DISCUSSION PAPER SERIES

DP15680
(v. 5)

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DEVELOPMENT ECONOMICS

CEPR

ISSN 0265-8003

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Discussion Paper DP15680
First Published 15 February 2022
This Revision 21 February 2023

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Abstract

Twenty percent of the world population depend on wildlife for income and food. We show how exogenous variation in the wealth of marine wildlife shapes human and economic development. For the period 1972–2018, we analyze half a million adult women and 1.5 million live births in 36 low- and middle-income countries. We document how short-run deteriorations near human settlements cause diets to be poorer in nutrients, increasing malnutrition among the most vulnerable population, pregnant women. These shocks have negative impacts on their children. When deteriorations are experienced in utero, they increase mortality, worsen physical development, and have long-lasting effects on economic well-being. Shocks operate in an unobserved way as parents do not raise health investments. Effects are larger in areas that are more dependent on marine resources and where overfishing depletes them.

JEL Classification: I15, Q20, Q54, O10

Keywords: Child, Climate change, Economic development, Health, Mortality, Natural resource, Ocean, Renewable resource

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Acknowledgements
We are grateful to the Pathfinders-OA project for providing access to data about ocean chemistry. We would also like to thank Mirko Abbritti, Antonella Bancalari, Robin Burgess, Emanuela Galasso, Esther Gehrke, Victoire Girard, Christopher Golden, Joseph Gomes, Martina Kirchberger, Katarina Kuske, Gianmarco Leon, Humberto Llavador, Brendon McConnell, Jean-Philippe Platteau, Marcello Sartarelli, Jamie Shutler, Christine Valente, Greg Veramendi, and seminar participants at 2020 BREAD/CEPR/STICERD/TCD Conference on Development Economics, NEUDC @ Dartmouth University, EUDN Workshop, 2021 European Winter Meeting of the Econometric Society, 2021 DSE Winter School, Barcelona Summer Forum, the 9th IZA Workshop on Environment, Health and Labor Markets, Complutense University of Madrid, and University of Navarra for helpful comments. This work was funded by Fundação para a Ciência e a Tecnologia (UIDB/00124/2020, UIDP/00124/2020 and Social Sciences DataLab - PINFRA/22209/2016), POR Lisboa and POR Norte (Social Sciences DataLab, PIN- FRA/22209/2016). A related version of this paper was previously circulated as The Ocean and Early-Childhood Mortality and Development.

One in five people relies on wildlife for income and food (UN-IPBES, 2019). However, there exists no evidence quantifying the effect of an abundant wildlife on human and economic development. This paper focuses on the ocean. Marine wildlife provides essential nutrients to more than 3 billion people, and sustains the marine capture sector, which employs 1% of the world's population (FAO, 2022).[1]

We study the consequences of short-run exogenous changes in the wealth of marine wildlife, which we label as the ocean's *resource wealth*. We proxy resource wealth using spatial and temporal variation in the pH of ocean's waters near human settlements. Lower values of pH, which indicate water acidity, impact the quantity, quality and composition of marine wildlife that is available locally to harvest and consume.[2] This impact is crucial in light of climate change, since the global average of pH is decreasing. This process is known as *ocean acidification* (IPCC, 2022).

We estimate short- and long-run effects on mortality, human capital, and economic well-being 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 the coastal areas of 36 low- and middle-income countries (L&MICs) across Africa, Asia, and Latin America. These communities are the most dependent on marine wildlife for income and food, and also the most reliant on local resources. L&MICs host 97% percent of all workers employed in marine capture; more than 90% of them work in small-scale and artisanal fisheries servicing local consumption (The World Bank, 2012). Seafood provides 26% of all the animal proteins that are consumed in L&MICs, which exceeds the global average of 17% (FAO, 2022). Countries like Bangladesh, Cambodia, the Gambia, Ghana, Indonesia, Sierra Leone, and Sri Lanka reach peaks of, at least, 50%.

For identification, we exploit the natural variation of the ocean's pH. In a specific month, pH near a human settlement can deviate exogenously from its long-run level and be

[1] A large literature studies the land productivity in agricultural and subsoil extractive activities. The ocean's productivity is not comparable due to the open-access essence of its resources (Collier, 2010).

[2] Effects are heterogeneous across species, allowing for some species to potentially benefit from more acidic habitats. Doney et al. (2020) provides a literature review of the effect of water acidity on marine life. Acidity impacts the physiology of species, including their physical development, chance of survival, nutritional content, and toxicity. In addition, acidity degrades marine habitats like coral reefs, disrupting food chains. Appendix B.2 discusses other variables that have a more direct effect on the quantity.

relatively more (or less) acidic. This short-run variation is similar to the one of weather, which is widely used in the literature to identify exogenous short-run shocks to climate.[3] We exploit data on pH at a high spatial and temporal resolution and define *shocks* as short-run deviations in pH levels from the spatially-specific (and seasonally-adjusted) long-run trend. Deviations are obtained by absorbing residual unobserved heterogeneity with multi-way fixed effects (FEs). This approach makes relatively few identifying assumptions and allows for unusually strong causal interpretation (Dell et al., 2014). Identifying assumptions are supported by several checks described in Sections 2 and 3.

The causal pathway from resource wealth to economic development operates through a nutritional channel. We document that negative shocks reduces the probability to consume seafood, a source of nutrients that are essential during pregnancy (FAO, 2020). This decrease is not fully compensated by increases in the consumption of alternative sources of nutrients. Importantly, we show that these shocks are likely driven by changes in the supply of seafood that have limited effects on aggregate income.[4] We show that coastal areas' night-time luminosity, a proxy for human and economic development (Henderson et al., 2012; Bruederle and Hodler, 2018), is unaffected by short-run shocks to the ocean's resource wealth. In comparison, a shock to agricultural income like a drought significantly reduces luminosity in the same area.

The shift towards a less-nutrient diet results in an increase in malnutrition that is specific to the most vulnerable population, pregnant women. Motivated by maternal malnutrition being a critical risk factor for children's health (Black et al., 2013; Victora et al., 2021), we study the effect of early-in-life exposure to resource wealth by exploiting information on individuals' geolocation and date of birth. We show a significant effect on mortality early in life. This effect is specific to larger deviations in acidity (negative shocks) that are experienced *in utero* and gradually converges to zero by the first year of life. A negative one standard deviation shock raises neonatal mortality–the probability

[3] Globally and locally, the ocean's pH is affected by winds, temperature, sea ice, precipitation, runoff, and ocean circulation (Feely et al., 2008). Appendix B.2 provides a comparison between pH and weather variables. To avoid the confounding effects of pollution on acidity, we measure pH in open rather than coastal waters (Section 1). In addition, we report estimates controlling for coastal pollution and excluding areas near estuaries–the main source of coastal pollution (Section 3).

[4] Fisheries absorb shocks by diversifying catch, compensating a reduced availability of commonly-consumed species with other abundant species (see, eg., Anderson et al., 2017).

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 largest impacts on mortality are recorded where dependence on seafood is larger. Further, consistent with income being unaffected, we show that impacts are not driven by a reduction in the total local supply of seafood that is available for consumption, and thus by changes in the average seafood price. Restricting the sample to one of the most fish-dependent country in the world, the Philippines, we match children with *in-utero* exposure to both the average seafood price in the local market and to resource wealth.[5] We show that experiencing higher average prices contributes significantly to mortality, but shocks to resource wealth operate independently. Therefore, this result highlights that effects are likely driven by the composition, rather than the total supply of seafood. A change in composition can reduce nutrient intake (see Section 3.1). Trade can only amplify this channel as L&MICs tend to export high-quality fish caught in their waters and supplement local demand with imports of low-quality fish (Pauly and Zeller, 2016).

Early-in-life exposure operates in absence of adaptation that is contemporaneous to the shock. Parental investments on child health are unaffected, and the effect on neonatal mortality is homogeneous along households' wealth and education. Results 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. These results also confirm the absence of income shocks at household level, as investments should adjust (see, e.g., Baird et al., 2011). It is therefore likely that parents do not observe shocks or are unaware of their effects. Micronutrient deficiency is the most plausible mechanism. Shortfalls can occur without deficits in caloric intake, making them difficult to detect without proper healthcare or knowledge (McGovern et al., 2017). This issue, known as hidden hunger, affects over two billion people worldwide, particularly in L&MICs (Lowe, 2021).

Early-in-life exposure not only impact mortality rates, but also physical development, and long-term economic outcomes. Anthropometric measurements show that, on aver-

[5] Due to data limitations, we cannot perform an analysis on prices at our temporal and geographical scale (Section 1).

age, children who live past their first month of life have slightly better health. Therefore, mortality has higher incidence among the frailer children. Among female children, we observe instead a significant increase in stunting, which prevails over mortality selection. The negative consequences among female children persist into adulthood, accompanied by a worsening of economic well-being. These results highlight the long-run consequences of maternal malnutrition.

Our findings contribute to different strands of the literature. First, they provide new evidence on the roots of child development by studying a shock with unique features. A large number of studies cover shocks that are either observable or have direct effects on health.[6] 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). In light of the centrality of parental investments for early childhood development (Attanasio et al., 2020), lack of adaptation to this type of shock contradicts available evidence. Adaptation is observed in the case of undernutrition occurring during events such as famines and prolonged fasting (Razzaque et al., 1990; Almond and Mazumder, 2011; Majid, 2015), or when malnutrition is addressed with nutrient supplementation (Adhvaryu and Nyshadham, 2016). We further supplement this literature by providing novel evidence on the long-run impacts of maternal malnutrition.

Second, the study provides new evidence on the importance of wildlife for economic development. There is a body of evidence showing how wildlife shaped institutions (Bowles and Choi, 2019; Mayshar et al., 2022) and long-run economic development (Michalopoulos and Papaioannou, 2013; Dalgaard et al., 2020). Our findings focuses on the short-run effects of wildlife, complementing the nascent literature on biodiversity and poverty (see, e.g., Dasgupta, 2021).

