.

ALMOND, D., J. CURRIE, AND V. DUQUE (2018): "Childhood circumstances and adult outcomes: Act II," *Journal of Economic Literature*, 56, 1360–1446.

ALMOND, D. AND B. MAZUMDER (2011): "Health capital and the prenatal environment: the effect of Ramadan observance during pregnancy," *American Economic Journal: Applied Economics*, 3, 56–85.

ARCEO, E., R. HANNA, AND P. OLIVA (2016): "Does the effect of pollution on infant mortality differ between developing and developed countries? Evidence from Mexico City," *The Economic Journal*, 126, 257–280.

ATTANASIO, O., S. CATTAN, E. FITZSIMONS, ET AL. (2020): "Estimating the production function for human capital: results from a randomized controlled trial in Colombia," *American Economic Review*, 110, 48–85.

AUFFHAMMER, M. (2018): "Quantifying economic damages from climate change," *Journal of Economic Perspectives*, 32, 33–52.

AXBARD, S. (2016): "Income opportunities and sea piracy in Indonesia: Evidence from satellite data," *American Economic Journal: Applied Economics*, 8, 154–94.

BAIRD, S., J. FRIEDMAN, AND N. SCHADY (2011): "Aggregate income shocks and infant mortality in the developing world," *Review of Economics and Statistics*, 93, 847–856.

BARRECA, A., K. CLAY, O. DESCHÊNES, ET AL. (2016): "Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over the twentieth century," *Journal of Political Economy*, 124, 105–159.

BARRETT, C. B., A. J. TRAVIS, AND P. DASGUPTA (2011): "On biodiversity conservation and poverty traps," *Proceedings of the National Academy of Sciences*, 108, 13907–13912.

BARRIOS, S., L. BERTINELLI, AND E. STROBL (2010): "Trends in Rainfall and Economic Growth in Africa: A Neglected Cause of the African Growth Tragedy," *The Review of Economics and Statistics*, 92, 350–366.

BERTHELON, M., D. KRUGER, AND R. SANCHEZ (2021): "Maternal stress during pregnancy and early childhood development," *Economics & Human Biology*, 43, 101047.

BHALOTRA, S. (2010): "Fatal fluctuations? Cyclicality in infant mortality in India," *Journal of Development Economics*, 93, 7–19.

BIANCHI, D., D. A. CAROZZA, E. D. GALBRAITH, ET AL. (2021): "Estimating global biomass and biogeochemical cycling of marine fish with and without fishing," *Science advances*, 7, eabd7554.

BLACK, R. E., C. G. VICTORA, S. P. WALKER, ET AL. (2013): "Maternal and child undernutrition and overweight in low-income and middle-income countries," *The Lancet*, 382, 427 – 451.

BLACK, S. E., A. BÜTIKOFER, P. J. DEVEREUX, AND K. G. SALVANES (2019): "This is only a test? Long-run and intergenerational impacts of prenatal exposure to radioactive fallout," *Review of Economics and Statistics*, 101, 531–546.

BRUEDERLE, A. AND R. HODLER (2018): "Nighttime lights as a proxy for human development at the local level," *PloS one*, 13, e0202231.

BURGESS, R., M. HANSEN, B. A. OLKEN, ET AL. (2012): "The political economy of deforestation in the tropics," *The Quarterly Journal of Economics*, 127, 1707–1754.

BURKE, M. AND K. EMERICK (2016): "Adaptation to Climate Change: Evidence from US Agriculture," *American Economic Journal: Economic Policy*, 8, 106–40.

CAMERON, A. C., J. B. GELBACH, AND D. L. MILLER (2011): "Robust inference with multiway clustering," *Journal of Business & Economic Statistics*, 29, 238–249.

CHAY, K. Y. AND M. GREENSTONE (2003): "The impact of air pollution on infant mortality: Evidence from geographic variation in pollution shocks induced by a recession," *The Quarterly Journal of Economics*, 118, 1121–1167.

CLARK, C. W. (1973): "Profit maximization and the extinction of animal species," *Journal of Political Economy*, 81, 950–961.

COLLIER, P. (2010): *The plundered planet: Why we must–and how we can–manage nature for global prosperity*, Oxford University Press.

COLT, S. G. AND G. P. KNAPP (2016): "Economic effects of an ocean acidification catastrophe," *American Economic Review*, 106, 615–19.

CORNO, L., N. HILDEBRANDT, AND A. VOENA (2020): "Age of marriage, weather shocks, and the direction of marriage payments," *Econometrica*, 88, 879–915.

CROFT, T. N., A. M. J. MARSHALL, AND C. K. ALLEN (2018): "Guide to DHS Statistics," Demographic and Health Surveys Program.

DALGAARD, C.-J., A. S. KNUDSEN, AND P. SELAYA (2020): "The Bounty of the Sea and Long-run development," *Journal of Economic Growth*, 25, 259–295.

DASGUPTA, P. (2021): "The Economics of Biodiversity: The Dasgupta Review," Tech. rep., London: HM Treasury.

DEATON, A. (2007): "Height, health, and development," *Proceedings of the national academy of sciences*, 104, 13232–13237.

DELL, M., B. F. JONES, AND B. A. OLKEN (2014): "What do we learn from the weather? The new climate-economy literature," *Journal of Economic Literature*, 52, 740–98.

DESCHÊNES, O. AND M. GREENSTONE (2011): "Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US," *American Economic Journal: Applied Economics*, 3, 152–85.

DESCHÊNES, O. AND E. MORETTI (2009): "Extreme weather events, mortality, and migration," *The Review of Economics and Statistics*, 91, 659–681.

DONEY, S. C., D. S. BUSCH, S. R. COOLEY, AND K. J. KROEKER (2020): "The Impacts of Ocean Acidification on Marine Ecosystems and Reliant Human Communities," *Annual Review of Environment and Resources*, 45.

ELVIDGE, C. D., M. ZHIZHIN, K. BAUGH, AND F.-C. HSU (2015): "Automatic boat identification system for VIIRS low light imaging data," *Remote sensing*, 7, 3020–3036.

FAO (2020a): "Fish and human nutrition," Food and Agriculture Organization of the United Nations.

——— (2020b): *The State of World Fisheries and Aquaculture*, Food and Agriculture Organization of the United Nations. Fisheries Department.

FEELY, R. A., C. L. SABINE, J. M. HERNANDEZ-AYON, ET AL. (2008): "Evidence for upwelling of corrosive "acidified" water onto the continental shelf," *Science*, 320, 1490–1492.

GELCICH, S., P. BUCKLEY, J. K. PINNEGAR, ET AL. (2014): "Public awareness, concerns, and priorities about anthropogenic impacts on marine environments," *Proceedings of the National Academy of Sciences*, 111, 15042–15047.

GERTLER, P., J. HECKMAN, R. PINTO, ET AL. (2014): "Labor market returns to an early childhood stimulation intervention in Jamaica," *Science*, 344, 998–1001.

GERUSO, M. AND D. SPEARS (2018a): "Heat, Humidity, and Infant Mortality in the Developing World," NBER working paper no. 24870, National Bureau of Economic Research.

——— (2018b): "Neighborhood sanitation and infant mortality," *American Economic Journal: Applied Economics*, 10, 125–62.

GOLDEN, C. D., E. H. ALLISON, W. W. CHEUNG, ET AL. (2016): "Nutrition: Fall in fish catch threatens human health," *Nature News*, 534, 317.

GRÖGER, A. AND Y. ZYLBERBERG (2016): "Internal Labor Migration as a Shock Coping Strategy: Evidence from a Typhoon," *American Economic Journal: Applied Economics*, 8, 123–153.

HEFT-NEAL, S., J. BURNEY, E. BENDAVID, AND M. BURKE (2018): "Robust relationship between air quality and infant mortality in Africa," *Nature*, 559, 254.

HENDERSON, J. V., A. STOREYGARD, AND D. N. WEIL (2012): "Measuring economic growth from outer space," *American Economic Review*, 102, 994–1028.

HEUTEL, G., N. H. MILLER, AND D. MOLITOR (2017): "Adaptation and the mortality effects of temperature across US climate regions," NBER working paper no. 23271, National Bureau of Economic Research.

HICKS, C. C., P. J. COHEN, N. A. GRAHAM, ET AL. (2019): "Harnessing global fisheries to tackle micronutrient deficiencies," *Nature*, 574, 95–98.

HODDINOTT, J., H. ALDERMAN, J. R. BEHRMAN, ET AL. (2013): "The economic rationale for investing in stunting reduction," *Maternal & child nutrition*, 9, 69–82.

HSIANG, S. M. AND A. S. JINA (2014): "The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones," NBER working paper no. 20352, National Bureau of Economic Research.

HUANG, L. AND M. D. SMITH (2014): "The Dynamic Efficiency Costs of Common-Pool Resource Exploitation," *American Economic Review*, 104, 4071–4103.

IPCC (2013): "Working group I contribution to the Intergovernmental Panel on Climate Change Fifth Assessment Report Climate Change 2013: The Physical Science Basis," Summary for Policymakers - IPCC WGI AR5.

Isen, A., M. Rossin-Slater, and W. R. Walker (2017): "Every breath you take—every dollar you'll make: The long-term consequences of the clean air act of 1970," *Journal of Political Economy*, 125, 848–902.

Jayachandran, S. (2013): "Liquidity constraints and deforestation: The limitations of payments for ecosystem services," *American Economic Review*, 103, 309–13.

Jean, N., M. Burke, M. Xie, et al. (2016): "Combining satellite imagery and machine learning to predict poverty," *Science*, 353, 790–794.

Jensen, R. (2007): "The digital provide: Information (technology), market performance, and welfare in the South Indian fisheries sector," *The Quarterly Journal of Economics*, 122, 879–924.

Keeling, R. F., A. Körtzinger, and N. Gruber (2010): "Ocean Deoxygenation in a Warming World," *Annual Review of Marine Science*, 2, 199–229, pMID: 21141663.

Kremer, M. and C. Morcom (2000): "Elephants," *American Economic Review*, 90, 212–234.

Kroodsma, D. A., J. Mayorga, T. Hochberg, et al. (2018): "Tracking the global footprint of fisheries," *Science*, 359, 904–908.

Kudamatsu, M. (2012): "Has democratization reduced infant mortality in Sub-Saharan Africa? Evidence from micro data," *Journal of the European Economic Association*, 10, 1294–1317.

Maire, E., N. A. Graham, M. A. MacNeil, et al. (2021): "Micronutrient supply from global marine fisheries under climate change and overfishing," *Current Biology*, 31, 4132–4138.

Majid, M. F. (2015): "The persistent effects of in utero nutrition shocks over the life cycle: Evidence from Ramadan fasting," *Journal of Development Economics*, 117, 48–57.

MALTHUS, T. R. (1872): *An Essay on the Principle of Population.*

MCGOVERN, M. E., A. KRISHNA, V. M. AGUAYO, AND S. SUBRAMANIAN (2017): "A review of the evidence linking child stunting to economic outcomes," *International journal of epidemiology*, 46, 1171–1191.

MILLER, D. L., N. SHENHAV, AND M. Z. GROSZ (2021): "Selection into identification in fixed effects models, with application to Head Start," *Journal of Human Resources*, forthcoming.

NOUSSAIR, C. N., D. VAN SOEST, AND J. STOOP (2015): "Cooperation in a Dynamic Fishing Game: A Framed Field Experiment," *American Economic Review*, 105, 408–13.

PAULY, D. AND D. ZELLER (2016): "Catch reconstructions reveal that global marine fisheries catches are higher than reported and declining," *Nature Communications*, 7, 10244.

PAXSON, C. AND N. SCHADY (2005): "Child health and economic crisis in Peru," *The World Bank Economic Review*, 19, 203–223.

RAZZAQUE, A., N. ALAM, L. WAI, AND A. FOSTER (1990): "Sustained Effects of the 1974–5 Famine on Infant and Child Mortality in a Rural Area of Bangladesh," *Population Studies*, 44, 145–154, pMID: 11612523.

SABIA, R., D. FERNÁNDEZ-PRIETO, J. SHUTLER, ET AL. (2015): "Remote sensing of surface ocean PH exploiting sea surface salinity satellite observations," in *2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*, 106–109.

SALA, E., J. MAYORGA, D. BRADLEY, ET AL. (2021): "Protecting the global ocean for biodiversity, food and climate," *Nature*, 592, 397–402.

SMITH, V. L. (1969): "On models of commercial fishing," *Journal of Political Economy*, 77, 181–198.

STAVINS, R. N. (2011): "The problem of the commons: still unsettled after 100 years," *American Economic Review*, 101, 81–108.

THE WORLD BANK (2012): “Hidden harvest: The global contribution of capture fisheries,” Report number 66469-glb, The World Bank, FAO, World Fish and Agriculture and Rural Development.

TOTTERDELL, I. (2019): “Description and evaluation of the Diat-HadOCC model v1.0: the ocean biogeochemical component of HadGEM2-ES,” *Geoscientific Model Development*, 12, 4497–4549.

UNITED NATIONS (2003): “Ecosystems and Human Well-Being: A Framework For Assessment.” United Nations, Island Press, Washington DC.

——— (2012): “The right to food - Interim report of the Special Rapporteur on the right to food,” United Nations General Assembly A/67/268 - Sixty-seventh session.

——— (2021): “The role of aquatic foods in sustainable healthy diets,” UN Nutrition Discussion Paper.

VAN DER PLOEG, F. (2011): “Natural resources: curse or blessing?” *Journal of Economic Literature*, 49, 366–420.

VICTORA, C. G., P. CHRISTIAN, L. P. VIDALETTI, ET AL. (2021): “Revisiting maternal and child undernutrition in low-income and middle-income countries: variable progress towards an unfinished agenda,” *The Lancet*.