We also provide novel evidence on the role of overexploitative practices like deforestation (Burgess et al., 2012; Jayachandran, 2013), overfishing (Stavins, 2011), and poaching (Kremer and Morcom, 2000). In the territorial waters of L&MICs, half of

[6] Almond et al. (2018) provides a review of this literature. Studies related to our setting cover the effect of atmospheric events (Maccini and Yang, 2009; Heft-Neal et al., 2018; Geruso and Spears, 2018a; Adhvaryu et al., 2020), and environmental contamination or degradation (Chay and Greenstone, 2003; Arceo et al., 2016; Isen et al., 2017; Geruso and Spears, 2018b; Black et al., 2019; Berazneva and Byker, 2022).

total catch is obtained through extractive forms of fishing, almost entirely by vessels flagged to higher-income countries (Golden et al., 2016; McCauley et al., 2018). These forms of fishing not only deplete marine biodiversity, but also generate no economic benefit for local communities. In an analysis of heterogeneous effects, we show how negative resource shocks are amplified only in areas with higher intensity of extractive fishing. In areas with more inclusive forms of fishing, shocks are instead compensated. Thus, our results show how overexploitation limits nature's ability to act as insurance against short-run shocks.

Finally, because climate change affects pH in the long run, these results further our understanding of its effects. Our counterfactual analysis shows that short-run shocks to ocean's pH can translate into large aggregate effects on mortality in the long run. This evidence adds to a nascent literature on the predicted economic impacts of ocean acidification (Colt and Knapp, 2016), and, more generally, to the literature measuring the impacts of climate change (Auffhammer et al., 2013; Auffhammer, 2018).

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. Appendix Table A4 presents descriptive statistics for these variables.

Mortality, human capital and adaptive 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 human development and nutrition, such as height, weight and hemoglobin concentration in blood samples. 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 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 community (or cluster), which represents a village or a neighborhood. Our dataset includes all available surveys with geocoordinates and only considers countries with direct access to the ocean. We use all available surveys and re-weight observations to correct for oversampling of countries with multiple surveys.[8]

We restrict the sample to coastal areas. Using geolocation of communities, we follow United Nations (2003) and define a *coastal area* 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. Figure 1 shows the geographical coverage of the study area. 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 A.2 details the procedure used to compute distances, while Appendix B.1 discusses alternative definitions of coastal areas.

Resource wealth. Because marine wildlife presence is not directly observable, we exploit variations in their natural habitat, measured by the ocean's chemical composition. We focus on water pH at the surface, i.e., a logarithmic scale indicating at lower (higher) values the acidity (basicity) of an aqueous solution. Chemical features of the ocean in open waters are obtained from the HadGEM2 - Earth System dataset provided by the European Space Agency (ESA) Pathfinders-OA project (Sabia et al., 2015).[9] Data are provided as monthly global raster data at the $1°\times1°$ resolution for the period 1972–2018. Each community in the DHS is matched with a data point in the ocean using the shortest straight-line distance.

[7]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]Appendix A.1 provides the full list of countries and surveys. Results are robust to different selection criteria. For questions that are omitted in specific survey rounds, we re-compute weights to account for this selection.

[9]The produced series from the model matches available information from observational data (Totterdell, 2019). 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).

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 confirm its similarity with weather systems. 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.

We supplement data with other variables that could affect resource wealth in the ocean and inland in the coastal area. First, we gather information about other chemical features of the ocean from using the HadGEM2 - Earth System dataset. Second, using the ERA5 database, we supplement data with other meteorological features in the same location in the ocean 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.

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 night-time luminosity per 100,000 inhabitants in a gridded dataset at the $0.5°\times0.5°$ resolution, selecting only grid cells where DHS clusters used in the main analysis are present.

Ocean's exploitation. We use geographically-granular data about the intensity and the type of exploitation. First, we consider a form of *extractive fishing* by focusing on industrial fishing. We use 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 $1°\times1°$ resolution summing fishing hours within each cell over the available period. Because industrial fishing patterns have low sensitivity to economic and environmental variation (Kroodsma et al., 2018), time-invariant heterogeneity is likely capturing suitability for industrial fishing, rather than 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 define *night-time fishing* using the Automatic Boat Identification System for VIIRS Low Light Imaging Data (Elvidge et al., 2015). It provides the time and geolocation of boats using nightlight as 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 local scale, thus potentially contributing to the local economy. Similar to the measure of extractive fishing, we build a global grid at the $1°\times1°$ 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 Table B13 shows that fishing patterns are primarily driven by differences in geography, while individual characteristics are comparable in areas with high versus low intensities of both types of fishing. The intensity of night-time fishing is highly comparable in areas with high versus low intensities of extractive fishing. Appendix Figure B14 shows an example of the geographical distribution.

Seafood prices. Local variation in seafood prices at the geographical and temporal scale of our analysis is not available. We gather prices for the Philippines, a unique setting in our context: its coastline is the 5th largest in the world, it is home to 9% of global coral reefs, and depends highly on fish. We gather monthly retail seafood prices at the province level for the period 1990–2018 from the Philippine Statistics Authority. Prices are spatially heterogeneous and their pattern over time is in line with the global trend (Appendix Figure B15).

2 Empirical strategy

Temporal and geographical variation in pH is similar to the one of weather. Short-run variation in pH occurs around a global trend with within-year seasonality, just like air temperature or rainfall. We thus follow a standard approach in the literature on the effects of weather shocks (see, e.g., Dell et al., 2014). We define a *shock* as the short-run deviation in water pH levels from the spatially-specific long-run trend (corrected for seasonality). 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).

Contemporaneous exposure is computed by matching $R_{vc,mt}$ with individual information about children and women using the location of interview and the date of the interview. The *early-in-life exposure* is computed by matching $R_{vc,mt}$ with individual information using the location and the date of birth. [10] 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. The exogeneity of the shock is supported by balance on observable characteristics in areas affected by different shocks (Appendix B.5).

For both contemporaneous and early-in-life exposures to the shock, we estimate the causal effect of a shock, β, with the following specification:

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

where $y_{ivc,mt}$ is the outcome of interest for individual i in month m of year t in community v of macro-region c, $\mathbf{X}_{ivc,mt}$ is a vector of demographic and weather control variables, $\Omega_{vc,mt}$ is a set of FEs, and $\epsilon_{ivc,mt}$ are idiosyncratic errors assumed to be clustered at the ocean raster data point.[11]

The set of FEs define the shock in terms of deviations and capture unobserved heterogeneity in both the ocean's pH and the outcome variable once controlling for the following FEs. First, *time effects* remove unobserved characteristics of the date of interview or birth by controlling for year by month FEs. Second, because we exploit within-year variation, we remove *spatially-specific seasonality* by including macro-region by (in-

[10] As standard in the literature, we assume that the location of surveying corresponds to the location of birth. We do not highlight potential issues associated with selective migration (Appendix B.7).

[11] When the outcome variable refers to children, *demographic controls* include the child's gender and birth order, the number of twins born with the child, mother's age at birth and at the time of the interview (including square terms), mother's years of education, the household head's gender and age, and household size. When the outcome variable refers to adult women, these 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).

terview or birth) month FEs. Third, we remove *spatially-specific trends* by including location FEs, which capture time-invariant (observed or unobserved) spatial characteristics, and macro-region by (interview or birth) year FEs, which capture unobserved variation in trends. Controlling for seasonality and trends is important for identification because climate change impacts pH with spatially-heterogeneous effects, such that some regions exhibit faster or slower acidification and/or more amplified or compressed within-year variation than others.[12]

For location FEs, we use different alternatives depending on whether we are focusing on contemporaneous or early-in-life exposure. For contemporaneous impacts, we cannot exploit within-community variation because every individual in the community is interviewed at the same time. In this case, the *benchmark* specification includes location FEs corresponding to the grid cells in which the communities lie. For early-in-life exposure, the *benchmark* specification includes instead community FEs thanks to thanks to the within-community temporal variation originating from birth dates. When we can also exploit within-family variation, we estimate a *within-sibling* specification including mother-specific FEs. The latter strategy restricts the analysis to siblings and allows controlling for mothers and households' time-invariant characteristics. Appendix Figure B4 shows the evolution of the average shock in the sample of children over time, reinforcing the nature of abnormal deviation in pH of our main independent variable.

We support the validity of the identifying assumption with a variety of tests. In particular, we address issues related to non-random selection driven by FEs. 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 restrict 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

[12] To guarantee sufficient variation in the ocean's pH, which varies at the $1° \times 1°$ resolution, we define macro-regions using administrative indicators, such as the country or the district of the community or global grids at different resolutions. Administrative boundaries are the standard in the literature, while grids dissuade concerns about the potential endogeneity of administrative boundaries.

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 main specification with the within-sibling identifying sample (see, e.g., Alesina et al., 2021).

3 Results

Section 3.1 discusses the causal pathway of the effect of resource wealth by focusing on exposure to the shock that is contemporaneous to the time of measurement. Section 3.2 focuses on the effect of early-in-life exposure on mortality, parental adaptation, human capital, and economic well-being. Section 3.3 analyzes how these effects vary according to the prevalent method of marine resource exploitation near the community.

3.1 Defining the causal pathway of nature's wealth

We begin by testing whether nature's wealth operates through nutrition and health, two important correlates of economic development (Strauss and Thomas, 1998). We look at whether a shock induces changes in nutrition by estimating the contemporaneous effect of a resource wealth on malnutrition among women. We use micronutrient deficiency as a direct measure of malnutrition. We proxy deficiency using objective measurements of anemia, performed by the enumerators on a random subset of women in the sample. Anemia captures the presence of low levels of hemoglobin, a protein in red blood cells that carry oxygen in the blood. Columns (1)–(2) in Table 1 show that lower resource wealth leads to a higher prevalence of anemia, but only among pregnant women. An effect specific to this vulnerable population is not surprising because, during pregnancy, the human body requires more iron to supply the growing fetus (Luke, 1991). A 0.01

decrease in pH at the time of the interview leads to an increase in anemia prevalence of 1.7 percentage points among pregnant women (3.7% over the sample mean of 45.4%).

Anemia is often caused by a lack of iron. We therefore look at the propensity to consume an iron-rich diet. The DHS program asks, in a limited number of surveys and respondents (see Appendix A.1), whether a mother consumed different kinds of food in the 24 hours previous to the interview. We first focus on whether women consumed seafood, a naturally-available source of iron and other micronutrients that are crucial during pregnancy (FAO, 2020).[13] Second, we focus on whether women consume other iron-rich food (poultry, red meat, liver, beans, legumes, nuts and dark leafy greens). Columns (3)–(4) in Table 1 shows that a lower resource wealth leads to reduced consumption of seafood among all women. The reduction is larger among pregnant women, at 6.2 percentage points (18.6% over the sample mean of 33.4%). This decrease is compensated by a not-statistically-significant increase in the consumption of other iron-rich foods of 4.5 percentage point (5.3% over the sample mean of 85.1%).[14]

A deterioration of income associated with fishing can explain these changes in diet and the resulting maternal malnutrition. Because fishing is a primary economic activity in coastal areas, a reduced household income would push individuals towards cheaper calories. To test this channel, we look at satellite-based night-time luminosity. For this analysis, we build a gridded dataset at the $0.5° \times 0.5°$ spatial resolution and construct a yearly panel of night-time luminosity in the coastal area covered by DHS. We estimate equation (1) at the level of the grid cell, matching data about night-time luminosity with two resource shocks: one to agricultural productivity, as captured by the presence of a drought, and one to the ocean's resource wealth. The first surely captures an income shock given the importance of rainfall on agriculture and the reliance of L&MICs on this economic activity (see, e.g., Barrios et al., 2010). We define drought using an indicator variable taking value one when annual rainfall in the grid cell is below the

[13] *Iron* and *iodine* support brain development and growth in children, 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.

[14] Estimating equation (1) defining contemporaneous exposure as the average pH in multiple months close to the interview leads to similar conclusions.

15th percentile of the grid cell's historical rainfall distribution (see, e.g., Corno et al., 2020 for this approach). We follow the same approach to define a shock affecting the ocean's resources and we define an *acidity shock* with an indicator variable taking value one when the yearly average pH in the nearest open ocean's point is below the 15th percentile of the grid cell's historical distribution. Shocks are comparable in our sample, but are not simultaneous: the acidity shock affects 14.6% of observations, and droughts affect 12.9%, but their correlation coefficient is -0.05.

Table 2 presents the results. Estimates of the effect of an acidity shock are never significantly different from zero, and are unaffected by controlling for the presence of droughts (Appendix Table 2). As expected, droughts have a significant negative effect on night-time luminosity in coastal areas. The magnitude is about ten times as large as a comparable shock in the ocean's waters. Section 3.2 provides further evidence against income shocks at the household level. While we cannot exclude that ocean acidification may influence aggregate income in the long run, we conclude that short-run variation in the ocean's resource wealth operates primarily through nutritional deprivation.

In absence of any impact on income, changes in diets are likely driven by a change in the composition of marine wildlife that is available for consumption. Recent scientific evidence highlights how commonly-consumed species are less resilient to acidification and overfishing (Jones and Cheung, 2018), but they also have better nutritional content as compared to more resilient species (Falkenberg et al., 2020; Maire et al., 2021). If commonly-consumed species are preferred over more resilient species, then increases in the (relative) price of commonly-consumed species would increase consumption of more resilient species, but reduce the consumption of commonly-consumed species and the overall consumption of seafood. Malnutrition can therefore arise from short-run variation in resource wealth in absence of any income effect.

3.2 The effect of early-in-life exposure

Mortality. Table 3 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. Figure 2 shows estimates using alternative specifications, including alternative sets of control variables, different time FEs,and different definitions of macro-regions.

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 3). 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.[15]

These estimates are robust to a wide variety of checks. First, while changing the set of FEs alters our identifying assumptions and our measure of a shock, estimates are highly stable (Figure 2). At standard confidence levels, estimates are always negative and significantly different from zero. Second, results are not driven by selection into identification (Appendix B.4). 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. The latter allows rejecting the null hypothesis of a nil effect at the 5% significance level for all estimates in Table 3 (Appendix B.6).

The effect on NMR is driven by exposure to lower levels of pH during the gestation. Figure 3 presents an analysis based on bin variation of pH rather than continuous, as in

[15]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).

Deschênes and Greenstone (2011). 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. We highlight that the effect is driven by negative (or acidity) shocks, suggesting an important role of ocean acidification. In addition, 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 posterior to the period considered for the death). These results reinforce the role of maternal malnutrition and how it impacts children.

The effect on mortality is prevalent in the neonatal period. We estimate how resource wealth experienced *in utero* impacts the probability of 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).[16] 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.[17]

Heterogeneity in neonatal mortality. Impacts are concentrated in communities that rely more heavily on the ocean's resources. Figure 5 shows estimates of the effect of resource wealth on NMR allowing estimates to vary flexibly with distance from the

[16] We select the sample based on time from birth to avoid selecting children who are alive and younger than x. 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). We do not observe any effect on the estimates due to these potential issues. Appendix B.8 presents estimates of the effect on mortality rates at standard times.

[17] This mechanism is known in the literature as *death harvesting* (see, e.g., Heutel et al., 2021).

ocean's shore (Panel A), and from other water bodies (Panel B).[18] The largest effect on NMR 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.

Effects are also larger where seafood represents a higher share of total animal proteins consumed, in countries with a positive trade balance for fish products (Appendix B.3), and where artisanal fisheries are a central activity, such as in proximity to reefs (Appendix B.3). Coral reefs are essential for subsistence and artisanal fisheries, with approximately 500 million people deriving food or income from them, and are paying a high cost from ocean acidification (Doney et al., 2020).

To verify whether neonatal mortality is driven by reductions in the overall supply of seafood or by the composition of supply, we also look at seafood markets. Drops in the overall supply of seafood available for local consumption should reflect in increases in the average price of seafood. We thus compare the effect of *in-utero* exposure to resource wealth and to the average price of seafood in the local market. Due to data limitations, we restrict our analysis to the Philippines (see Section 1). We compute exposure to the average seafood price while *in utero* matching retail prices with individual information using the date and the province of birth. For identification, we rely on deviations in average retail seafood (log-)prices from the spatially-specific (and seasonally-adjusted) long-run trend by adding this variable in equation (1).

Table 4 shows that 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% increase in the average seafood price 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 highlights the link between seafood consumption and maternal health. However, the two channels operate independently on mortality. In line, for the full sample, we cannot identify any

[18] 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).

heterogeneous effect with respect to the ability to purchase more nutritious food.[19]

Adaptation. Table 5 examines parental adaptation. Columns (1)–(2) 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) to 2 (high investment). Appendix B12 shows estimates for 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.

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 parental adaptation following the observation of child health is limited. We also do not observe any significant effect on morbidity and anemia prevalence among children at the time of the measurement (Appendix B.9).

Human capital accumulation. Table 6 shows the effects of resource wealth experienced *in utero* on physical development built upon anthropometry. 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

[19] The effect is homogeneous across a wide array of individual characteristics (Appendix B.10). The effect is also independent from other shocks that have more direct effects on fish stocks, and robust to adding (potentially-endogenous) controls for income processes contemporaneous to the shock (Appendix B.2). We consider the presence of human activity using a measure of pollution in coastal waters; the presence of conflict (see, e.g., Axbard, 2016); and adverse weather events (see, e.g., Hsiang and Jina, 2014; Gröger and Zylberberg, 2016).

under-nutrition and infectious diseases since conception.[20] 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 measurements performed by the enumerators on a random subset of children and adults. These measures are conditional on the individual being alive at the time of the interview, and therefore need to be interpreted in light of the results on mortality.

Panel A 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. These differences are not associated with contemporaneous nutrition.[21] Neonatal mortality is primarily affecting the frailer children, in line with mortality selection prevailing over a scarring effect (see, e.g., Deaton, 2007).

Mortality selection is driven primarily by male children. Male children experience only a slightly larger and not statistically different mortality as compared to female children (Appendix B.10). However, when looking at physical development among female children, we highlight the prevalence of a scarring effect (Panel B). We do not observe any significant effect on variables associated with weight, but we record a significant effect on stunting. A 0.01 negative shock increases the probability of a girl to be stunted by 1.3 percentage points (5.7% relative to the sample mean).

The scarring effect on girls is persistent in the long-run. Panel C shows 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–an impact of 2.3% relative to the sample mean–is smaller among adults as compared to children.

[20]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.

[21]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).

Table 7 focuses on long-run impacts on the economic well-being of women. 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 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 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 experience *in utero* has long-run consequences that are not limited to anthropometrics. 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 the probability to work in the sample of main women by 0.01 children and 1.6 percentage points, respectively. We do not observe any effect on schooling and cognitive skills. The effects on economic well-being are small in magnitude, but statistically detectable even in the long-run.

3.3 Heterogeneity by resource exploitation

To understand how the availability of wildlife interacts with its exploitation, we turn our attention to heterogeneity of the effects discussed in Section 3.2 with respect to the type and intensity of fishing activities (see Section 1 for definitions). For comparability, we quantify the effect of a one-standard-deviation decrease in pH experienced while *in utero* (labeled as a *scarcity shock*), and 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 NMR and on physical development among children. The effect on both NMR and the effect on physical development are homogeneous along the intensity of night-time fishing. We observe instead heterogeneous effects by intensity of extractive fishing. Areas characterized by high intensity present a significantly larger effect on NMR as compared to areas where extractive fishing is absent. A scarcity shock leads to a 1.4% increase in NMR in areas where extractive fishing is absent and 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. A scarcity shock leads to an improvement in physical development by 0.7% in areas where extractive fishing is absent and by 4.3% in areas where extractive fishing is largest.

Panel B of Figure 6 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*. 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% over the sample mean.

Extractive fishing reduces significantly the ability to counteract short-run shocks. In fact, it amplifies their impacts. Night-time fishing tends to compensate these effects in the long run, but has no effect in the short run, in line with limited 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 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 summarize the results in this section.

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 the coastal area of all selected countries, acidification is responsible for an increase in neonatal deaths. NMR attributed to acidification ranges, in aggregate terms, 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. These results highlight 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. Contributions of acidification are larger in countries that are more dependent on the ocean's resources.

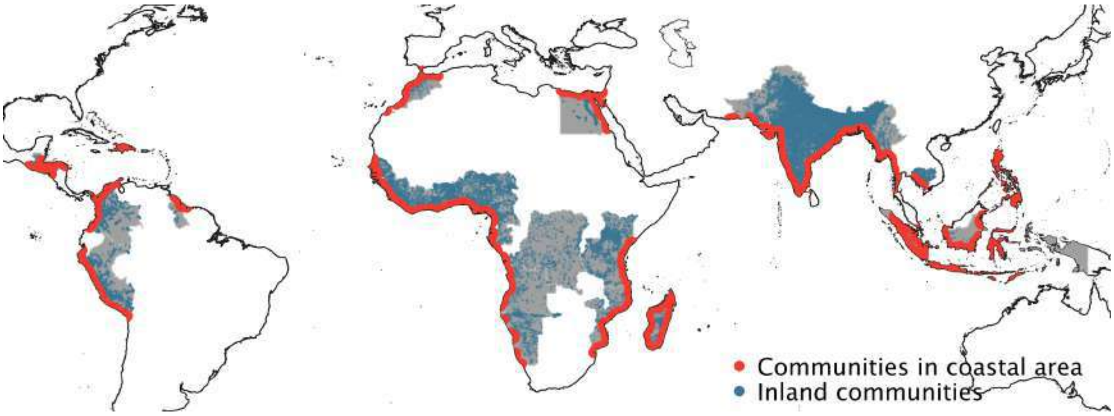
To capture long-run adaptation, we follow Dell et al. (2014) and estimate equation (1) interacting the ocean's pH while *in utero* with the spatially-specific initial conditions, proxied by the 1972–1975 (standardized) average pH in the correspondent ocean's point. The effect of resource wealth on NMR 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. For marine wildlife, the 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."