WAGNER, Z., S. HEFT-NEAL, Z. A. BHUTTA, ET AL. (2018): “Armed conflict and child mortality in Africa: a geospatial analysis,” *The Lancet*, 392, 857–865.

YE, Y. AND N. L. GUTIERREZ (2017): “Ending fishery overexploitation by expanding from local successes to globalized solutions,” *Nature Ecology & Evolution*, 1, 0179.

ONLINE APPENDIX

Supplementary material to *The Effect of Nature's Wealth on Human Development: Evidence from Renewable Resources*

Alex Armand, Ivan Kim Taveras

A Data and methodological procedures

A.1 Variables, data sources, and the selection of DHS surveys

Variable	Description
Altitude	Communities' elevation in meters from the SRTM–Digital Elevation Model for the specified coordinate location. The variable is available in the DHS surveys (ICF, 2019).
Basemaps	Basemaps were created using ArcGIS® software by Esri®. Basemaps are used in line with the Esri Master License Agreement, specifically for the inclusion of screen captures in academic publications. We use the *World Topographic Map*.
Behavioral adaptation	Information is based on parental health investments obtained from the DHS Program (ICF, 2019). We homogenize information across surveys and make use of the following variables: *Antenatal investment* is equal to 0 if no antenatal visit is completed, 1 if at least one visit is completed but without a health professional, and 2 if at least one visit is completed with a health professional. In Appendix B.9, this indicator is split into individual variables. *Any visit* is an indicator variable equal to 1 if the mother attended any visit during pregnancy for antenatal care, and 0 otherwise. *Number of antenatal care visits* is the number of visits attended during pregnancy for antenatal care (reported in logarithms, adding one unit to allow for zero values). *With health professional* is an indicator variable equal to 1 if the mother was attended by a health professional (doctor, nurse or other professional) during pregnancy, and 0 otherwise. *Delivery investment* is equal to 0 if delivery is performed outside a health center without a health professional, 1 if performed outside a health center with a health professional, and 2 if delivery is performed in a health center with a health professional. In Appendix B.9, this indicator is split into individual variables. *In health center* is an indicator variable equal to 1 if the mother gave birth in a health center, and 0 otherwise. *With health professional* is an indicator variable equal to 1 if delivery was attended by a health professional (doctor, nurse or other professional), and 0 otherwise. For *postnatal investment*, *healthcare* is an indicator variable equal to 1 if the mother or the child younger than 2 years old received postnatal care within 2 days of birth. *Breastfed* is an indicator variable equal to 1 if the mother reports ever breastfeeding the child, and 0 if the mother reports to have never breastfed the child. For cross-survey comparability, the sample is restricted to children who live with their mother and are alive, and are less than three years old. *Vaccinated* is an indicator variable equal to 1 if the mother reports or shows a vaccination card for the following doses: BCG, 3 doses of DPT-containing vaccines, 3 doses of polio vaccine (excluding polio vaccine given at birth), and 1 dose of MCV. It is 0 otherwise. The sample is restricted to children under three years old for comparability (Croft et al., 2018).
Child mortality	Information is based on the DHS Program surveys (ICF, 2019). DHS surveys collect respondents' full birth history and includes information on all children's year and month of birth, sex, birth order, whether they are twins, and the date of death when it applies. Note that only live births are recorded. This information is also used to create *age at first delivery*, and *fertility* (the number of live births at the time of the interview). We build mortality rates by multiplying the following indicators by 1,000 (the variables are set to missing if the date of the interview is before the end of the period considered for defining mortality): *Neonatal (NMR)*: indicator equal to 1 if the child died before their first month of life, and 0 otherwise. Note that the DHS Program reports two ages of death. The first is self-reported, while the second gives a calculated age from reported information. When dates of birth are not disclosed, these are imputed by the DHS Program (Croft et al., 2018). We also use 67 special cases of self-reported age of death (198 and 199, which indicate that age at death was reported as a number of days and that the exact number is unknown), but results are robust to dropping these cases. *Post-neonatal (PMR)*: indicator equal to 1 if the child died between the ages of 1–11 months, and 0 otherwise. *Child (CMR)*: indicator equal to 1 if the child died between the ages of 12–59 months, and 0 otherwise. *Infant (IMR)*: indicator equal to 1 if the child died between the ages of 0–11 months, and 0 otherwise. *Under-5 (U5MR)*: indicator to 1 if the child died between the ages of 0–59 months, and 0 otherwise.

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Variable	Description
Chlorophyll	Chlorophyll concentration in coastal waters is measured in mg/m^3 (AWV weights). We use data from the GlobColour project (d'Andon et al., 2009), which provides monthly global rasters for the period 1997–2018 at the 25-meter resolution by merging satellite imaging from five different sources made available by the European Space Agency and NASA.
Conflict	Number of violent events (and fatalities) in each cell for a specific year. The data are obtained from the Uppsala Conflict Data Program (UCDP) (Sundberg and Melander, 2013).
Distances	For shorelines, distance (in a straight line) between the DHS cluster and the closest shoreline. Water bodies are identified from the GSHHG database (Wessel and Smith, 1996). We use the following two bodies. For the *ocean's shoreline*, we consider level 1 (continental land masses and ocean islands, except Antarctica). For *other water bodies*, we consider levels 2, 3 and 4 (lakes, islands in lakes, and ponds in islands within lakes and all levels included in the river database). See Appendix A.2 for details about the procedure. For *coral reefs*, distance (in a straight line) between the DHS cluster and the closest coral reef. Geographical distribution of warm-water coral reefs is obtained from UNEP-WCMC (2018).
Drought	Drought is an indicator variable taking value 1 when annual rainfall in the grid cell is below the 15th percentile of the grid cell's rainfall distribution between 1992–2012 (Corno et al., 2020).
Economic well-being	The DHS records information on asset ownership and provide an asset-based wealth index ranging from 1 (poorest) to 5 (richest).
Extractive fishing	Total number of hours from industrial fishing activities in the cell built using data from the Global Fishing Watch (Kroodsma et al., 2018), which tracks more than 70,000 industrial fishing vessels from 2012 to 2016. Because variation is available only for the period 2012–2016, we first compute total fishing hours in a global grid at $1°\times1°$ resolution and then average each cell over the available period.
Fish dependency	Average fish protein supply as proportion of all animal protein supply. The data are obtained from the FAOSTAT database (FAO, 2019).
Fish prices	Monthly retail price for fish at the province level from 1990 to nowadays. The series is provided by the Philippine Statistics Authority (2020) provides. See Appendix B.11 for details.
Human capital	We make use of *schooling*, i.e., the number of completed years of education based on the respondent's self-reported highest level of education (comparable across countries), and of *cognitive skills*, i.e., an indicator variable of whether the respondent is able to read a whole sentence in her native language (as observed by enumerators) or has, at least, completed secondary schooling.
Marriage	DHS surveys collect respondents' civil status, date of birth and, when available, their partner's age in years. We make use of the following variables. *Married* is an indicator variable equal to 1 if the respondent is currently married or living in an union, and 0 otherwise. *Age difference with partner* is the difference in years between the respondent and her partner.
Nightlight	Average night-time light emission from the $0.5°\times0.5°$ DMSP-OLS Night-time Lights Time Series Version 4 calibrated (Elvidge et al., 2014). Values range between 0 (lowest luminosity) and 1 (highest observed value). The time series are available from 1992–2012 and are downloaded from the PRIO-GRID database (Tollefsen et al., 2012). Data are spatially merged to DHS clusters using their geolocation.
Night-time fishing	We use Automatic Boat Identification System for VIIRS Low Light Imaging Data (Elvidge et al., 2015) to identify detections. The algorithm detects boats using nightlight captured from satellite imaging (Visible Infrared Imaging Radiometer Suite (VIIRS) day/night band). Using individual daily detections (which include geolocation), we build a $1°\times1°$ global grid with the sum of detections for the period 2017–2019. We classify as boats only the strongest detections (quality flag rating equal to 1). Data are not available over the South Atlantic Anomaly. To avoid false positives, we set to missing DHS surveys for Peru.
Nutritional indicators	The DHS records objective measurements performed by the DHS data collection team. Standardized distributions are the CDC Standard Deviation-derived Growth Reference Curves (Croft et al., 2018). The following indicators are used: *Underweight* is, for children, an indicator variable equal to 1 if the weight-for-age z-score is smaller than 2 or, for adults, if the BMI is lower than 18.5, and 0 otherwise. *W/h (weight-for-height)* is the z-score from the reference curve, while *wasted* is an indicator variable equal to 1 if the weight-for-height z-score is smaller than 2, and 0 otherwise. *H/a (height-for-age)* is the z-score from the reference curve, while *stunted* is an indicator variable equal to 1 if the height-for-age z-score is smaller than 2, and 0 otherwise. *Physical development* is the average between height-for-age and weight-for-height z-scores from the reference curves.
Ocean chemistry	Data are obtained from the Hadley Global Environment Model 2 - Earth System model (Jones et al., 2011), provided by the European Space Agency's Pathfinders-OA project (Sabia et al., 2015). Data are provided as monthly global rasters at the $1°\times1°$ resolution for a series of chemical features of the ocean in open waters. We use two variables: pH at surface and dissolved O_2 concentration.
Ocean's features	We obtain sea surface temperature (SST), wind speed, total precipitations and air (2-meter) temperature in areas covered by the ocean using the ERA5 dataset (C3S, 2017). ERA5 provides hourly and monthly estimates of several atmospheric, land, and oceanic climate variables combining model data with observations from across the world. It provides a 0.25º x 0.25º hourly gridded dataset. For all variables, we average daily values to monthly data and spatially merge it to DHS clusters using their geolocation and each child's birth date.

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Variable	Description
Population	It measures population size as the number of persons in 1990, 1995, 2000, and 2005 within the PRIO-GRID grid cell. Information is obtained from the Gridded Population of the World version 3. The data are downloaded from the PRIO-GRID version 2.0 database (Tollefsen et al., 2012), a vector grid network with a resolution of 0.5°×0.5° covering all terrestrial areas of the world, and spatially merged to DHS clusters using their geolocation.
Protein consumption	Information is based on the DHS Program surveys (ICF, 2019). DHS surveys collect respondents' food consumption for a variety of items. This information is available only for a restricted number of surveys: Cambodia (2005), Dominican Republic (2007), Egypt (2008), Ghana (2008), Guatemala (2015), Guyana (2009), Haiti (2006), Liberia (2007), Madagascar (2008), Namibia (2006), Nigeria (2008), Philippines (2008), Sierra Leone (2008), and Timor-Leste (2009 and 2016). We focus on two indicator variables: *fish* is an indicator variable that equals 1 if the female respondent ate fresh or dried fish or shellfish, or foods containing those ingredients, during the day previous to the interview, and 0 otherwise; *meat and dairy* is an indicator variable that equals 1 if the female respondent ate any meat (beef, pork, lamb, or chicken), eggs, dairy products (cheese, yogurt, or other milk products), or foods containing those ingredients during the day previous to the interview, and 0 otherwise.
Trade balance	Sum of exports and re-exports of fish products, minus the sum of imports of fish products. The data are obtained from the FAOSTAT database (FAO, 2019). In the analysis of heterogeneity of the effect of the ocean's acidity, we opt for a time-invariant version for the period 1976-2017.
Weather	Yearly total amount of precipitation (in millimeters) in the cell is based on monthly meteorological statistics from the GPCP v.2.2 Combined Precipitation Data Set, which is available for the years 1979–2014. Yearly mean temperature (°C) in the cell is based on monthly meteorological statistics from GHCN/CAMS, which is available for the period 1948–2014. Data are downloaded from the PRIO-GRID version 2.0 database (Tollefsen et al., 2012), a vector grid network with a resolution of 0.5°×0.5° covering all terrestrial areas of the world, and spatially merged to DHS clusters using their geolocation.
Work	Indicator variable equal to 1 if the respondent is working, and 0 otherwise. DHS surveys record the employment status of respondents at the time of the interview.

Note. For time-varying variables, missing values are linearly interpolated.

Table A2 presents the Demographic and Health Surveys (DHS) included in the analysis. The availability of multiple surveys for some countries can lead to issues related to survey selection. Table A3 presents estimates of equation (1) assuming different rules for the selection of surveys. When including multiple surveys for the same country, each observation is weighted by the product of the DHS sampling weight with a re-weighting factor, i.e., the ratio between the sum of the DHS sampling weights at the country-survey level and the sum of the DHS sampling weights at the country level. For adult-level estimates, we re-weight observations following the same procedure, repeating the computation of weights for different variables because the inclusion in each survey is variable-dependent. For adult outcomes relative to schooling and work, we include only observations that completed both the education and work module. This selection affects only the India 2015–2016 survey, for which we select only the women that completed the *state module*), and we use the weights corresponding to this sample (IIPS and ICF, 2017).