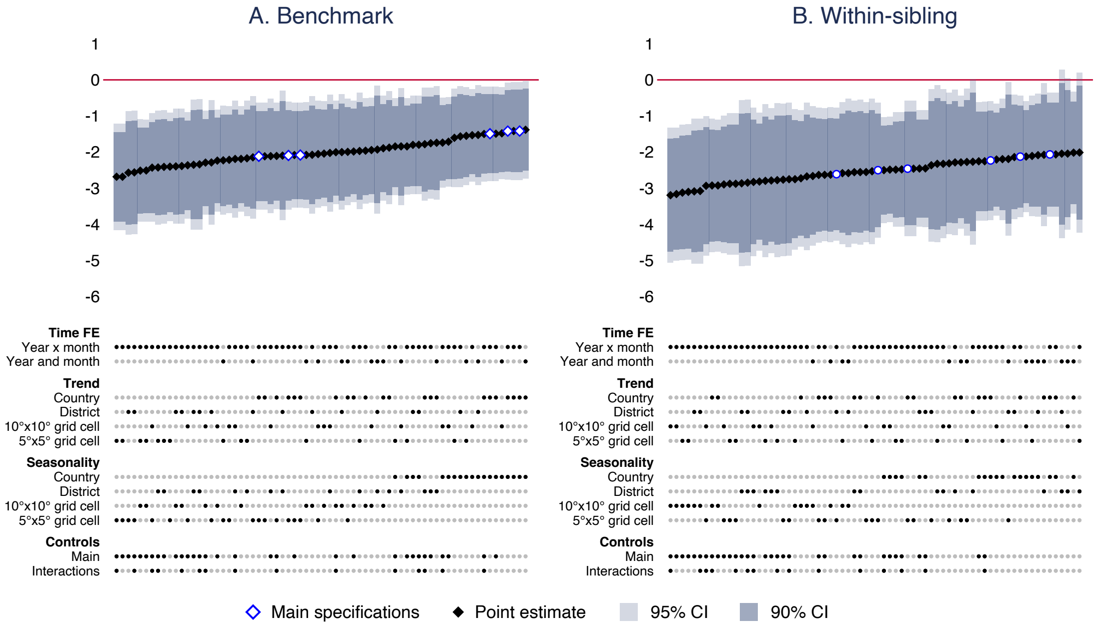
In the future, we should be wary of large effects of ocean acidification, even in the face of improved mitigation capacity. In absence of a strong natural resource governance and of effective mechanisms to incentivize conservation, policymakers need to channel resources efficiently to the communities 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 both short- and long-run consequences of malnutrition (Hoddinott et al., 2013; Gertler et al., 2014). Their implementation is particularly important for children in L&MICs, who are predicted to suffer the heaviest consequences of climate change (Hanna and Oliva, 2016).

Figure 1: Area covered by the study



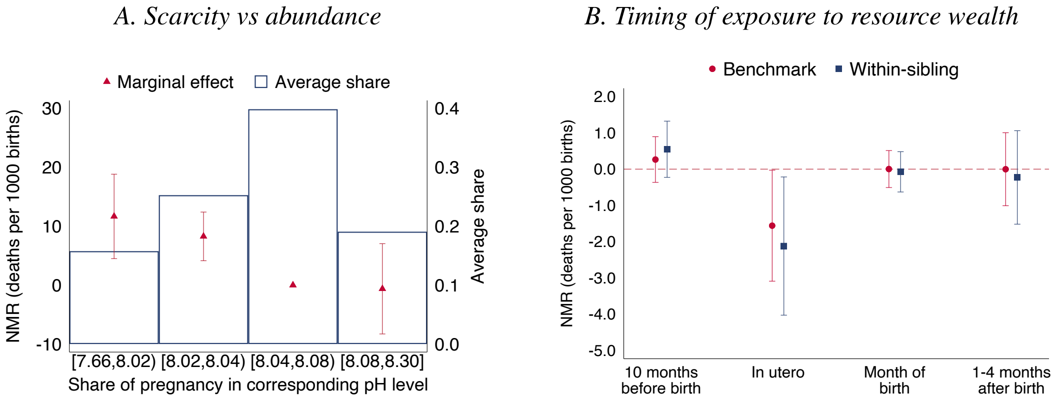
Note. Geographical distribution of selected communities in coastal areas. The shaded area represents all countries surveyed by the DHS with access to the ocean (the full list is reported in Appendix A.1). *Communities in coastal area* are villages and neighborhoods within 100 km from the ocean's shore. *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: Early-in-life exposure and neonatal mortality – alternative specifications



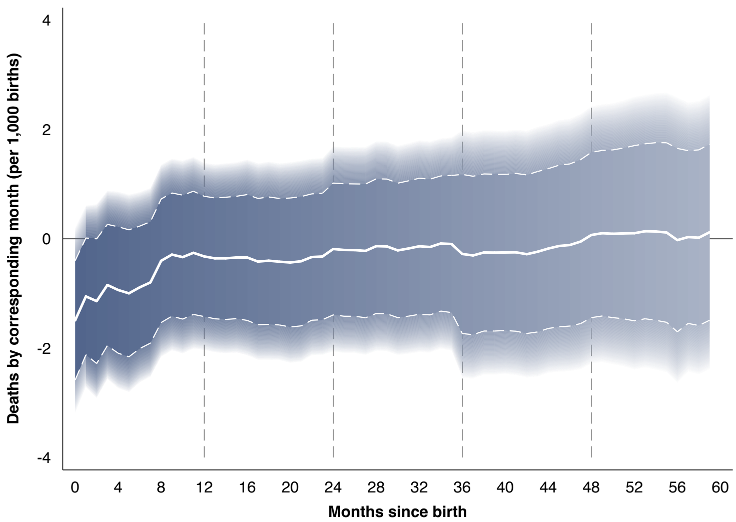
Note. Marginal effect of resource wealth under alternative sets of FEs in the benchmark specification (*Panel A*), and in the within-sibling specification (*Panel B*). The dependent variable is a dummy variable equal to 1 if the child died within the first month of life and 0 if the child survived, multiplied by 1,000. *In-utero 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 3. 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



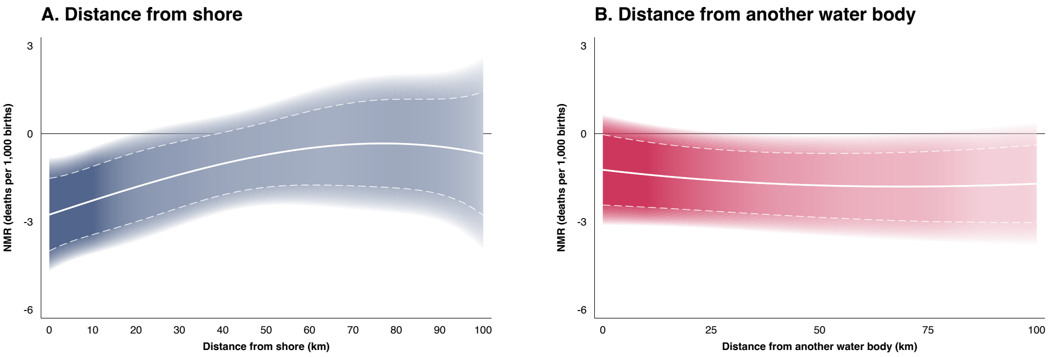
Note. Marginal effects of resource wealth by type of shock (*Panel A*), and by timing of exposure (*Panel B*). In *Panel A*, estimates are based on equation (1) where resource wealth is substituted by the share of time children were exposed *in utero* to different levels of the ocean's pH. We classify 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: Early-in-life exposure and mortality



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.

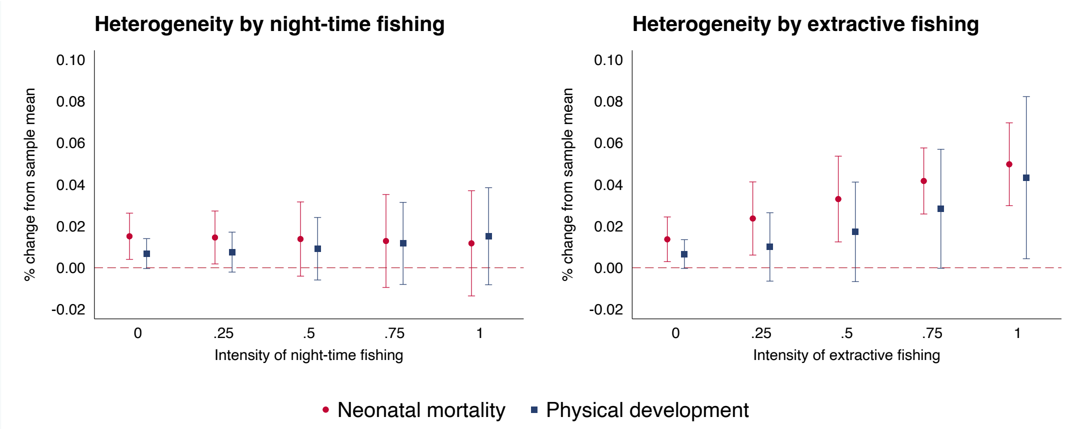
Figure 5: Early-in-life exposure and neonatal mortality, by distance from water bodies