Table A2: Sampled countries

Country	DHS surveys available	Birth years matched	Number of births
Angola	2015	1978-2016	42002
Bangladesh	2000, 2004, 2007, 2011, 2014	1972-2014	183734
Benin	1996, 2001, 2012	1972-2012	84351
Cambodia	2000, 2005, 2010, 2014	1972-2014	150872
Cameroon	1991, 2004, 2011	1972-2011	81516
Colombia	2010	1973-2010	89317
Comoros	2012	1975-2012	10957
DR Congo	2007, 2013	1972-2014	83313
Côte d'Ivoire	1994, 1998, 2012	1972-2012	57785
Dominican Republic	2007, 2013	1972-2013	76051
Egypt	1992, 1995, 2000, 2005, 2008, 2014	1972-2014	303549
Gabon	2012	1974-2012	22908
Ghana	1993, 1998, 2003, 2008, 2014	1972-2014	74319
Guatemala	2015	1978-2015	54993
Guinea	1999, 2005, 2012, 2018	1972-2018	104910
Guyana	2009	1974-2009	10538
Haiti	2000, 2006, 2012, 2016	1972-2017	106348
Honduras	2011	1974-2012	48315
India	2015	1975-2016	1308794
Indonesia	2003	1972-2003	75228
Kenya	2003, 2008, 2014	1972-2014	127484
Liberia	2007, 2013	1972-2013	52464
Madagascar	1997, 2008	1972-2009	68446
Morocco	2003	1972-2004	32256
Mozambique	2011	1974-2011	37946
Myanmar	2016	1980-2016	22989
Namibia	2000, 2006, 2013	1972-2013	51966
Nigeria	1990, 2003, 2008, 2013, 2018	1972-2018	394614
Pakistan	2006	1972-2007	38542
Peru	2000, 2004, 2005, 2006, 2007, 2008, 2009	1972-2009	182648
Philippines	2003, 2008, 2017	1972-2017	104246
Senegal	1993, 1997, 2005, 2010, 2012, 2014, 2015, 2016	1972-2016	216204
Sierra Leone	2008, 2013	1972-2013	68370
Tanzania	1999, 2010, 2015	1972-2016	77212
Timor-Leste	2009, 2016	1974-2016	64620
Togo	1998, 2013	1972-2014	51612

Note. From all DHS surveys available on May 2020, we include only surveys for countries with direct access to the ocean and surveys with available geocoding of primary sampling units. The number of births is computed as the total number of observations in the birth histories (*DHS birth recode*).

Table A3: Robustness to selection of surveys

Dependent variable:	**Neonatal Mortality Rate (deaths per 1,000 births)**			
DHS surveys:	*All*	*Latest*	*Largest*	*Random*
	(1)	(2)	(3)	(4)
Resource wealth	-1.491	-1.420	-1.803	-1.609
	(0.664)	(0.701)	(0.654)	(0.675)
	[0.025]	[0.043]	[0.006]	[0.018]
Mean (dep.var.)	30.474	26.601	27.328	29.036
Identifying observations	1,581,815	794,713	861,938	757,132
Singleton observations	25	32	35	30
Communities	31,380	17,389	18,476	16,416
Countries	36	36	36	36
Birth year range (min)	1972	1972	1972	1972
Birth year range (max)	2018	2018	2018	2018

Note. Estimates based on equation (1). The dependent variable is a dummy variable equal to 1 if the child died within the first month of life and 0 if the child survived, multiplied by 1,000. *Resource wealth* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. All specifications include community FEs, birth year by birth month FEs, country x birth year FEs, country x birth month FEs, and controls (see Section 2). In column (1), observations are re-weighted to correct for oversampling of countries surveyed multiple times (see Appendix A.1). Standard errors (in parenthesis) are clustered at the ocean raster data point, p-values are reported in brackets. "*Latest*" indicates that only the latest survey is selected, "*Largest*" indicates that the survey with the largest number of observations is selected, "*Random*" indicates that one random survey is selected among the available ones. Appendix A.1 provides further information on the variables and the list of surveys included in the study.

A.2 Distances

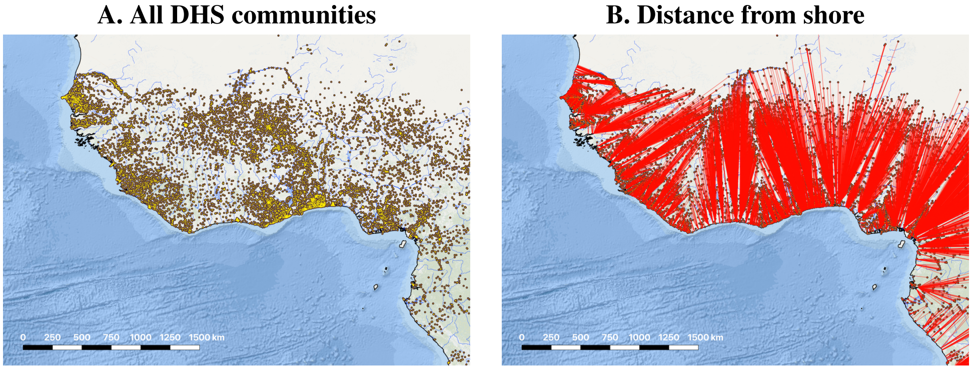
The computation of distances are based on the geocoding of DHS clusters. For each household, distance is the minimum straight distance to the coast and closest alternative water source computed using *v.distance* function in GRASS. Table A4 presents descriptive statistics for households living within and beyond 100 km from the shore. Figure A1 presents an example of the procedure for West Africa. We discuss robustness of main findings to measurement error in the geolocation in Appendix B.5.

Table A4: Descriptive statistics for coastal and inland areas

	Coastal area		**Inland area**		
	Mean	Std. dev.	Mean	Std. dev.	Observations
	(1)	(2)	(3)	(4)	(5)
A. Children					
Child is alive	0.92	0.27	0.91	0.29	4555492
Child is female	0.48	0.50	0.48	0.50	4555492
Birth order	2.54	1.81	2.66	1.84	4555492
Number of twins born with the child	0.03	0.23	0.03	0.22	4555492
Years since birth	12.28	7.87	12.09	7.76	4555492
Mother's age at birth	24.43	5.77	24.16	5.54	4555492
Ocean's pH (*in utero*)	8.05	0.03	8.06	0.03	4555492
B. Adult women					
Age at first delivery	20.88	4.23	20.45	3.82	1385467
Current age	30.65	9.80	29.97	9.76	1951250
Years of schooling	7.25	4.84	6.04	4.90	1376076
Ocean's pH (*in utero*)	8.06	0.03	8.07	0.03	977187
Primary education or less	0.41	0.49	0.49	0.50	1951201
Married	0.67	0.47	0.70	0.46	1950104
Working	0.54	0.50	0.55	0.50	1304776
Household head is female	0.22	0.41	0.17	0.38	1951247
Household head's age	46.10	13.11	46.37	13.17	1949918
Household members	5.62	3.03	6.06	3.11	1951250
Household wealth	3.72	1.28	3.22	1.39	1776572
Living in urban area	0.53	0.50	0.34	0.47	1951250
Distance from shore	31.26	30.21	462.44	289.57	1951250
Distance from another water body	47.32	102.12	24.87	23.98	1951250
Altitude	190.22	408.72	489.97	613.08	1951244
Temperature (° C)	26.09	3.21	24.92	3.70	1951250
Precipitations (mm)	1557.41	674.18	1298.33	673.22	1951250
Intensity of extractive fishing	0.06	0.20	0.05	0.13	1951250
Intensity of night-time fishing	0.09	0.20	0.08	0.16	1951250
C. Mortality rates					
Neonatal	27.51	163.55	37.24	189.34	4545390
Postneonatal	23.67	152.02	24.28	153.90	4200570
Child	21.69	145.68	27.67	164.02	3265547
Infant	50.66	219.30	60.78	238.93	4355601
Under-five	74.22	262.12	89.55	285.54	3504461

Note. Descriptive statistics by proximity to the ocean for all communities in selected countries with access to ocean. Coastal area includes all communities within 100 km from the ocean's shore (see Section 1). Inland area includes all communities that are farther away than 100 km from the ocean's shore. Means are reported in columns (1) and (3), standard deviations are reported in columns (2) and (4). Column (5) presents the total number of observations. *Years since birth* is measured at the time of the interview and is independent from the child being alive. *Mortality rates* are relative to 1,000 live births. *Ocean's pH (in utero)* is the average pH in the ocean's cell closest to an individual's community during the 9 months before birth; it refers to the date of birth of the child in Panel A and to the date of birth of the woman in Panel B. Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

Figure A1: Distance to ocean and other water sources: an example



Note. Geolocation of DHS communities (*Panel A*) and closest points to the ocean's shore (*Panel B*). Lines represent straight distance from a community to the closest point on the coast's shoreline or on the shoreline of another water body. Basemap source: Esri. See Appendix A.1 for data sources and attributions.

A.3 Coloring of shaded graphs

In selected graphs, the color intensity is reflecting the share of observations at a specific distance (or time). For Figures 4 and B8, the color intensity is the ratio between the difference between the (smoothed) density of the distribution of the number of observations in a specific iteration and 0.7 $\times$ the lower bound of the same distribution for all iterations, and the difference between the 99$^{\text{th}}$ percentile of the distribution of the number of observations in all iterations and 0.7 $\times$ the lower bound of the same distribution for all iterations. For Figures 5 and B1, the color intensity is defined as the ratio between the square root of the (smoothed) density of the distribution of the number of observations by distance from shore and the square root of the 90$^{\text{th}}$ percentile in the same distribution. Parameters are chosen to guarantee visibility.

B Supplementary results

B.1 Robustness to alternative definitions of coastal area

Table B1 shows how estimates of the effect of resource wealth on NMR vary under different criteria for defining coastal areas.

Proximity. We define coastal area using a proximity criteria based on 100km from the ocean's shore. Panel A of Figure B1 shows that the total number of live births

Table B1: The effect on neonatal mortality: varying sample selection criteria

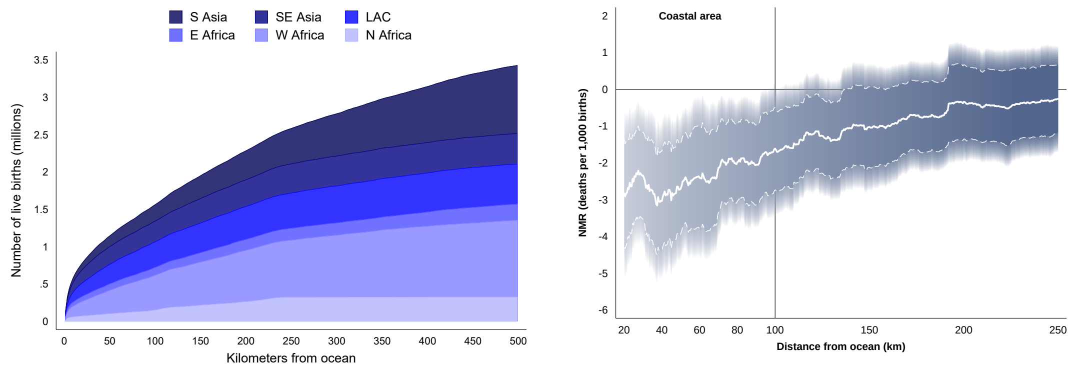
Dependent variable:	**Neonatal Mortality Rate (deaths per 1,000 births)**					
Altitude criteria:	$\leq$ *100m*	$\leq$ *100m*	-	-	$\leq$ *100m*	$\leq$ *100m*
Distance restriction:	-	-	$\leq$ *40km*	$\leq$ *40km*	$\leq$ *40km*	$\leq$ *40km*
Exclusion of estuaries:	-	*Yes*	-	*Yes*	-	*Yes*
	(1)	(2)	(3)	(4)	(5)	(6)
Resource wealth	-1.627	-1.593	-2.923	-3.072	-2.942	-3.071
	(0.776)	(0.759)	(0.797)	(0.944)	(0.836)	(0.996)
	[0.037]	[0.036]	[0.000]	[0.001]	[0.000]	[0.002]
Mean (dep.var.)	31.116	31.431	29.489	29.631	29.938	30.113
Identifying observations	1,137,356	978,016	1,061,342	893,056	845,155	685,815
Singleton observations	19	15	25	21	22	18
Communities	22,612	18,801	21,682	17,616	17,600	13,789
Countries	36	36	36	36	36	36
Birth year range (min)	1972	1972	1972	1972	1972	1972
Birth year range (max)	2018	2018	2018	2018	2018	2018

Note. Estimates based on equation (1). The dependent variable is a dummy variable equal to 1 if the child died within the first month of life and 0 if the child survived, multiplied by 1,000. *Resource wealth* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. The sample is restricted to coastal areas (see Section 1) and according to the criteria reported in column's header. *Estuaries* are defined as communities that are at a distance of 10 km or less from the ocean's shore and at a distance of 10 km or less from another water source. All specifications include community FEs, birth year by birth month FEs, country by birth year FEs, country by birth month FEs, and control variables (the full list of controls in Section 2). Standard errors (in parenthesis) are clustered at the ocean raster data point, p-values are reported in brackets. Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

considered is clearly affected by the distance bound. Panel B shows estimates of the effect of resource wealth on neonatal mortality by varying the distance bound from 20 to 250 km, allowing x to increase by 1 unit after each iteration. The largest magnitude is observed when distance is at most 40 km.

Figure B1: Sample selection by distance from shore

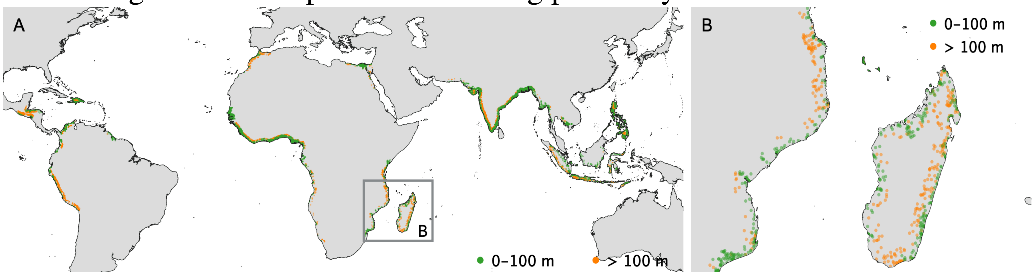
A. Number of live births B. Effect of resource wealth (*in utero*)



Note. Number of live births (decomposed by region) included in the dataset by distance from the shore (*Panel A*), and marginal effects of resource wealth on NMR by sample selection according to proximity to the shore (*Panel B*). Estimates are based on equation (1) when the sample is selected according to bounds (reported in the horizontal axis). Appendix A.2 details the procedure for computing distances. Each specification includes community FEs, birth year by birth month FEs, country by birth year FEs, country by birth month FEs, and control variables (see Section 2). The 90% confidence interval is indicated by dotted lines, beyond which the intervals are progressively shaded up to the 99% level. Within confidence bounds, darker colors indicate a larger number of observations (see Appendix A.3). Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

Altitude and estuaries. Figure B2 shows communities in coastal areas highlighting the ones selected according to the criteria of Christian and Mazzilli (2007), who select the land margin within 100 km of the coastline or less than 100 meters above the mean low tide. In addition, we can include or exclude areas where the ocean's chemical composition has a higher probability of human contamination, such as estuaries.