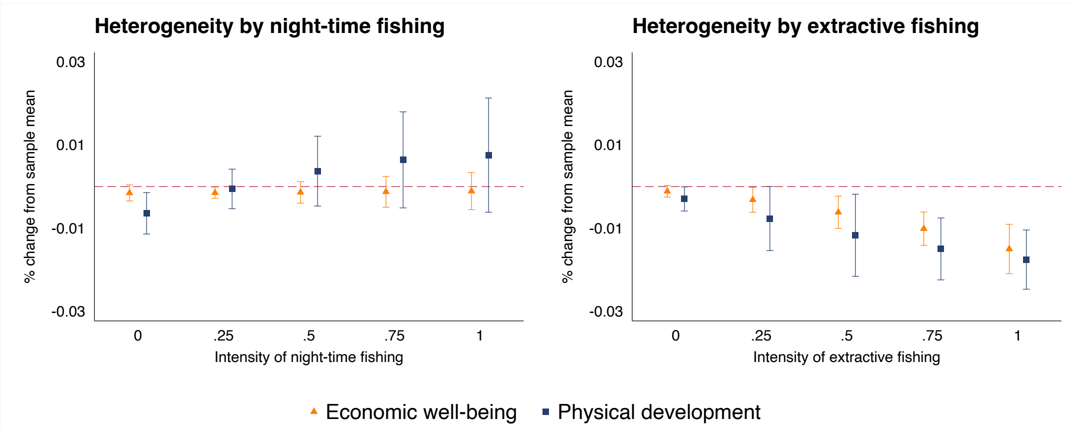
Note. Marginal effect of resource wealth on NMR as a function of distance from the shore (*Panel A*), and of distance from another water body (*Panel B*). The dependent variable is a dummy variable equal to 1 if the child died within the first month of life and 0 if the child survived, multiplied by 1,000. *In-utero 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*. *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: Contemporaneous exposure and malnutrition

Dependent variable:	**Prevalence of anemia**		**Food consumption** **Seafood**		**Other iron-rich food**	
Women in the sample:	*All*	*Pregnant*	*Mothers*	*Pregnant*	*Mothers*	*Pregnant*
	(1)	(2)	(3)	(4)	(5)	(6)
Current resource wealth	0.001	-0.017	0.026	0.062	0.005	-0.045
	(0.005)	(0.007)	(0.012)	(0.028)	(0.008)	(0.034)
	[0.840]	[0.013]	[0.028]	[0.030]	[0.548]	[0.180]
Mean (dep.var.)	0.427	0.454	0.296	0.334	0.870	0.851
Identifying observations	272,545	14,672	49,045	3,411	50,084	3,482
Singleton observations	2	36	2	42	2	46
Grid cells	473	416	239	172	246	175
Communities	17,370	8,993	5,952	2,191	6,083	2,237
Countries	26	26	14	13	14	14
Interview year range	2000–2018	2000–2018	2005–2016	2005–2016	2005–2016	2005–2016

Note. Estimates based on equation (1). *Current 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) (Croft et al., 2018). All specifications include location FEs using grid cells at the $1°\times1°$ resolution, interview month FEs, interview year FEs, country by interview month FEs, country by interview year FEs, and control variables (see Section 2, weather controls are measured at the time of interview). 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 2: Contemporaneous exposure and night-time luminosity

Dependent variable:	**Night-time luminosity in the coastal area (per 100,000 inhabitants)**					
	(1)	(2)	(3)	(4)	(5)	(6)
Acidity shock	-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 (1). The dependent variable is the satellite-based night-time 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. *Acidity shock* is an indicator variable taking value one when the yearly average pH in the nearest open ocean's waters is below the 15^{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^{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 3: Early-in-life exposure and neonatal mortality

Dependent variable:	**Neonatal Mortality Rate (deaths per 1,000 births)**					
	(1)	(2)	(3)	(4)	(5)	(6)
A. Benchmark specification						
In-utero 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						
In-utero 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. *In-utero 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 4: Early-in-life exposure, market prices and neonatal mortality

Dependent variable:	**Neonatal Mortality Rate (deaths per 1,000 births)**				
	(1)	(2)	(3)	(4)	(5)
In-utero resource wealth	-4.887		-4.997	-4.643	-4.728
	(2.620)		(2.630)	(2.629)	(2.685)
	[0.064]		[0.059]	[0.079]	[0.080]
Average seafood 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. *In-utero 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. Average seafood 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.

Table 5: Early-in-life exposure and parental adaptation

Dependent variables:	**Antenatal investment**	**Delivery investment**	**Postnatal investment**		
			Healthcare	Breastfed	Vaccinated
	(1)	(2)	(3)	(4)	(5)
In-utero 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]	[0.318]
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. *In-utero 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 6: Early-in-life exposure and physical development

Dependent variables:	Physical development	Z-scores		Indicators	
		W/h	H/a	Wasted	Stunted
	(1)	(2)	(3)	(4)	(5)
A. Short-run effects					
In-utero 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)					
In-utero 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)					
In-utero 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. *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 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 7: Early-in-life exposure and long-run 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)
In-utero 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. *In-utero 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.

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ONLINE APPENDIX

Supplementary material to *The Effect of Nature's Wealth on Economic Development: Evidence from Wildlife*

Alex Armand, Ivan Kim Taveras

A Data and methodological procedures

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

Variable	Description
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 3 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 3 years old for comparability (Croft et al., 2018).
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*.
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.
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).

(continued on next page)

Variable	Description
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 15^{th} 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 $1^{\circ}\times1^{\circ}$ 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).
Food intake	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: *seafood* 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; *other iron-rich food* is an indicator variable that equals 1 if the female respondent ate any poultry, red meat, liver, beans, legumes, nuts and dark leafy greens during the day previous to the interview, and 0 otherwise. We include these food items following the recommendations of the Harvard T.H. Chan School of Public Health.
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.
Night-time luminosity	Average night-time light emission from the $0.5^{\circ}\times0.5^{\circ}$ 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 $1^{\circ}\times1^{\circ}$ 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.
Nutrition	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: *Anemia* is an indicator variable equal to 1 if the woman has hemoglobin levels below 110 g/L, and 0 otherwise. *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 $1^{\circ}\times1^{\circ}$ 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.

(continued on next page)

Variable	Description
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.
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.
Seafood prices	Monthly retail price for seafood 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.
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)
In-utero 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	1972–2018	1972–2018	1972–2018	1972–2018

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. *In-utero 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.

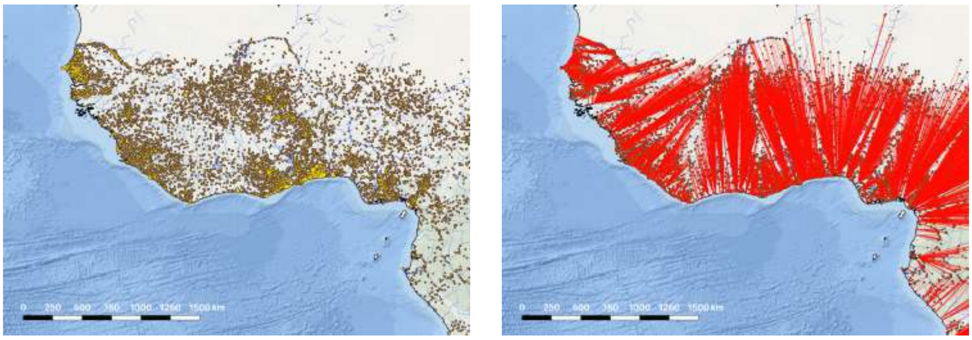
Table A4: Descriptive statistics for coastal and inland areas

	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

A. All DHS communities **B. Distance from shore**



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

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. In terms of **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 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. The largest magnitude is observed when distance is at most 40 km. In terms of **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 with higher human contamination, such as estuaries.

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

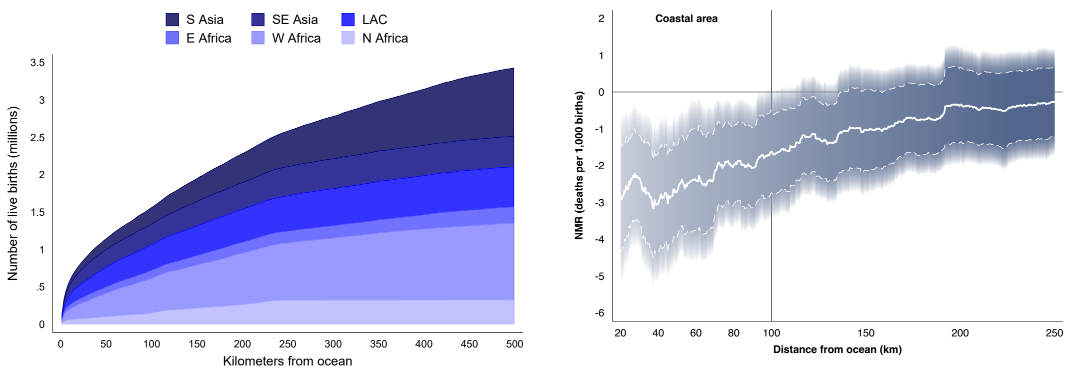
Dependent variable:	**Neonatal Mortality Rate (deaths per 1,000 births)**					
Altitude criteria:	$\leq$ *100m*	$\leq$ *100m*	-	-	$\leq$ *100m*	$\leq$ *100m*
Distance restriction:	-	-	$\leq$ *40km*	$\leq$ *40km*	$\leq$ *40km*	$\leq$ *40km*
Exclusion of estuaries:	-	*Yes*	-	*Yes*	-	*Yes*
	(1)	(2)	(3)	(4)	(5)	(6)
In-utero 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	1972–2018	1972–2018	1972–2018	1972–2018	1972–2018	1972–2018

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. *In-utero 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.

Figure B1: Sample selection by distance from shore

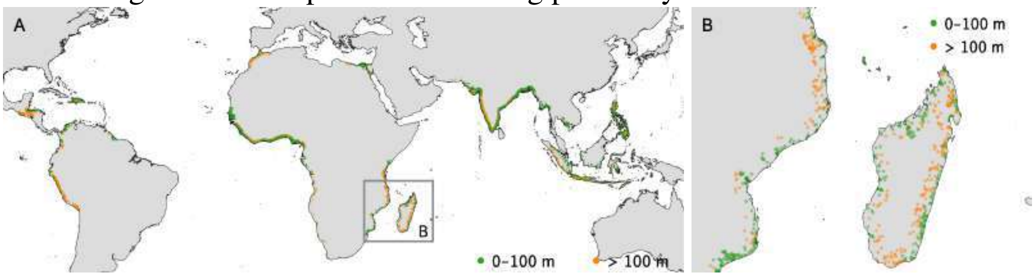
A. Number of live births

B. Effect of *in-utero* resource wealth



Note. Number of live births (decomposed by region) included in the dataset by distance from the shore (*Panel A*), and marginal effects of *in-utero* 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.

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

Figure B3 shows descriptive statistics of pH at surface averaged at global level. Figure B4 shows the evolution of the average resource 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 3, and the correspondent standardized effect.

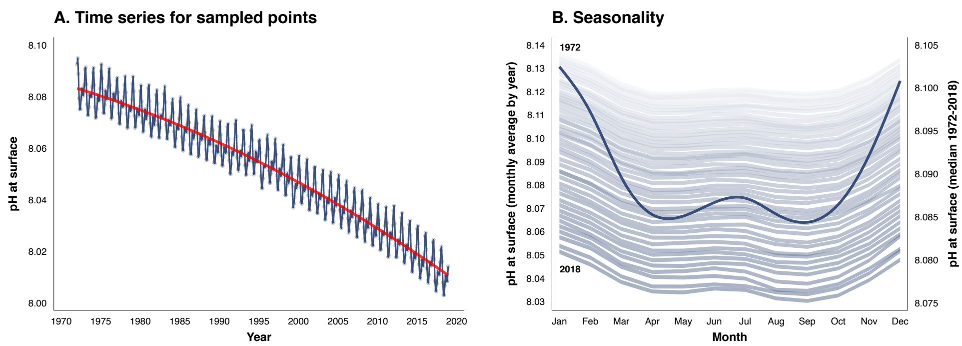
We focus next on other features in the ocean and in coastal areas that could influence income processes in sampled communities. In terms of **other ocean's characteristics**, Columns (1)–(7) in Table B3 presents estimates of the effect of resource wealth on NMR using equation (1) and controlling for 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. In terms of **pollution and other chemical features of the ocean**, Columns (8)–(9) in Table B3 presents estimates controlling for pollution in coastal waters. Higher contamination favors algae abundance, which negatively impacts the chance of survival of marine wildlife. We proxy pollution using a satellite-based measure of algae abundance (chlorophyll concentration) 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. At low levels of concentration (hypoxic conditions), marine wildlife

[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.

changes 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 (Free et al., 2019). 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. Panels E–F in Figure B5 presents the time series and the seasonality component for these variables.

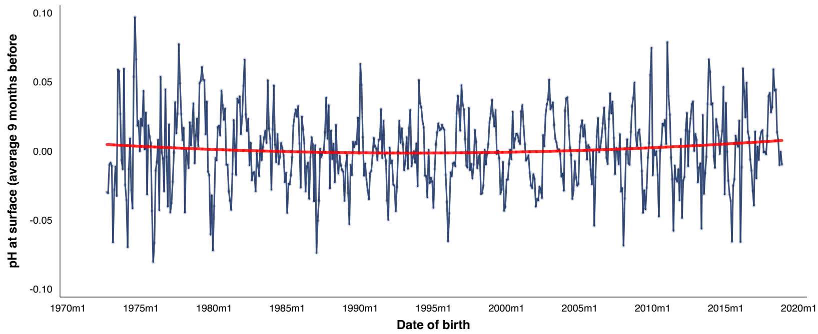
Finally, in terms of **conflict**, using information about conflict events from the Uppsala Conflict Data Program (UCDP) database at the 5°×5° resolution, we estimate equation (1) adding controls for the presence and the intensity of conflict while *in utero*. Table B4 presents estimates of the effect 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.

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 *in-utero* resource wealth



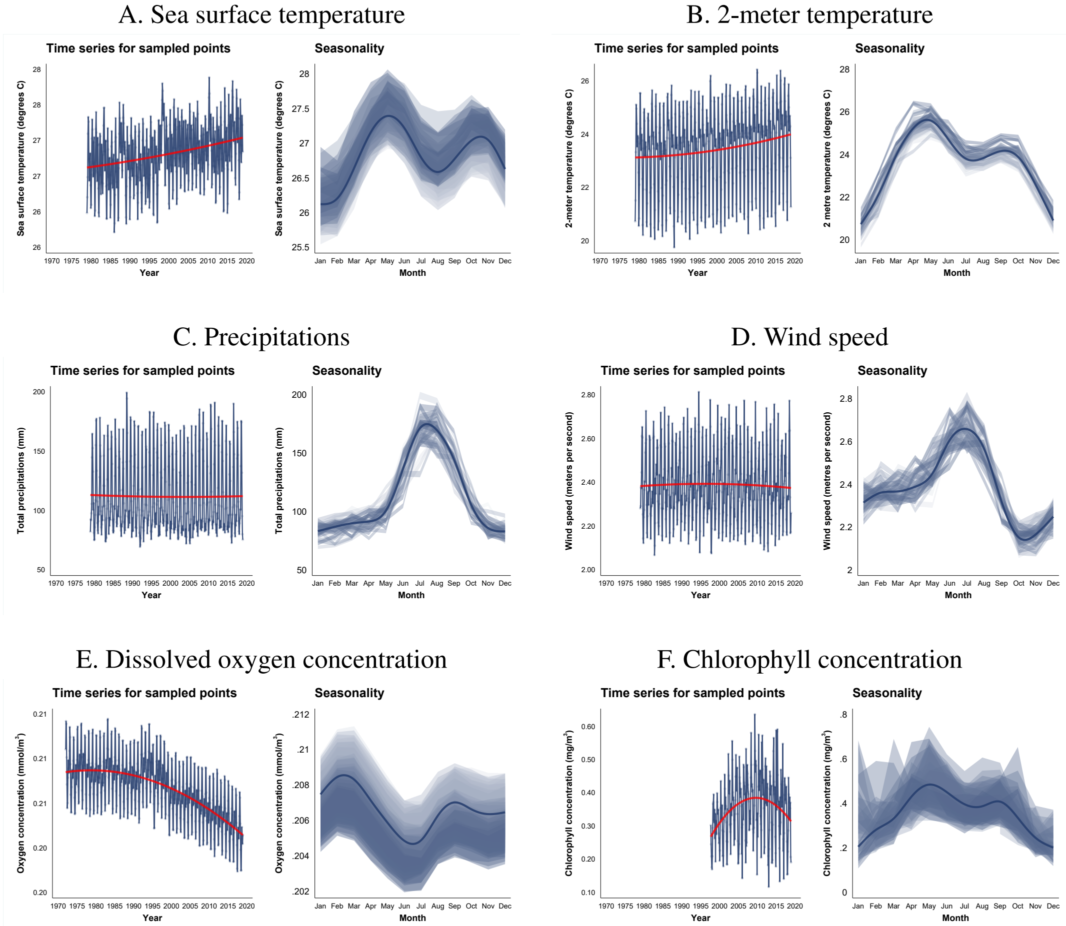
Note. Evolution over time of the average deviation in acidity levels from spatially-specific (and seasonally-adjusted) long-run trends. *In-utero resource wealth* is defined in Section 2 and is computed using the benchmark specification. Variation is restricted to cells matched to the sample. The solid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

Table B2: *In-utero* 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 3. 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									
In-utero 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]	
In-utero sea surface temperature	1.467	1.695					1.549		
	(0.925)	(0.918)					(1.064)		
	[0.113]	[0.066]					[0.146]		
In-utero wind speed			1.752	1.596			2.159		
			(1.510)	(1.505)			(1.547)		
			[0.247]	[0.290]			[0.164]		
In-utero total precipitations					0.008	0.007	0.009		
					(0.008)	(0.008)	(0.008)		
					[0.289]	[0.351]	[0.265]		
In-utero 2-meter temperature					0.674	0.902	0.040		
					(0.898)	(0.892)	(1.039)		
					[0.453]	[0.312]	[0.969]		
In-utero chlorophyll concentration								0.295	0.301
								(0.583)	(0.584)
								[0.614]	[0.606]
In-utero oxygen concentration							-0.069		
							(0.306)		
							[0.822]		
Location of birth									
In-utero temperature							-0.121		
							(0.427)		
							[0.778]		
In-utero total precipitations							-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	1979–2018	1979–2018	1979–2018	1979–2018	1979–2018	1979–2018	1979–2018	1998–2018	1998–2018

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. *In-utero 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°×5° 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.

Table B4: Comparing the effect size of resource wealth and conflict

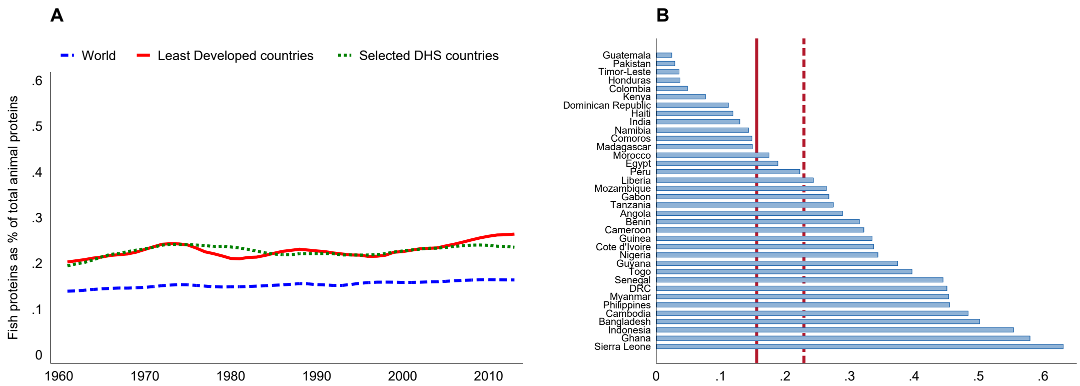
Dependent variable:	**NMR (deaths per 1,000 births)**					
	(1)	(2)	(3)	(4)	(5)	(6)
In-utero resource wealth	-1.006	-1.014	-1.010	-1.603	-1.614	-1.612
	(0.629)	(0.632)	(0.629)	(0.799)	(0.796)	(0.799)
	[0.110]	[0.109]	[0.109]	[0.045]	[0.043]	[0.044]
At least 1 violent event (*in utero*)	1.702			1.715		
	(1.107)			(1.128)		
	[0.125]			[0.129]		
In-utero fatalities		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	1984–2018	1984–2018	1984–2018	1984–2018	1984–2018	1984–2018
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. *In-utero 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 $5°\times5°$ cell by birth month FEs. Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

B.3 Seafood dependency

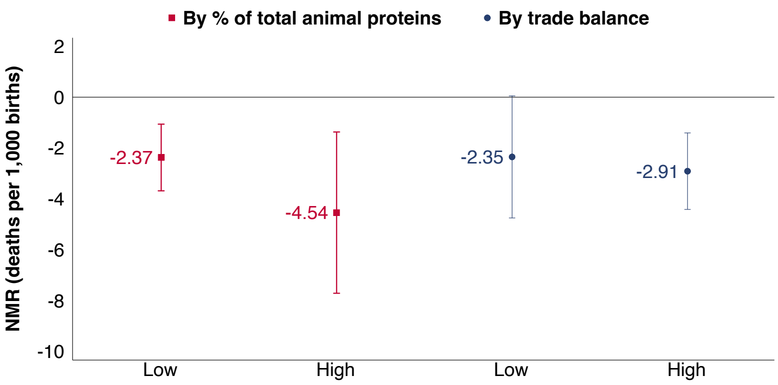
Figure B6 presents descriptive statistics for **seafood dependency**, defined as the share of total proteins of animal origin coming from seafood. Figure B7 presents the estimates of the heterogeneous effect of resource wealth on NMR distinguishing by a country's fish dependency in Panel A, and by the trade balance for fish products from the FAOSTAT database (FAO, 2019) in Panel B. As a separate measure of dependency on artisanal fishing, we focus on proximity to **coral reefs**. Figure B8 shows marginal effects of resource wealth on NMR 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.