Figure B2: Sample selection using proximity and altitude criteria



Note. Communities in coastal areas distinguished by altitude (*Panel A*), and an example (*Panel B*). The full list of countries and surveys included in the study is reported in Appendix A.1. See Section 1 for a definition of coastal area.

B.2 Coastal features and income processes

In our main analysis, we focus on ocean's pH as a proxy for resource wealth. Figure B3 shows descriptive statistics of pH at surface averaged at global level. Figure B4 shows the evolution of the average shock in the sample over time, computed as residual variation in pH, after conditioning on the set of FEs of the benchmark specification. Table B2 shows descriptive statistics of the measure of shock under the different specifications presented in Table 2, and the correspondent standardized effect. In this section, we focus on other features in the ocean and in coastal areas that could influence income processes in sampled communities.

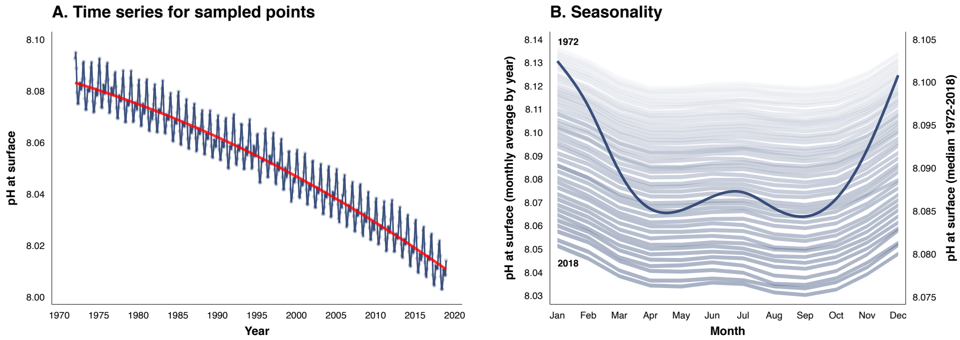
Other ocean's characteristics. Columns (1)–(7) in Table B3 presents estimates of the effect of resource wealth on NMR using equation (1) and controlling for a variety of ocean's characteristics obtained from the ERA5 dataset. Column (7) further controls for weather characteristics inland including yearly rainfall and temperature at the community level, using data from the PRIO-GRID database. Panels A–D in Figure B5 presents the time series and the seasonality component for these variables.

Pollution and other chemical features of the ocean. Columns (8)–(9) in Table B3 presents estimates controlling for pollution in coastal waters, which get contaminated from pollutants deriving from human activity and production. Higher contamination favors algae abundance, which negatively impacts the chance of survival of marine life. We proxy pollution using a measure of algae abundance in coastal waters (chlorophyll concentration) based on satellite data obtained from the GlobColour project from 1997–2018.[2] The presence of pollution also impacts the availability of another input to marine life that is more closely related to fish survival, i.e., oxygen. In our main analysis, we always control for the (dissolved) oxygen concentration in the ocean's water. At low levels of concentration (hypoxic conditions), marine life change behavior to reach areas with higher oxygen levels, while at extremely low levels (dead-zones), mortality prevails. It is important to note that oxygen concentration is also affected by climate change because higher temperatures lead to reduced oxygen concentration. The global sea surface temperature (SST) increased by 0.7 °C since the end of the 19th century (Keeling et al., 2010). In column (7) we also control for this variable obtained from the HadGEM2-ES model. Because pH and oxygen concentration are chemical properties determined by common factors, to isolate the effect of the ocean's pH in equation (1), we always include as control the residual variation in oxygen concentration, rather than its levels. Residual variation is computed as residuals of a linear regression of oxygen concentration in grid cell i at time t on the contemporaneous pH in the same grid cell. Controlling for other chemical features does not affect these estimates.[3] Panels E–F in Figure B5 presents the time series and the seasonality component for these variables.

[2]We do not use this variable as control in the main text due to the potential endogeneity of chlorophyll concentration with idiosyncratic shocks related to child mortality.

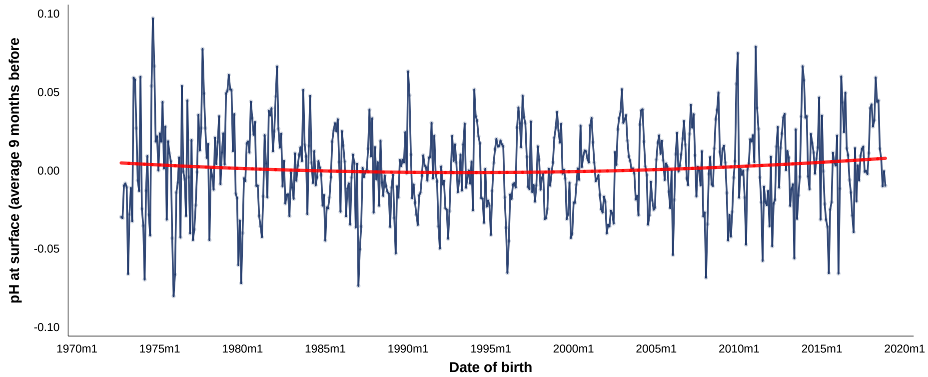
[3]A large literature highlights how the ocean's chemical composition impacts the chance of survival, the reproductive behavior, size, and spatial distribution of all marine species Doney et al. (2020).

Figure B3: Variation in the ocean's acidity for communities in the coastal area



Note. Yearly average pH at surface in the period 1972–2018 (*Panel A*), and monthly comparison between mean pH for each year in the left axis, and median pH for the whole period in the right axis (*Panel B*). Variation is restricted to cells matched to the sample's communities. In Panel A, the solid red line shows the quadratic trend in the series.

Figure B4: Evolution over time of shocks in resource wealth



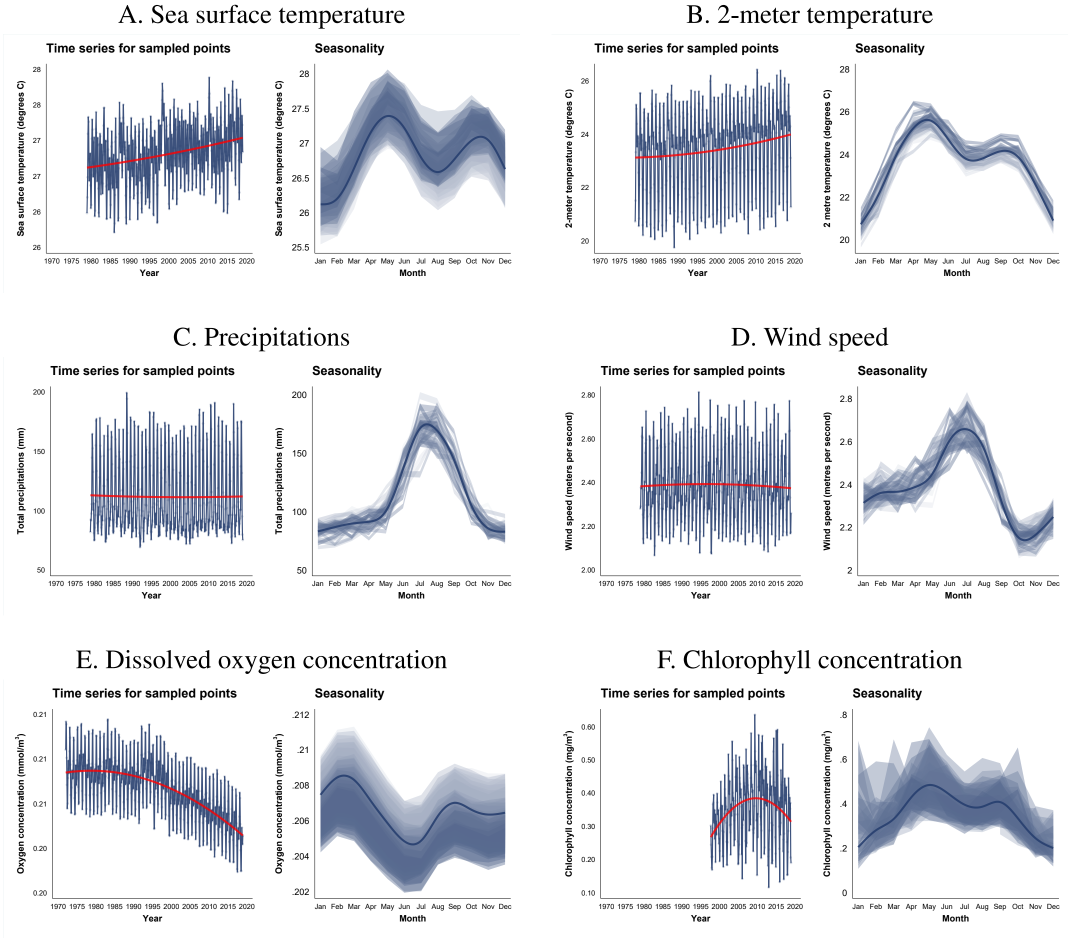
Note. Evolution over time of the average deviation in acidity levels from spatially-specific (and seasonally-adjusted) long-run trends. *Resource wealth* is defined in Section 2 and is computed using the benchmark specification. Variation is restricted to cells matched to the sample using the nearest cell in the open waters. The solid red line shows the quadratic trend over the period.

Table B2: Resource wealth and standardized effects

	Benchmark specification				Within-sibling specification			
	Mean	**Std. dev.**	**Effect**	**Std. effect**	**Mean**	**Std. dev.**	**Effect**	**Std. effect**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Shock (specification 1)	-0.00	0.38	-1.42	-0.54	0.00	0.30	-2.06	-0.63
Shock (specification 2)	-0.00	0.37	-1.42	-0.53	0.00	0.30	-2.13	-0.64
Shock (specification 3)	-0.00	0.37	-1.49	-0.56	0.00	0.30	-2.23	-0.67
Shock (specification 4)	-0.00	0.26	-2.12	-0.55	-0.00	0.22	-2.46	-0.53
Shock (specification 5)	-0.00	0.25	-2.09	-0.53	-0.00	0.21	-2.50	-0.53
Shock (specification 6)	-0.00	0.25	-2.08	-0.53	-0.00	0.21	-2.61	-0.55

Note. Descriptive statistics of shocks in resource wealth under the benchmark and the within-sibling specifications. Columns (3) and (7) refer to the point estimates in Table 2. The standardized effect is rescaling point estimates in terms of standard deviations in the residual variation of resource wealth. Residual variation is obtained from the residuals of a linear regression using the ocean's pH experienced *in utero* as dependent variable and the set of FEs used in equation (1) as independent variables.

Figure B5: Additional weather characteristics in the ocean's matched areas



Note. Descriptive statistics of weather characteristics measured in the same point where ocean's acidity is measured. The figures on the left present yearly averages, with the solid red line showing the quadratic trends in the series. The figures on the right show the monthly averages for each year in the sample, with the darker line representing the median in the whole period. Variation is restricted to cells matched to the sample's communities. Each community is assigned with a value using the nearest cell in the ocean. Appendix A.1 provides further information on the variables.

Table B3: Neonatal mortality and shocks to income processes

Dependent variable:	**Neonatal Mortality Rate (deaths per 1,000 births)**								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Closest point in the ocean									
Resource wealth	-2.034		-2.192		-2.140		-2.084	-3.284	
	(0.745)		(0.744)		(0.741)		(0.743)	(1.513)	
	[0.007]		[0.003]		[0.004]		[0.005]	[0.031]	
Sea surface temperature (*in utero*)	1.467	1.695					1.549		
	(0.925)	(0.918)					(1.064)		
	[0.113]	[0.066]					[0.146]		
Wind speed (*in utero*)			1.752	1.596			2.159		
			(1.510)	(1.505)			(1.547)		
			[0.247]	[0.290]			[0.164]		
Total precipitations (*in utero*)					0.008	0.007	0.009		
					(0.008)	(0.008)	(0.008)		
					[0.289]	[0.351]	[0.265]		
2-meter temperature (*in utero*)					0.674	0.902	0.040		
					(0.898)	(0.892)	(1.039)		
					[0.453]	[0.312]	[0.969]		
Chlorophyll concentration (*in utero*)								0.295	0.301
								(0.583)	(0.584)
								[0.614]	[0.606]
Oxygen concentration (*in utero*)							-0.069		
							(0.306)		
							[0.822]		
Location of birth									
Temperature (*year of birth*)							-0.121		
							(0.427)		
							[0.778]		
Total precipitations (*year of birth*)							-0.003		
							(0.002)		
							[0.126]		
Mean (dep.var.)	29.645	29.645	29.645	29.645	29.645	29.645	29.645	24.937	24.937
Identifying observations	1,518,357	1,518,357	1,518,357	1,518,357	1,518,357	1,518,357	1,518,357	451,212	451,212
Singleton observations	23	23	23	23	23	23	23	247	247
Communities	31,380	31,380	31,380	31,380	31,380	31,380	31,380	16,409	16,409
Countries	36	36	36	36	36	36	36	36	36
Birth year range (min)	1979	1979	1979	1979	1979	1979	1979	1998	1998
Birth year range (max)	2018	2018	2018	2018	2018	2018	2018	2018	2018

Note. Estimates based on equation (1). The dependent variable is a dummy variable equal to 1 if the child died within the first month of life and 0 if the child survived, multiplied by 1,000. *Resource wealth* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the woman's community during the 9 months before her birth. *In utero* indicates that the variable is the average value in the ocean's cell closest to the child's community during the 9 months before birth. *Year of birth* indicates that the variable is the average value in the child's community's grid cell in the year of birth. The sample is restricted to coastal areas (see Section 1). In columns (8)–(9), the sample is further restricted to births between 1997–2018 due to data availability (observations are reweighted to account for dropped surveys), and to areas away from estuaries to alleviate endogeneity concerns. Standard errors (in parenthesis) are clustered at the ocean raster data point, p-values are reported in brackets. All specifications include community FEs, birth year by birth month FEs, country by birth year FEs, $5°\times5°$ grid cell by birth month FEs, and demographic controls (see Section 2). Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

Conflict. Using information about conflict events from the Uppsala Conflict Data Program (UCDP) database at the $5° \times 5°$ resolution, we estimate equation (1) adding controls for the presence and the intensity of conflict while *in utero*. Table B4 presents estimates of the effect on NMR. Due to data availability, the birth year range is reduced to children born after 1984. For comparability, columns (3) and (6) are therefore restricted to the sample included in column (1) and (4), respectively.

Table B4: Comparing the effect size of ocean acidification and conflict

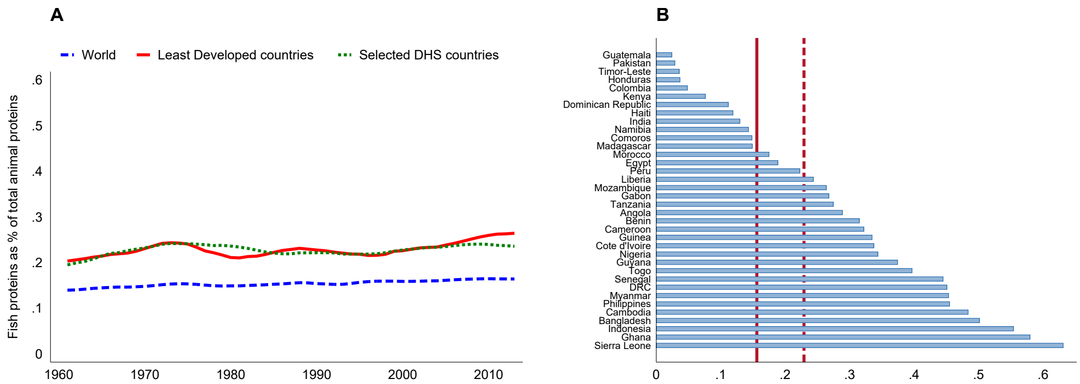
Dependent variable:	**NMR (deaths per 1,000 births)**					
	(1)	(2)	(3)	(4)	(5)	(6)
Resource wealth	-1.006	-1.014	-1.010	-1.603	-1.614	-1.612
	(0.629)	(0.632)	(0.629)	(0.799)	(0.796)	(0.799)
	[0.110]	[0.109]	[0.109]	[0.045]	[0.043]	[0.044]
At least 1 violent event (in utero)	1.702			1.715		
	(1.107)			(1.128)		
	[0.125]			[0.129]		
Fatalities (in utero)		1.591			1.616	
		(0.848)			(0.840)	
		[0.061]			[0.055]	
Mean (dep.var.)	27.657	27.657	27.657	27.657	27.657	27.657
Identifying observations	1,257,991	1,257,991	1,257,991	1,257,984	1,257,984	1,257,984
Singleton observations	82	82	0	89	89	0
Communities	31,284	31,284	31,284	31,284	31,284	31,284
Countries	36	36	36	36	36	36
Birth year range (min)	1984	1984	1984	1984	1984	1984
Birth year range (max)	2018	2018	2018	2018	2018	2018
Seasonality	Country	Country	Country	Cell	Cell	Cell

Note. Estimates based on equation (1). The dependent variable is a dummy variable equal to 1 if the child died within the first month of life and 0 if the child survived, multiplied by 1,000. *Resource wealth* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. The sample is restricted to coastal areas (see Section 1). Standard errors (in parenthesis) are clustered at the ocean raster data point, p-values are reported in brackets. All specifications include community FEs, birth year by birth month FEs, country by birth year FEs, and control variables (see Section 2). Controls for local seasonality are either country by birth month FEs or $5° \times 5°$ cell by birth month FEs. Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

B.3 Fish dependency

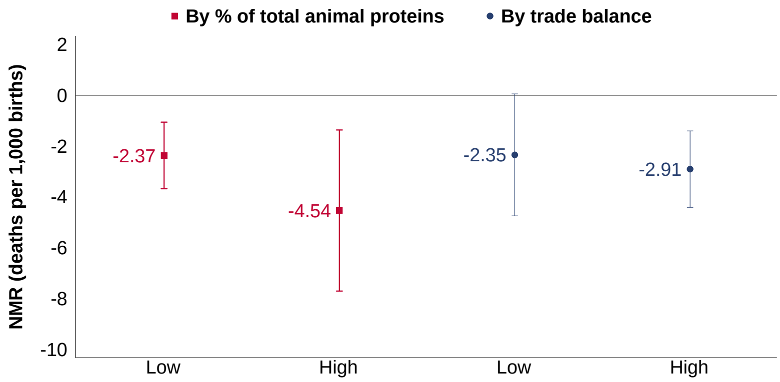
Figure B6 presents descriptive statistics for fish dependency, defined as the share of total proteins of animal origin coming from fish. Figure B7 presents the estimates of the heterogeneous effect of resource wealth on neonatal mortality distinguishing by a country's fish dependency in Panel A, and by the trade balance for fish products from the FAOSTAT database (FAO, 2019) in Panel B. As a separate measure of fish dependency, we focus on proximity to coral reefs, a proxy for dependency on artisanal fishing. Figure B8 shows marginal effects of resource wealth on neonatal mortality as a function of distance from the closest coral reef as obtained from UNEP-WCMC (2018). Distance is computed as a straight line between the community and the closest coral reef, subtracting the distance from the ocean's shore. Panel A shows the marginal effects assuming a zero distance from the ocean's shore, while Panel B assumes a distance of 40km.

Figure B6: Fish dependency amd trade balance for fish products



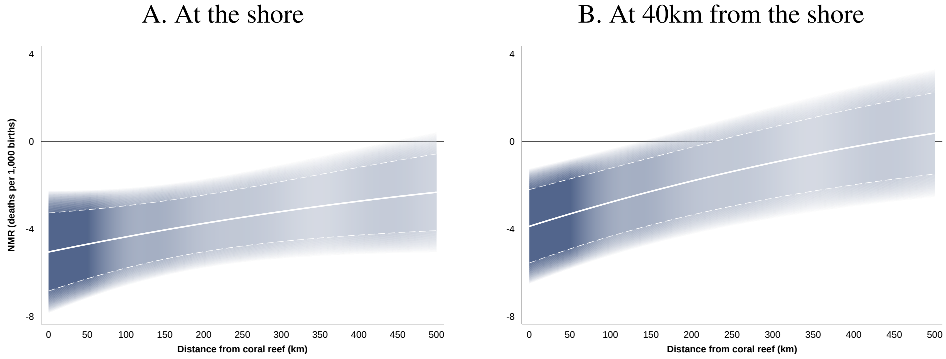
Note. Average value of fish proteins as share of total animal proteins by selected area (*Panel A*) or by country (*Panel B*). In Panel A, aggregate measures are computed by averaging the value of fish dependency in each country included in the group, weighted by population. In Panel B, vertical lines indicate the world's average (solid) and the average among the selected countries (dashed).

Figure B7: Fish dependency and heterogeneous effect of resource wealth on NMR



Note. Heterogeneous effect by dependency on fish proteins as a % of total animal proteins, and by trade balance for fish products. Marginal effects are estimated using equation (1) restricting the sample to the corresponding group. Dependency as a % of total animal proteins is *high* if the country is in the top tercile of the sample distribution of the 1960–2013 average fish dependency. Dependency by trade balance is *high* if the country is in the top tercile of the sample distribution of the 1976–2017 average trade balance for fish products. The sample is restricted to the coastal area (see Section 1). Standard errors are clustered at the ocean raster data point. Confidence intervals at 90% level. All specifications include community FEs, birth year by birth month FEs, 5°×5° grid cell by birth year FEs, 5°×5° grid cell by birth month FEs, and control variables (see Section 2). Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

Figure B8: Resource wealth and neonatal mortality, by distance to coral reefs

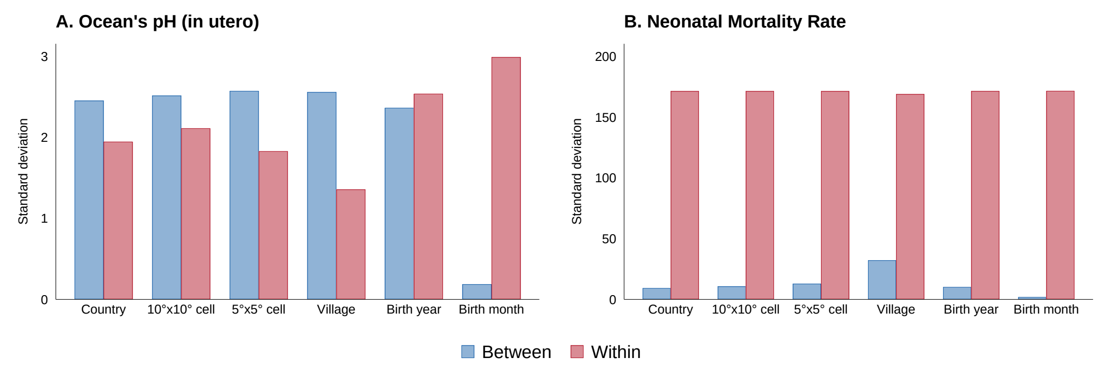


Note. Marginal effect of resource wealth on NMR as a function of shortest distance from a coral reef and assuming 0 distance from the ocean's shore (*Panel A*), or a distance of 40 km (*Panel B*). The dependent variable is a dummy variable equal to 1 if the child died within the first month of life and 0 if the child survived, multiplied by 1,000. *Resource wealth* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. Estimates are based on equation (1) introducing interactions between the shock and a cubic polynomial in distance. The specification includes community FEs, birth month by birth year FEs, country by birth year FEs, country by birth month FEs, and control variables (see Section 2). The sample is restricted to the coastal area (see Section 1). Standard errors are clustered at the ocean raster data point. The 90% confidence interval is indicated by dotted lines, beyond which the intervals are progressively shaded up to the 99% level. Within confidence bounds, darker colors indicate a larger number of observations (see Appendix A.3). Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

B.4 Issues related to identification

Figure B9 presents the between and within decomposition of the overall variation of the ocean's pH while *in utero* (Panel A) and NMR (Panel B) in the sample. The identifying assumptions of the within-sibling specification can lead to non-random sample selection (Miller et al., 2021). Table B5 shows the observable differences between mothers with a single child (excluded in the within-sibling specification) and mothers with multiple children. To verify the validity of our estimates of the effect of resource wealth on neonatal mortality to the inclusion of mother-specific FEs, columns (1)–(3) in Table B6 estimate the benchmark specification restricting the sample to the identifying observations of the within-sibling specification. Columns (4)–(6) provide estimates of the effect using the identifying sample of the within-sibling specification and re-weighting as in Miller et al. (2021) to recover the overall effect on the population of interest (mothers with at least one birth). The re-weighting procedure is based on observable characteristics. To estimate the probability to be in the identifying sample of the within-sibling specification, we use a probit model and include mother and weather characteristics.

Figure B9: Between and within variation decomposition



Note. Decomposition of the sample standard deviation of the ocean's pH experienced *in utero* (*Panel A*), and of NMR (*Panel B*). The sample is restricted to the coastal area (see Section 1). Geographical and time variables for which the decomposition is computed are reported at the bottom of each figure. Appendix A.1 provides further information on the variables and the list of surveys included in the study.