Figure B6: Seafood dependency and trade balance for fish products



Note. Average value of seafood 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 seafood 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).

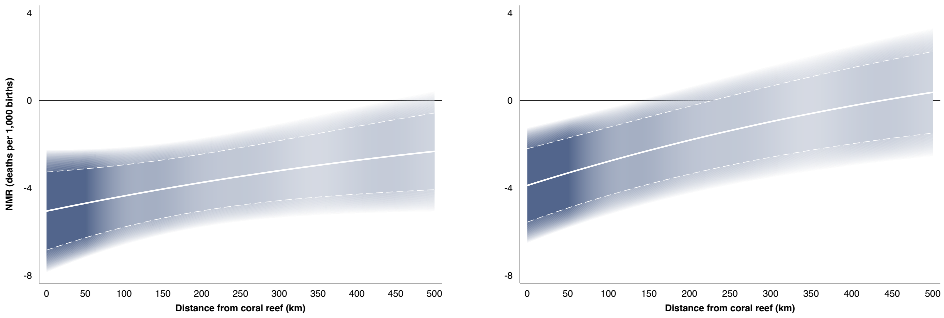
Figure B7: The effect of *in-utero* resource wealth on NMR, by fish dependency



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: *In-utero* resource wealth and neonatal mortality, by distance to coral reefs

A. At the shore B. At 40km from the shore

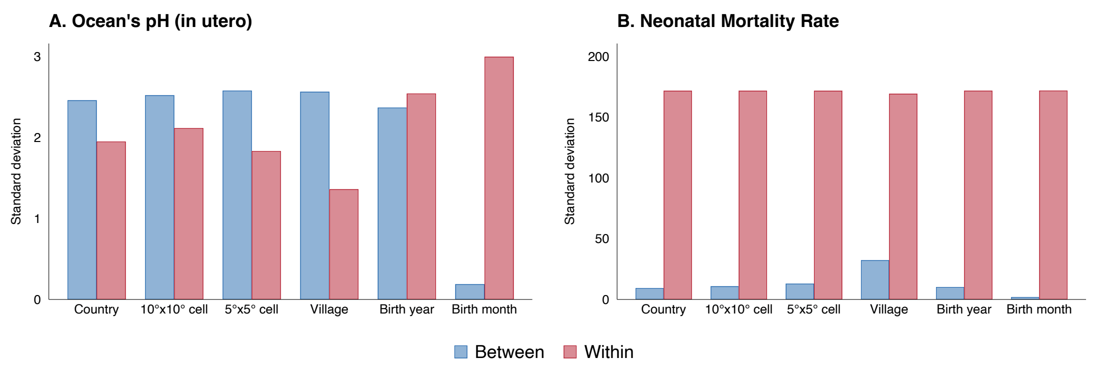


Note. Marginal effect of *in-utero* resource wealth on NMR as a function of shortest distance from a coral reef and assuming 0 distance from the ocean's shore (*Panel A*), or a distance of 40 km (*Panel B*). The dependent variable is a dummy variable equal to 1 if the child died within the first month of life and 0 if the child survived, multiplied by 1,000. *In-utero 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 of being 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)
In-utero 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	1972–2018	1972–2018	1972–2018	1972–2018	1972–2018	1972–2018
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. *In-utero 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°×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.

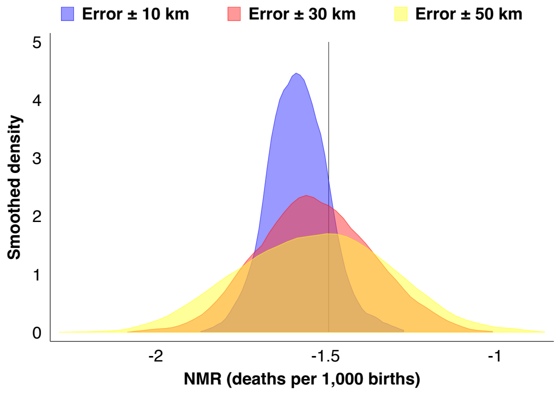
Table B7: Placebo test: balance on observable characteristics

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)
In-utero 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	1972–2018	1972–2018	1972–2018	1972–2018	1972–2018	1972–2018	1972–2018	1972–2018

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. *In-utero 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 3). 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

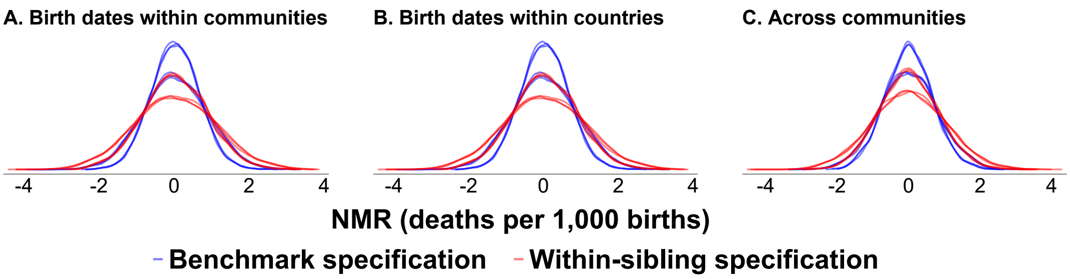
Table B8 shows estimates of equation (1) for NMR using different assumptions for the clustering of standard errors (reported in column). In addition, focusing on Table 3, we implement three different permutation-based inference tests. In the *birth dates within communities* test, birth dates are randomly 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)
In-utero 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	1972–2018	1972–2018	1972–2018	1972–2018	1972–2018	1972–2018

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. *In-utero 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 3	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, *in-utero 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 3. 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 3 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)
In-utero 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	1980–2018	1980–2018	1980–2018	1980–2018	1980–2018	1980–2018
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. *In-utero 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)
In-utero 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	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 mother of the child migrated to the community of the interview in the first 5 years of life of the child, and 0 otherwise. *In-utero 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 rates

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)
In-utero 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	1972–2018	1972–2018	1972–2018	1972–2018	1972–2018	1972–2018	1972–2018	1972–2018
Controls	-	Yes	-	Yes	-	Yes	-	Yes

Note. Estimates based on equation (1). The dependent variables are reported in the column's header. *In-utero 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

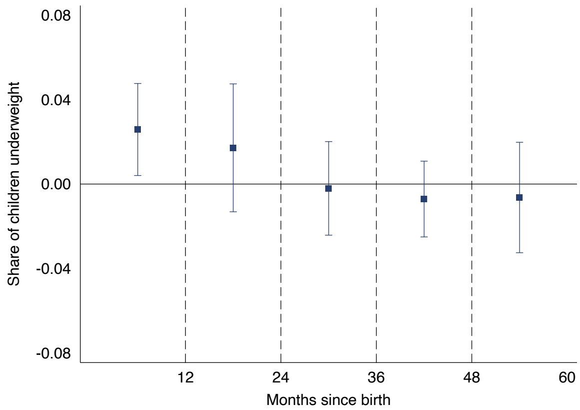
Table B12 shows estimates of the effect of resource wealth on parental health investments and on health outcomes associated with poor contemporaneous nutrition. To provide further evidence about the nutritional channel, Figure shows instead the effect of the resource shock on the probability of being 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.

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)
In-utero resource shock	-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]	[0.063]	[0.221]	[0.677]	[0.765]
Mean (dep.var.)	1.643	0.442	0.354	0.638	0.391	0.558
Identifying observations	263,819	494,305	491,838	267,900	339,407	114,370
Singleton observations	1,099	131	131	1,032	871	1,437
Communities	29,943	31,304	31,163	30,031	29,932	15,844
Countries	36	36	36	36	36	27
Birth year range	1985–2018	1972–2018	1972–2018	1985–2018	1985–2018	1995–2018

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. *In-utero 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