Table B5: Comparison of mothers with a single child versus multiple children

	One child		Multiple children		
	Mean	Std. dev.	Mean	Std. dev.	Observations
	(1)	(2)	(3)	(4)	(5)
A. Children					
Child is alive	0.97	0.16	0.92	0.27	1587285
Child is female	0.47	0.50	0.49	0.50	1587285
Birth order	1.00	0.00	2.68	1.82	1587285
Number of twins born with the child	0.00	0.00	0.04	0.24	1587285
Years since birth	6.04	6.55	12.86	7.73	1587285
Mother's age at birth	22.51	4.71	24.61	5.82	1587285
B. Adult women					
Age at first delivery	22.51	4.71	20.37	3.94	495310
Current age	28.54	7.99	36.19	7.66	495310
Years of schooling	8.39	4.62	5.99	4.82	441192
Primary education or less	0.31	0.46	0.55	0.50	495286
Married	0.81	0.40	0.89	0.31	495309
Working	0.54	0.50	0.60	0.49	425306
Household head is female	0.23	0.42	0.19	0.39	495310
Household head's age	45.04	15.18	44.62	11.97	494936
Household members	5.13	3.08	5.72	2.89	495310
Household wealth	3.82	1.25	3.58	1.32	434418
Living in urban area	0.57	0.49	0.49	0.50	495310
Distance from shore	31.14	30.00	32.47	30.23	495310
Distance from another water body	39.07	81.02	46.61	100.49	495310
Altitude	179.28	396.98	187.48	401.10	495310
Temperature (° C)	26.17	3.12	26.19	3.06	495310
Precipitations (mm)	1609.01	659.60	1549.09	683.53	495310
Intensity of extractive fishing	0.06	0.20	0.06	0.19	495310
Intensity of night-time fishing	0.09	0.19	0.09	0.20	495310

Note. Descriptive statistics by the number of children of the mother (reported in column's header). Means are reported in columns (1) and (3), standard deviations in columns (2) and (4). Column (5) presents the total number of observations. *Years since birth* is measured at the time of the interview and is independent from the child being alive. Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

Table B6: The effect on neonatal mortality: identification checks

Dependent variable:	Neonatal Mortality Rate (deaths per 1,000 births)					
Check:	*Benchmark specification with within-sibling identifying sample*			*Re-weighting procedure*		
	(1)	(2)	(3)	(4)	(5)	(6)
Resource wealth	-1.939	-1.950	-2.000	-2.740	-2.785	-2.883
	(0.792)	(0.790)	(0.776)	(0.996)	(1.001)	(0.990)
	[0.015]	[0.014]	[0.010]	[0.006]	[0.006]	[0.004]
Mean (dep.var.)	31.476	31.476	31.476	31.478	31.478	31.478
Identifying observations	1,474,941	1,474,941	1,474,941	1,474,349	1,474,349	1,474,349
Singleton observations	0	0	0	108,741	108,741	108,741
Communities	31,356	31,356	31,356	31,356	31,356	31,356
Countries	36	36	36	36	36	36
Birth year range (min)	1972	1972	1972	1972	1972	1972
Birth year range (max)	2018	2018	2018	2018	2018	2018
Weather controls	-	Yes	Yes	-	Yes	Yes
Demographic controls	-	-	Yes	-	-	Yes

Note. In columns (1)–(3), estimates are based on equation (1) using the benchmark specification and restricting the sample to the identifying sample of the within-sibling specification. In columns (4)–(6), estimates are based on equation (1) using the within-sibling specification and the re-weighting procedure of Miller et al. (2021). The dependent variable is a dummy variable equal to 1 if the child died within the first month of life and 0 if the child survived, multiplied by 1,000. *Resource wealth* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. The sample is restricted to coastal areas (see Section 1). Standard errors (in parenthesis) are clustered at the ocean raster data point, p-values are reported in brackets. All specifications include community FEs, birth year by birth month FEs, country by birth year FEs, and $5° \times 5°$ cell by birth month FEs. The full list of controls is presented in Section 2. Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

B.5 Falsification and placebo tests

Balance across mother characteristics. Table B7 presents estimates of equation (1) without control variables where the dependent variable is replaced by demographic controls. None of the estimates is statistically significant, supporting the exogeneity of the shock with respect to observable characteristics.

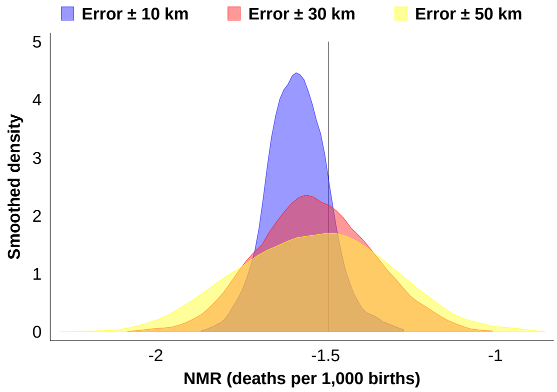
Table B7: Placebo test: balance on observable characteristics

Dependent variable:	Age at first delivery	Age at delivery	Age at inter-view	Schooling	Primary educ. or less	Married	Working	Wealth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Resource wealth	0.009	0.002	0.002	0.014	0.000	-0.000	-0.001	0.002
	(0.016)	(0.021)	(0.021)	(0.016)	(0.002)	(0.001)	(0.002)	(0.003)
	[0.558]	[0.934]	[0.935]	[0.382]	[0.981]	[0.787]	[0.654]	[0.396]
Mean (dep.var.)	20.094	25.086	36.682	4.916	0.669	0.887	0.558	3.120
Identifying observations	1,583,706	1,583,706	1,583,706	1,583,065	1,583,630	1,583,705	1,454,950	1,339,312
Singleton observations	25	25	25	25	25	25	28	31
Communities	31,380	31,380	31,380	31,380	31,380	31,380	28,828	27,039
Countries	36	36	36	36	36	36	36	36
Birth year range (min)	1972	1972	1972	1972	1972	1972	1972	1972
Birth year range (max)	2018	2018	2018	2018	2018	2018	2018	2018

Note. Estimates based on equation (1) without control variables. The dependent variable is a dummy variable equal to 1 if the child died within the first month of life and 0 if the child survived, multiplied by 1,000. *Resource wealth* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. The sample is restricted to coastal areas (see Section 1). Standard errors (in parenthesis) are clustered at the ocean raster data point, p-values are reported in brackets. The full set of controls is reported in the bottom panel of the table, control variables are excluded. Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

Measurement error in the distance from the ocean. To ensure respondents' confidentiality, GPS coordinates for all DHS surveys are randomly displaced within a maximum of 2 km for urban neighborhoods, and 10 km for rural villages. We simulate a random error in the measurement of the distance of $\pm$ 10 km, $\pm$ 30 km, and $\pm$ 50 km. We iterate the simulation 1,000 times, each time generating a new distance from the ocean and estimating (1) for households that were left within 100 km from the shoreline. Figure B10 shows the distribution of the coefficients in all iterations.

Figure B10: The effect on neonatal mortality, by magnitude of measurement error



Note. Distribution of the marginal effect of resource wealth on NMR, estimated using (1) and introducing measurement error in the distance from the ocean. The procedure performs 1,000 iterations. The vertical line represents our benchmark point estimate (column 3 in Table 2). The distribution fits are estimated non-parametrically using kernel density estimation and assuming an Epanechnikov kernel function. Bandwidths are estimated by Silverman's rule of thumb. The sample is restricted to the coastal area (see Section 1). Appendix A.1 provides further information on the variables and the full list of surveys included in the study.

B.6 Supplementary results on inference

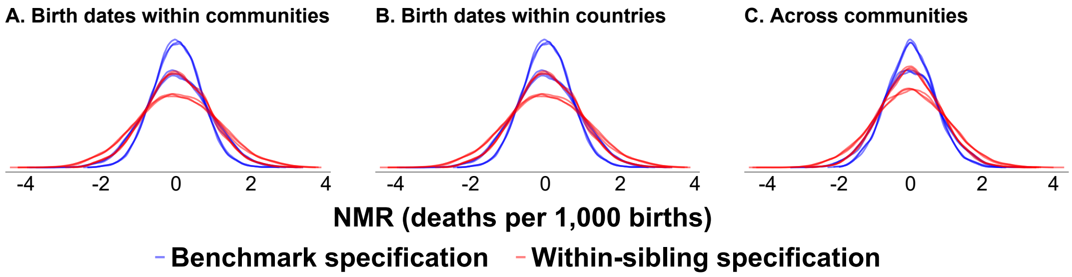
Table B8 shows estimates of equation (1) for NMR using different assumptions for the clustering of standard errors (reported in column). In addition, focusing on Table 2, we implement three different permutation-based inference tests. In the *birth dates within communities* test, birth dates are randomly reassigned within each community. In the *birth dates within countries* test, birth dates are randomly reassigned within each country, independently from the community and the survey. In the *across communities* test, mothers (and their children) are randomly allocated to different communities, independently from the country and the survey. Figure B11 shows the distribution of estimates using 5,000 iterations in each test and the empirical p-values.

Table B8: Robustness to assumptions about standard errors

Dependent variable:	**Neonatal Mortality Rate (deaths per 1,000 births)**					
Level of clustering:	None	1°x1° grid cell	Matched ocean cell	5°x5° grid cell	Country x survey year	Community
	(1)	(2)	(3)	(4)	(5)	(6)
Resource wealth	-1.491	-1.491	-1.491	-1.491	-1.491	-1.491
	(0.664)	(0.625)	(0.359)	(0.667)	(0.645)	(0.610)
	[0.025]	[0.017]	[0.000]	[0.026]	[0.023]	[0.015]
Mean (dep.var.)	30.474	30.474	30.474	30.474	30.474	30.474
Identifying observations	1,581,815	1,581,815	1,581,815	1,581,815	1,581,815	1,581,815
Singleton observations	25	25	25	25	25	25
Communities	31,380	31,380	31,380	31,380	31,380	31,380
Countries	36	36	36	36	36	36
Birth year range (min)	1972	1972	1972	1972	1972	1972
Birth year range (max)	2018	2018	2018	2018	2018	2018

Note. Estimates based on equation (1). The dependent variable is a dummy variable equal to 1 if the child died within the first month of life and 0 if the child survived, multiplied by 1,000. *Resource wealth* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. The sample is restricted to the coastal area (Section 1). All specifications include community FEs, birth year by birth month FEs, country by birth year FEs, country by birth month FEs, and control variables (see Section 2). Standard errors are reported in parenthesis, p-values are reported in brackets. Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

Figure B11: The effect on neonatal mortality: permutation-based inference



	Coefficients in Table 2	Empirical p-values A	B	C
Benchmark specification				
Specification 1	-1.417	0.012	0.012	0.014
Specification 2	-1.419	0.012	0.012	0.016
Specification 3	-1.491	0.009	0.009	0.010
Specification 4	-2.117	0.006	0.006	0.005
Specification 5	-2.094	0.008	0.008	0.006
Specification 6	-2.083	0.008	0.008	0.005
Within-sibling specification				
Specification 1	-2.065	0.007	0.007	0.005
Specification 2	-2.126	0.006	0.006	0.005
Specification 3	-2.232	0.005	0.005	0.005
Specification 4	-2.459	0.007	0.007	0.006
Specification 5	-2.502	0.009	0.009	0.007
Specification 6	-2.612	0.007	0.007	0.005

Note. Distributions of marginal effects of resource wealth on NMR when birth dates are randomly reassigned. Tests are described in Appendix B.6, and are based on 5,000 iterations. In each iteration, *resource wealth* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. Each graph depicts the empirical distribution of estimates using the specification in each of the columns in Table 2. In each iteration, marginal effects are estimated using equation (1). The sample is restricted to the coastal area (see Section 1). Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

B.7 Recall bias and selective migration

Table B9 replicates Table 2 by restricting the sample to recent births (at most 10 years prior to the interview). Estimates are robust to restricting the sample to more recent births, such as within the time period considered for under-5 mortality. Table B10 shows estimates of the effect of resource wealth on the probability that the mother migrated to the community of the interview within the first five years following delivery.

Table B9: The effect on neonatal mortality: restricting the sample to recent births

Dependent variable:	**Neonatal Mortality Rate (deaths per 1,000 births)**					
	(1)	(2)	(3)	(4)	(5)	(6)
Resource wealth	-2.552	-2.418	-2.460	-2.059	-2.055	-2.142
	(1.316)	(1.331)	(1.307)	(1.143)	(1.149)	(1.133)
	[0.053]	[0.070]	[0.060]	[0.072]	[0.074]	[0.059]
Mean (dep.var.)	26.914	26.914	26.917	26.914	26.914	26.918
Identifying observations	746,982	746,982	745,962	746,960	746,960	745,940
Singleton observations	142	142	142	164	164	164
Communities	31,183	31,183	31,183	31,182	31,182	31,182
Countries	36	36	36	36	36	36
Birth year range (min)	1980	1980	1980	1980	1980	1980
Birth year range (max)	2018	2018	2018	2018	2018	2018
Weather controls	-	Yes	Yes	-	Yes	Yes
Demographic controls	-	-	Yes	-	-	Yes
Seasonality	Country	Country	Country	Cell	Cell	Cell

Note. Estimates based on equation (1) restricting the sample to births within 10 years of the interview. The dependent variable is a dummy variable equal to 1 if the child died within the first month of life and 0 if the child survived, multiplied by 1,000. *Resource wealth* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. The sample is restricted to the coastal area (see Section 1). All specifications include community FEs, birth year by birth month FEs, country by birth year FEs, and control variables (see Section 2). Controls for local seasonality are either country by birth month FEs or $5° \times 5°$ cell by birth month FEs. Standard errors (in parenthesis) are clustered at the ocean raster data point, p-values are reported in brackets. Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

Table B10: Post-delivery selective migration

Dependent variable:	Mother migrated to community 0-4 years after delivery of child					
	(1)	(2)	(3)	(4)	(5)	(6)
Resource wealth	-0.000	-0.000	-0.000	0.001	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
	[0.958]	[0.908]	[0.988]	[0.840]	[0.612]	[0.627]
Mean (dep.var.)	0.112	0.112	0.112	0.112	0.112	0.112
Identifying observations	1,016,246	1,016,246	1,015,068	1,016,242	1,016,242	1,015,064
Singleton observations	15	15	15	19	19	19
Communities	21,884	21,884	21,884	21,884	21,884	21,884
Countries	28	28	28	28	28	28
Birth year range (min)	1972	1972	1972	1972	1972	1972
Birth year range (max)	2018	2018	2018	2018	2018	2018
Weather controls	-	Yes	Yes	-	Yes	Yes
Demographic controls	-	-	Yes	-	-	Yes
Seasonality	Country	Country	Country	Cell	Cell	Cell

Note. Estimates based on equation (1). The dependent variable is a dummy variable equal to 1 if the mother of the child migrated to the community of the interview in the first 5 years of life of the child, and 0 otherwise. *Resource wealth* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. The sample is restricted to the coastal area (see Section 1). All specifications include community FEs, birth year by birth month FEs, country by birth year FEs, and control variables (see Section 2). Controls for local seasonality are either country by birth month FEs or $5° \times 5°$ cell by birth month FEs. Standard errors (in parenthesis) are clustered at the ocean raster data point, p-values are reported in brackets. Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

B.8 Early-life mortality

Table B11 presents estimates of the effect of resource wealth on early-life mortality.

Table B11: The effect on early-life mortality rates (per 1,000 live births)

Dependent variables:	Post-neonatal (PMR)		Child (CMR)		Infant (IMR)		Under-5 (U5MR)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Resource wealth	1.169	1.076	-0.104	-0.044	-0.275	-0.407	-0.370	-0.435
	(0.479)	(0.490)	(0.320)	(0.330)	(0.707)	(0.666)	(0.821)	(0.795)
	[0.015]	[0.028]	[0.746]	[0.895]	[0.698]	[0.542]	[0.652]	[0.585]
Mean (dep.var.)	27.927	27.919	26.950	26.932	57.550	57.543	82.949	82.925
Identifying observations	1,535,443	1,533,608	1,492,560	1,490,789	1,583,706	1,581,815	1,583,706	1,581,815
Singleton observations	25	25	26	26	25	25	25	25
Communities	31,378	31,378	31,377	31,377	31,380	31,380	31,380	31,380
Countries	36	36	36	36	36	36	36	36
Birth year range (min)	1972	1972	1972	1972	1972	1972	1972	1972
Birth year range (max)	2018	2018	2018	2018	2018	2018	2018	2018
Controls	-	Yes	-	Yes	-	Yes	-	Yes

Note. Estimates based on equation (1). The dependent variables are reported in the column's header. *Resource wealth* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. The sample is restricted to coastal areas (see Section 1). Standard errors (in parenthesis) are clustered at the ocean raster data point, p-values are reported in brackets. All specifications include community FEs, birth year by birth month FEs, country by birth year FEs, country by birth month FEs. The full list of controls is presented in Section 2 and refer to weather and demographic covariates. Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

B.9 Parental investments

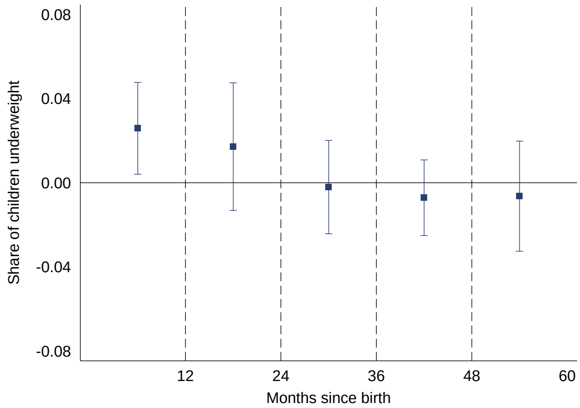
Table B12 shows estimates of the effect of resource wealth on parental health investments and on health outcomes associated with poor contemporaneous nutrition. To provide further evidence about the nutritional channel, Figure shows instead the effect of the resource shock on the probability of being underweight, distinguishing by the age of the child at the time of the measurement. The dependent variable is an indicator variable equal to 1 if the child has a weight-for-age z-score below negative 2 standard deviations, and 0 otherwise. Finally, as an additional check about nutritional choices at the time of the interview, Table B13 shows the effect of resource wealth on female respondents' consumption of animal proteins, distinguishing between fish and meat and dairy. Data are available for a subset of surveys (see Appendix A.1).

Table B12: Parental investments and postnatal nutritional outcomes

	ANTENATAL		DELIVERY		NUTRITION	
Dependent variables:	**Number of visits**	**w/ health professional**	**In health center**	**w/ health professional**	**Morbidity**	**Anemia**
	(1)	(2)	(3)	(4)	(5)	(6)
Resource wealth	-0.001	0.004	0.003	-0.003	-0.002	0.002
	(0.009)	(0.002)	(0.002)	(0.003)	(0.004)	(0.006)
	[0.940]	[0.025]	[0.067]	[0.221]	[0.677]	[0.741]
Mean (dep.var.)	1.643	0.442	0.355	0.638	0.391	0.558
Identifying observations	263,819	494,305	494,375	267,900	339,407	114,370
Singleton observations	1,099	131	131	1,032	871	1,437
Communities	29,943	31,304	31,304	30,031	29,932	15,844
Countries	36	36	36	36	36	27
Birth year range (min)	1985	1972	1972	1985	1985	1995
Birth year range (max)	2018	2018	2018	2018	2018	2018

Note. Estimates based on equation (1). The dependent variables are reported in the column's header. *Morbidity* is an indicator variable equal to 1 if the child has experienced fever, cough or diarrhea in the weeks previous to the interview, and 0 otherwise. *Anemia* is an indicator variable equal to 1 if the child has hemoglobin levels below 110 g/L, and 0 otherwise. *Resource wealth* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. The sample is restricted to coastal areas (see Section 1). Standard errors (in parenthesis) are clustered at the ocean raster data point, p-values are reported in brackets. For cross-survey comparability, the samples are restricted to the last birth, independently from the child being alive. All specifications include community FEs, birth year by birth month FEs, country by birth year FEs, country by birth month FEs, and control variables (see Section 2). Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

Figure B12: Effect on the probability of being underweight



Note. Marginal effect of resource weath experienced *in utero* on the probability of the child to be underweight. The dependent variable is an indicator variable equal to 1 if the child has a weight-for-age z-score below negative 2 standard deviations, and 0 otherwise. Confidence intervals at 90% level. Estimates are based on equation (1) including community FEs, birth month by birth year FEs, country by birth year FEs, country by birth month FEs, and control variables (see Section 2). Standard errors are clustered at the ocean raster data point. Appendix A.1 provides further information on the variables and for the list of surveys included in the study.

Table B13: Protein consumption at the time of the interview

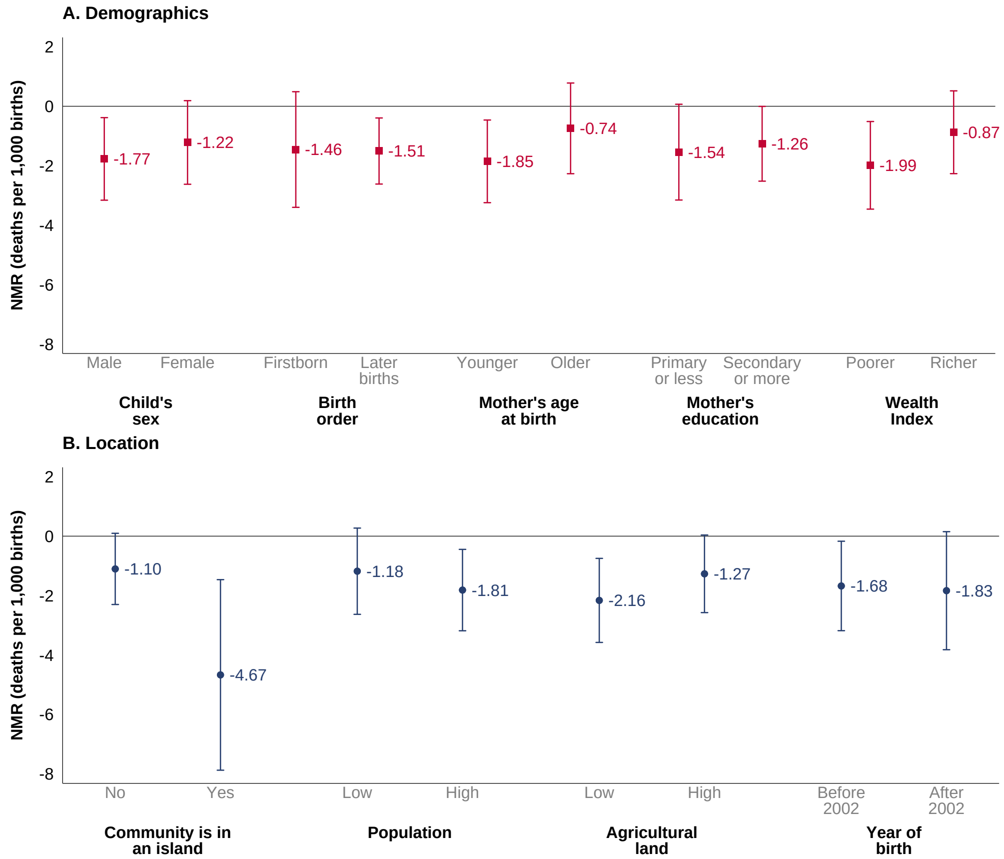
Dependent variable:	**Female respondent consumed [food] in the day previous to the interview**			
Sub-sample:	*All women*		*Mothers with $\geq$ one child under 3 y.o.*	
	(1)	(2)	(3)	(4)
A. Fish				
Resource wealth (time of interview)	0.016	0.003	0.013	0.004
	(0.017)	(0.017)	(0.017)	(0.018)
	[0.333]	[0.862]	[0.448]	[0.838]
Observations	49045	49043	36226	36223
Grid cells	239	239	239	239
B. Meat and dairy				
Resource wealth (time of interview)	0.000	0.004	0.008	0.008
	(0.015)	(0.016)	(0.013)	(0.014)
	[0.996]	[0.817]	[0.554]	[0.551]
Observations	49037	49035	36212	36209
Grid cells	239	239	239	239
Seasonality	Country	Cell	Country	Cell

Note. Estimates based on equation (1). *Resource wealth* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the female respondent's community in the month of the interview. The sample is restricted to coastal areas (see Section 1) and in columns (5)–(8) to households with at least a child under 3 years old (due to cross-survey comparability, Croft et al., 2018). All specifications include location FEs using grid cells at the 1°×1° resolution, year by birth month FEs, and country by interview year FEs, and control variables (see Section 2, weather controls are meaasured at the time of interview). Controls for local seasonality are either country by interview month FEs or 5°×5° cell by interview month FEs. Standard errors (in parenthesis) are clustered at the ocean raster data point, p-values are reported in brackets. Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

B.10 Heterogeneous effects

Figure B13 presents estimates of heterogeneous effects for children and mothers' demographics (Panel A) and for location characteristics (Panel B).

Figure B13: Heterogeneous effect of resource wealth on NMR



Note. Heterogeneous effects of ocean's pH while *in utero* on NMR by child and mother's demographics (*Panel A*), and by location's characteristics (*Panel B*). Marginal effects are estimated using equation (1) restricting the sample to the corresponding group. For mother's age at birth, wealth index, agricultural land, population, fish as a % of animal proteins, and fishing hours, we create a dummy variable indicating whether an observation is above or below the full sample's median of the variable of interest. Agricultural land and population are set at the 1970 level. Standard errors are clustered at the ocean raster data point. Confidence intervals at 90% level. All specifications include community FEs, birth year by birth month FEs, country by birth year FEs, country by birth month FEs, and control variables (see Section 2). Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

B.11 Fishing and fish prices

For **night-time** and **extractive fishing**, Figure B14 shows an example of the geographical variation. To test whether we observe heterogeneous effects by intensity of extractive and night-time fishing, we estimate equation (1) on the set of outcomes presented in Figure 6 by adding interaction terms between the ocean's pH while *in utero* and each of these variables. We perform two tests assuming a linear or a quadratic functions, and computing p-values for the joint tests of equality to 0 of the coefficients on the interaction term(s). Table B.11 reports F-statistics and p-values for a joint-test of equality to zero of the interaction terms. A rejection of the test indicates heterogeneous effects. We highlight significant heterogeneous effects by extractive fishing on neonatal mortality, economic well-being and long-run physical development. For **fish prices**, the Philippine Statistics Authority (2020) provides monthly retail prices at the province-species level. Figure B15 shows the evolution of prices and spatial distribution of the median fish price for the period 1990 – 2018.

Table B14: Test of heterogeneous effects of resource wealth

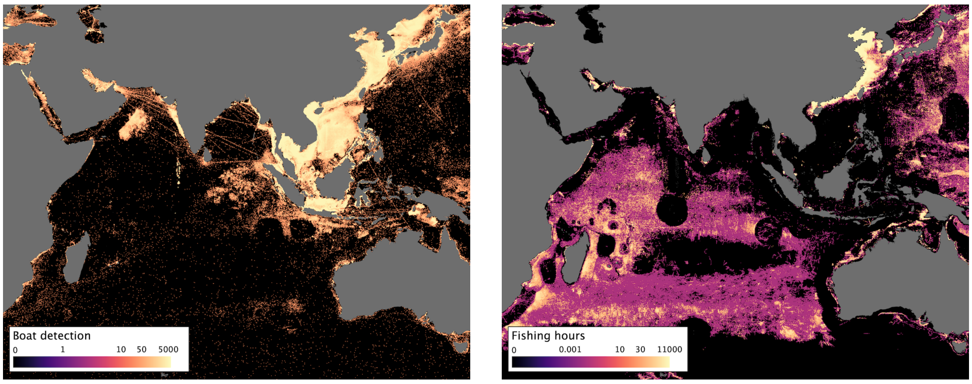
Type of interaction	**Linear**		**Linear+quadratic**	
	F	p-value	F	p-value
	(1)	(2)	(3)	(4)
Panel A. Short-run effects (all children)				
NMR				
Intensity of extractive fishing	32.111	0.000	16.769	0.000
Intensity of night-time fishing	0.165	0.685	0.260	0.771
Physical development				
Intensity of extractive fishing	2.009	0.157	1.253	0.287
Intensity of night-time fishing	0.447	0.504	1.403	0.248
Panel B. Long-run effects (female)				
Economic well-being				
Intensity of extractive fishing	16.334	0.000	8.204	0.000
Intensity of night-time fishing	0.042	0.838	0.086	0.917
Physical development				
Intensity of extractive fishing	13.497	0.000	10.608	0.000
Intensity of night-time fishing	1.032	0.311	1.623	0.199

Note. The table reports F-statistics and p-values for joint tests of equality to zero of the estimates on the interaction term(s). Estimates are based on equation (1) adding interaction terms between the ocean's pH while *in utero* and the variables presented in the left column. The sample is restricted to coastal areas (see Section 1). Standard errors are clustered at the ocean raster data point. All specifications include cluster fixed effects, birth year by birth month fixed effects, country by birth year fixed effects (local trend), country by birth month fixed effects (local seasonality), and time-varying controls (climatic/weather and demographic). The full list of controls is presented in Section 1. Observations are re-weighted to correct for oversampling of countries surveyed multiple times (see Appendix A.1). The ocean's pH (*in utero*) is the average value in the cell closest to the child's cluster during the 9 months before birth, and is multiplied by a factor of 100. Appendix A.1 provides further information on the variables and the list of surveys included in the study. We exclude DHS surveys for Peru as information for the intensity of night-time fishing is not available (see Appendix A.1).

Figure B14: Geographical distribution of fishing: an example

A. Night-time fishing

B. Extractive fishing

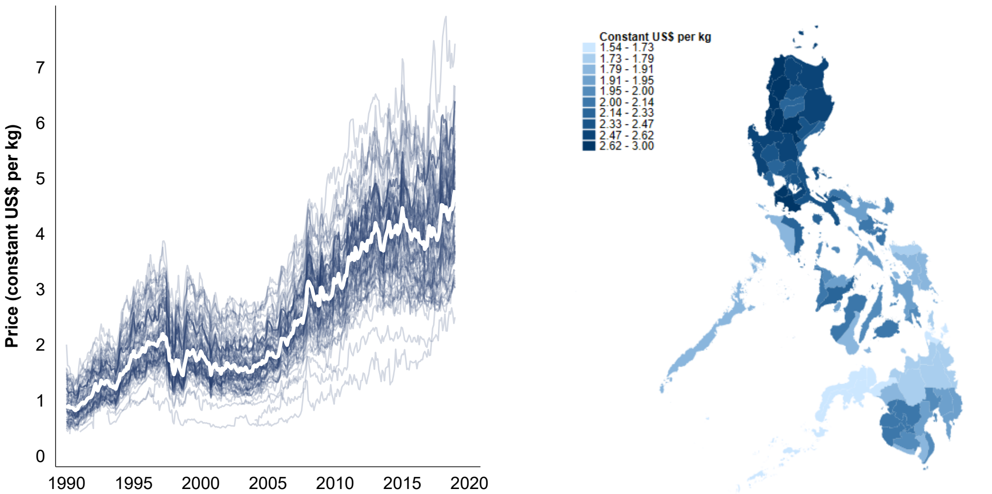


Note. Example of the geographical distribution of the intensity of night-time fishing (*Panel A*), and extractive fishing (*Panel B*). The resolution is 0.1°×0.1° in Panel A, and 0.25°×0.25° in Panel B. Color scales are based on quantiles. Appendix A.1 provides further details about the variables.

Figure B15: Time series and spatial distribution of retail price for fish

A. Time series

B. Spatial distribution of the median price

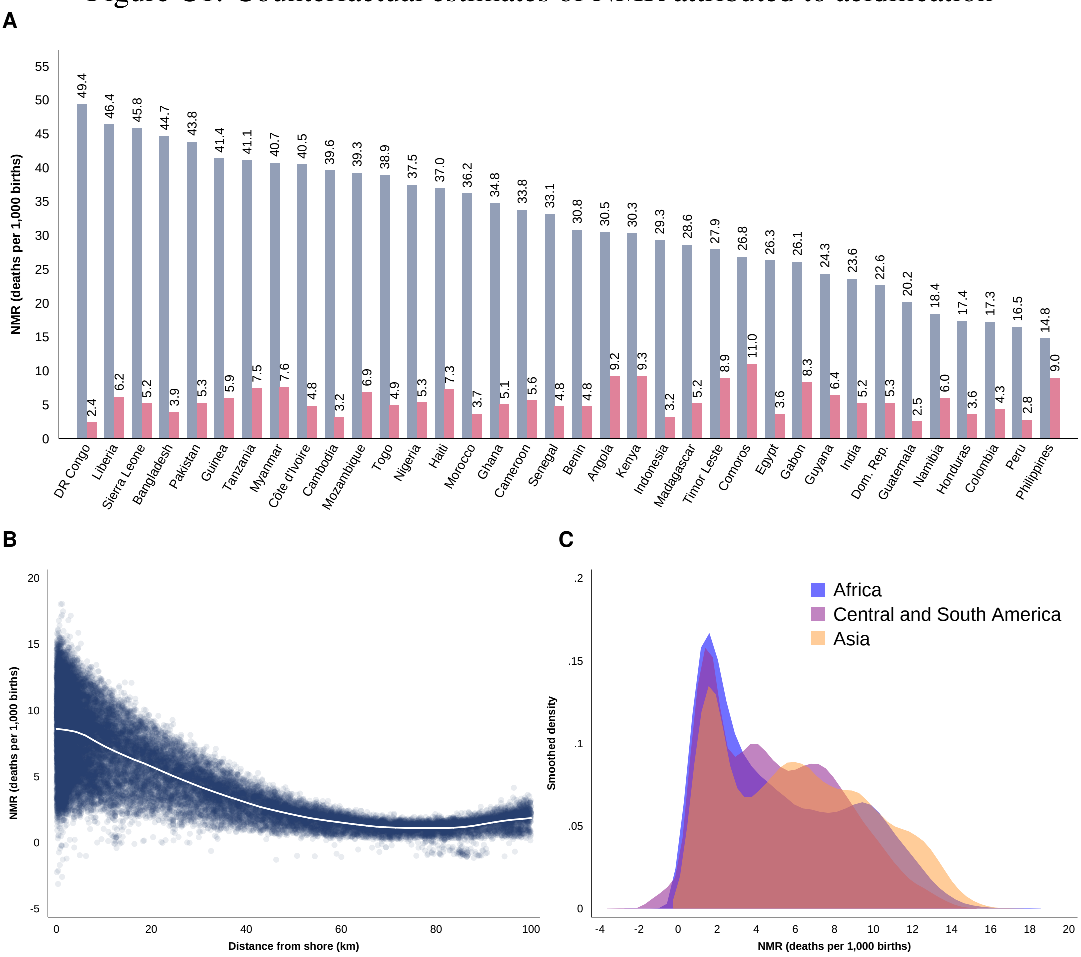


Note. Evolution over time of the province-level fish prices (*Panel A*) and spatial distribution of the 1990 – 2018 median fish price (*Panel B*). Prices are obtained for the following species: indian mackerel, milkfish, threadfin bream, blue crab, caesio, anchovies, frigate tuna, tilapia, tiger prawn, slipmouth, and roundscad. Prices in Philippine Peso per kg are converted in constant US$ (base 2010) using exchange rates and CPI from the IMF (2020). In Panel A, each price is the (unweighted) average of all available prices. Missing data are imputed using linear interpolation for each province and species.

C Aggregate effects of ocean acidification

Counterfactual estimates. We predict birth-level NMR ($\widehat{NMR}_{ikmtvc}$) using equation (1) allowing for a flexible form in the distance from shore. The counterfactual prediction ($\widehat{NMR}^{1975}_{ikmtvc}$) is obtained by imposing *in utero* exposure to the ocean's chemical composition at the 1975 level (allowing for seasonal variation) keeping other variables constant. NMR attributed to acidification (Δ_{ikmtvc}) is computed as the community-level average of $\widehat{NMR}_{ikmtvc} - \widehat{NMR}^{1975}_{ikmtvc}$. Figure C1 presents summary statistics.

Figure C1: Counterfactual estimates of NMR attributed to acidification



Note. Panel A presetns the country-level average NMR in the coastal area (left bar) and average NMR attributed to acidification (right bar). Panel B shows the relationship between NMR attributed to acidification and distance from shore is estimated using a local polynomial regression. Panel C shows the distributions are estimated using a kernel density estimator. Estimators in Panels B–C assume an Epanechnikov function and a width of the smoothing window around each point determined using a rule-of-thumb.

Acidification shocks and adaptation. To test for adaptation, Table C1 re-estimates Table 2 interacting the ocean's ph while *in utero* with a location's initial conditions, namely the (standardized) average ocean's pH from 1972–1975.

Table C1: The effect on neonatal mortality: initial conditions

	Dependent variable: NMR (deaths per 1,000 births)					
	(1)	(2)	(3)	(4)	(5)	(6)
Resource wealth	-1.970	-2.017	-2.195	-2.273	-2.302	-2.329
	(0.717)	(0.697)	(0.685)	(0.783)	(0.785)	(0.771)
	[0.006]	[0.004]	[0.001]	[0.004]	[0.004]	[0.003]
× initial conditions	1.110	1.106	1.303	1.119	1.095	1.299
	(0.322)	(0.325)	(0.319)	(0.329)	(0.329)	(0.315)
	[0.001]	[0.001]	[0.000]	[0.001]	[0.001]	[0.000]
Mean (dep.var.)	30.473	30.473	30.474	30.474	30.474	30.475
Identifying observations	1,583,706	1,583,706	1,581,815	1,583,703	1,583,703	1,581,812
Singleton observations	25	25	25	28	28	28
Communities	31,380	31,380	31,380	31,380	31,380	31,380
Countries	36	36	36	36	36	36
Birth year range (min)	1972	1972	1972	1972	1972	1972
Birth year range (max)	2018	2018	2018	2018	2018	2018
Weather controls	-	Yes	Yes	-	Yes	Yes
Demographic controls	-	-	Yes	-	-	Yes
Seasonality	Country	Country	Country	Cell	Cell	Cell

Note. Estimates based on equation (1). The dependent variable is a dummy variable equal to 1 if the child died within the first month of life and 0 if the child survived, multiplied by 1,000. *Resource shock* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. *Initial conditions* refer to a location's (standardized) average between 1972–1975. The sample is restricted to coastal areas (see Section 1). Standard errors (in parenthesis) are clustered at the ocean raster data point, p-values are reported in brackets. All specifications include community FEs, birth year by birth month FEs, country by birth year FEs. Controls for local seasonality are either country by birth month FEs or 5°×5° cell by birth month FEs. The full list of controls is presented in Section 2. Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

Appendix Bibliography

C3S (2017): "ERA5: Fifth generation of ECMWF atmospheric reanalyses of the global climate," Copernicus Climate Change Service Climate Data Store (CDS).

Christian, R. R. and S. Mazzilli (2007): "Defining the coast and sentinel ecosystems for coastal observations of global change," *Hydrobiologia*, 577, 55–70.

Croft, T. N., A. M. J. Marshall, and C. K. Allen (2018): "Guide to DHS Statistics," Demographic and Health Surveys Program.

d'Andon, O. F., A. Mangin, S. Lavender, et al. (2009): "GlobColour - The European Service for Ocean Colour," in *Proceedings of the 2009 IEEE International Geoscience & Remote Sensing Symposium*.

Elvidge, C., D. Feng-Chi Hsu, K. E. Baugh, and T. Ghosh (2014): "National Trends in Satellite Observed Lighting: 1992-2012," Ed. Qihao Weng. CRC Press.

Elvidge, C. D., M. Zhizhin, K. Baugh, and F.-C. Hsu (2015): "Automatic boat identification system for VIIRS low light imaging data," *Remote sensing*, 7, 3020–3036.

FAO (2019): "FAOSTAT – Food Balance Sheets," Food and Agriculture Organization of the United Nations.

ICF (2019): "Demographic and Health Surveys 1991-2018 (various datasets)," Calverton, Maryland: ICF International. https://www.dhsprogram.com.

IIPS and ICF (2017): "National Family Health Survey NFHS-4 2015-16: India," Tech. rep., International Institute for Population Sciences, Mumbai: IIPS.

IMF (2020): "International Financial Statistics," International Monetary Fund.

Jones, C., J. Hughes, N. Bellouin, et al. (2011): "The HadGEM2-ES implementation of CMIP5 centennial simulations," *Geoscientific Model Development*, 4, 543–570.

Keeling, R. F., A. Körtzinger, and N. Gruber (2010): "Ocean Deoxygenation in a Warming World," *Annual Review of Marine Science*, 2, 199–229, pMID: 21141663.

Kroodsma, D. A., J. Mayorga, T. Hochberg, et al. (2018): "Tracking the global footprint of fisheries," *Science*, 359, 904–908.

Miller, D. L., N. Shenhav, and M. Z. Grosz (2021): "Selection into identification in fixed effects models, with application to Head Start," *Journal of Human Resources*, forthcoming.

Philippine Statistics Authority (2020): "Fish: Retail Prices of Agricultural Commodities," Dataset accessed 08.02.2020 at openstat.psa.gov.ph.

Sabia, R., D. Fernández-Prieto, J. Shutler, et al. (2015): "Remote sensing of surface ocean PH exploiting sea surface salinity satellite observations," in *2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*, 106–109.

Sundberg, R. and E. Melander (2013): "Introducing the UCDP georeferenced event dataset," *Journal of Peace Research*, 50, 523–532.

Tollefsen, A. F., H. Strand, and H. Buhaug (2012): "PRIO-GRID: A unified spatial data structure," *Journal of Peace Research*, 49, 363–374.

UNEP-WCMC (2018): "Global distribution of coral reefs," UNEP World Conservation Monitoring Centre and the WorldFish Centre.

Wessel, P. and W. H. Smith (1996): "A global, self-consistent, hierarchical, high-resolution shoreline database," *Journal of Geophysical Research: Solid Earth*, 101, 8741–8743.