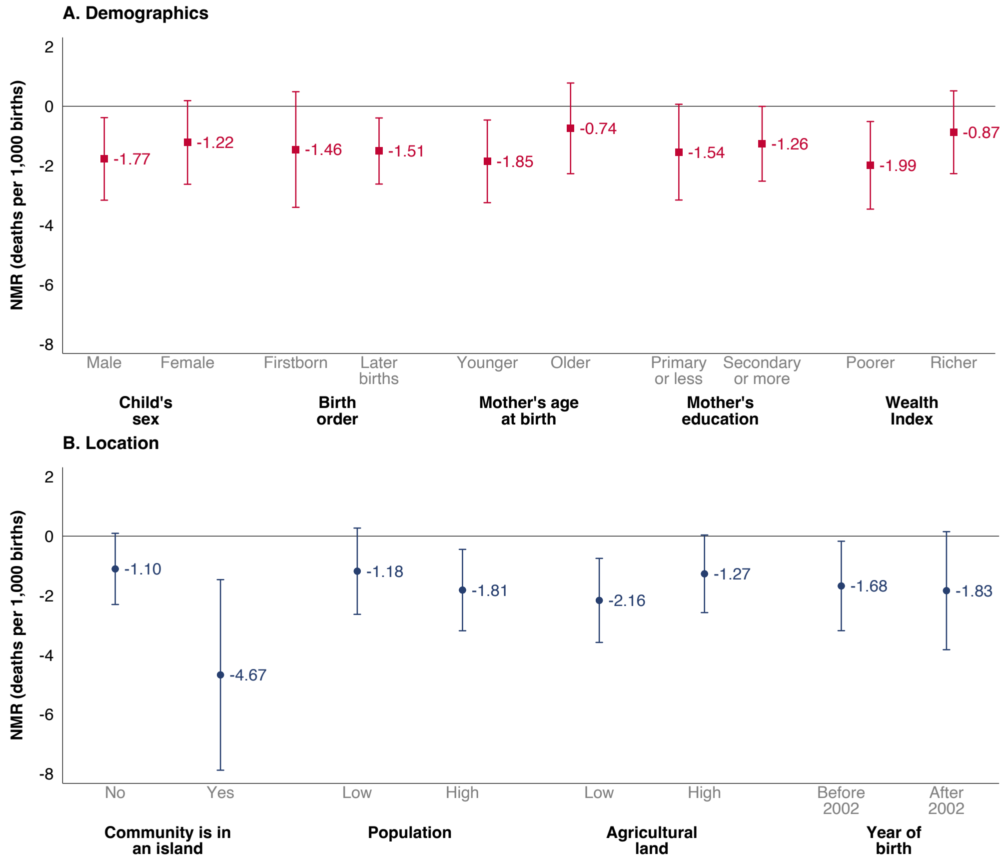


Note. Marginal effect of *in-utero* resource wealth on the probability of the child to be underweight. The dependent variable is an indicator variable equal to 1 if the child has a weight-for-age z-score below negative 2 standard deviations, and 0 otherwise. Confidence intervals at 90% level. Estimates 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.

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 *in-utero* resource wealth on NMR



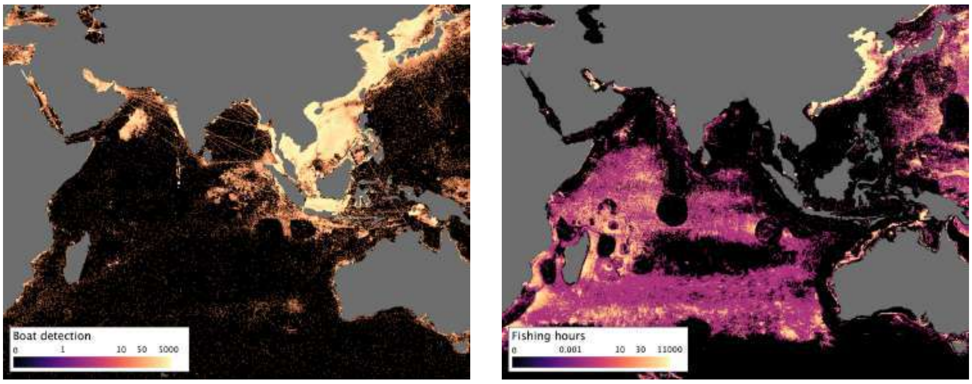
Note. Heterogeneous effects of ocean's pH while *in utero* on NMR by child and mother's demographics (*Panel A*), and by location's characteristics (*Panel B*). Marginal effects are estimated using equation (1) restricting the sample to the corresponding group. For mother's age at birth, wealth index, 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 seafood prices

For **night-time** and **extractive fishing**, Figure B14 shows an example of the geographical variation, while Table B13 shows descriptive statistics comparing areas with low versus high intensity of both types of fishing. 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 **seafood prices**, the Philippine Statistics Authority (2020) provides monthly retail prices at the province-species level. Figure B15 shows the evolution of prices and the spatial distribution of the median seafood price for the period 1990 – 2018.

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.

Table B13: Descriptive statistics by degree of extractive and night-time fishing

	Extractive fishing				Nighttime fishing				
	High intensity		Low intensity		High intensity		Low intensity		
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A. Children									
Child is alive	0.91	0.28	0.93	0.26	0.93	0.26	0.92	0.27	1,587,285
Child is female	0.48	0.50	0.48	0.50	0.48	0.50	0.49	0.50	1,587,285
Birth order	2.53	1.79	2.55	1.81	2.49	1.75	2.59	1.86	1,587,285
Number of twins born with the child	0.04	0.25	0.03	0.22	0.03	0.24	0.03	0.23	1,587,285
Years since birth	12.11	7.87	12.36	7.87	12.36	7.86	12.21	7.88	1,587,285
Mother's age at birth	24.34	5.78	24.47	5.76	24.38	5.65	24.47	5.88	1,587,285
Ocean's pH (*in utero*)	8.05	0.03	8.05	0.03	8.06	0.03	8.05	0.03	1,587,285
Antenatal care with health professional	0.28	0.45	0.26	0.44	0.26	0.44	0.28	0.45	706,086
Delivery care with health professional	0.25	0.43	0.24	0.42	0.24	0.43	0.24	0.43	706,156
Delivery care in health center	0.79	0.41	0.71	0.45	0.75	0.43	0.72	0.45	269,314
B. Adult women									
Age at first delivery	20.87	4.28	20.89	4.21	20.98	4.22	20.78	4.25	495,310
Current age	30.35	9.73	30.79	9.84	30.82	9.72	30.47	9.89	706,381
Years of schooling	6.54	5.03	7.54	4.73	7.33	4.89	7.18	4.79	629,359
Ocean's pH (*in utero*)	8.06	0.03	8.07	0.03	8.07	0.03	8.06	0.03	434,621
Primary education or less	0.42	0.49	0.40	0.49	0.40	0.49	0.42	0.49	706,351
Married	0.65	0.48	0.68	0.47	0.69	0.46	0.65	0.48	705,238
Working	0.59	0.49	0.51	0.50	0.51	0.50	0.56	0.50	606,687
Household head is female	0.21	0.41	0.22	0.41	0.19	0.39	0.25	0.43	706,381
Household head's age	46.49	13.14	45.91	13.09	46.55	13.10	45.64	13.11	705,813
Household members	5.88	3.38	5.50	2.84	5.76	3.24	5.48	2.79	706,381
Household wealth	3.78	1.30	3.69	1.28	3.77	1.25	3.66	1.32	624,057
Living in urban area	0.64	0.48	0.49	0.50	0.56	0.50	0.50	0.50	706,381
Distance from shore	28.56	30.88	32.53	29.80	31.39	30.03	31.13	30.39	706,381
Distance from another water body	33.34	30.96	53.89	121.41	28.71	34.67	66.05	137.88	706,381
Altitude	189.37	479.06	190.63	371.10	99.23	206.89	281.77	524.73	706,381
Latitude	8.78	13.34	11.38	11.38	14.05	11.35	7.03	11.82	706,381
Longitude	24.97	58.04	34.16	74.98	45.87	59.94	16.49	76.32	706,381
Temperature (° C)	25.80	3.93	26.22	2.79	26.49	2.54	25.68	3.72	706,381
Precipitations (mm)	1344.55	591.54	1657.39	687.29	1608.57	722.23	1505.94	617.84	706,381
Nightlight	0.17	0.12	0.15	0.11	0.19	0.14	0.13	0.08	706,381
Intensity of extractive fishing	0.20	0.31	0.00	0.00	0.11	0.26	0.02	0.06	706,381
Intensity of night-time fishing	0.08	0.10	0.09	0.23	0.17	0.25	0.00	0.00	706,381
C. Mortality rates									
Neonatal	29.41	168.95	26.65	161.05	28.28	165.76	26.74	161.33	1,583,731
Postneonatal	25.13	156.53	23.01	149.94	21.67	145.60	25.66	158.11	1,470,093
Child	26.56	160.78	19.54	138.41	20.57	141.94	22.82	149.33	1,141,371
Infant	54.00	226.01	49.16	216.20	49.44	216.79	51.87	221.77	1,516,640
Under-five	81.81	274.08	70.84	256.55	71.72	258.02	76.72	266.15	1,217,000

Note. Descriptive statistics of coastal areas by degree of extractive and night-time fishing. We define areas with above-median extractive or nighttime fishing intensity as *High intensity*. Conversely, we define areas with below-median extractive or nighttime fishing intensity as *Low intensity*. Coastal area includes all communities within 100 km from the ocean's shore (see Section 1). Means are reported in columns (1), (3), (5), and (7); standard deviations are reported in columns (2), (4), (6), and (8). Column (9) 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.

Table B14: Test of heterogeneous effects of resource wealth

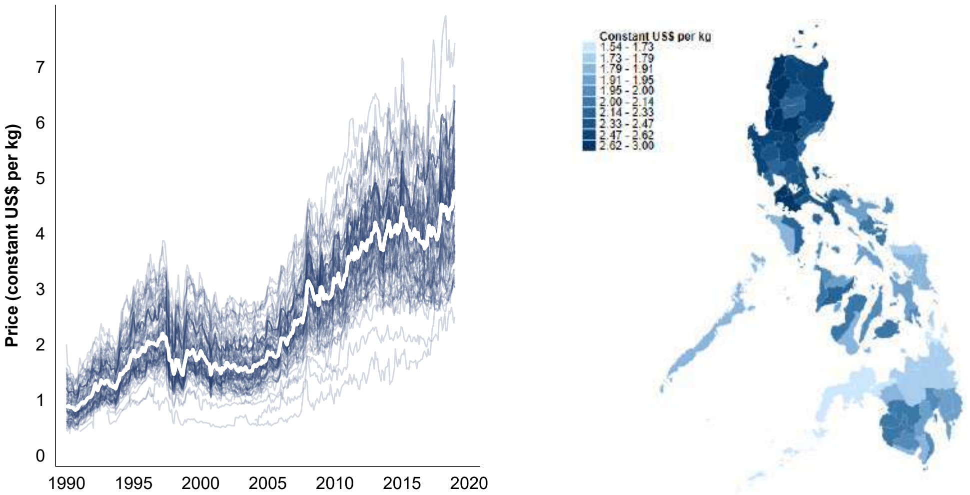
Type of interaction	**Linear**		**Linear+quadratic**	
	F	p-value	F	p-value
	(1)	(2)	(3)	(4)
Panel A. Short-run effects (all children)				
NMR				
Intensity of extractive fishing	32.111	0.000	16.769	0.000
Intensity of night-time fishing	0.165	0.685	0.260	0.771
Physical development				
Intensity of extractive 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). *In-utero resource wealth* 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 B15: Time series and spatial distribution of the average seafood retail price

A. Time series

B. Spatial distribution of the median price

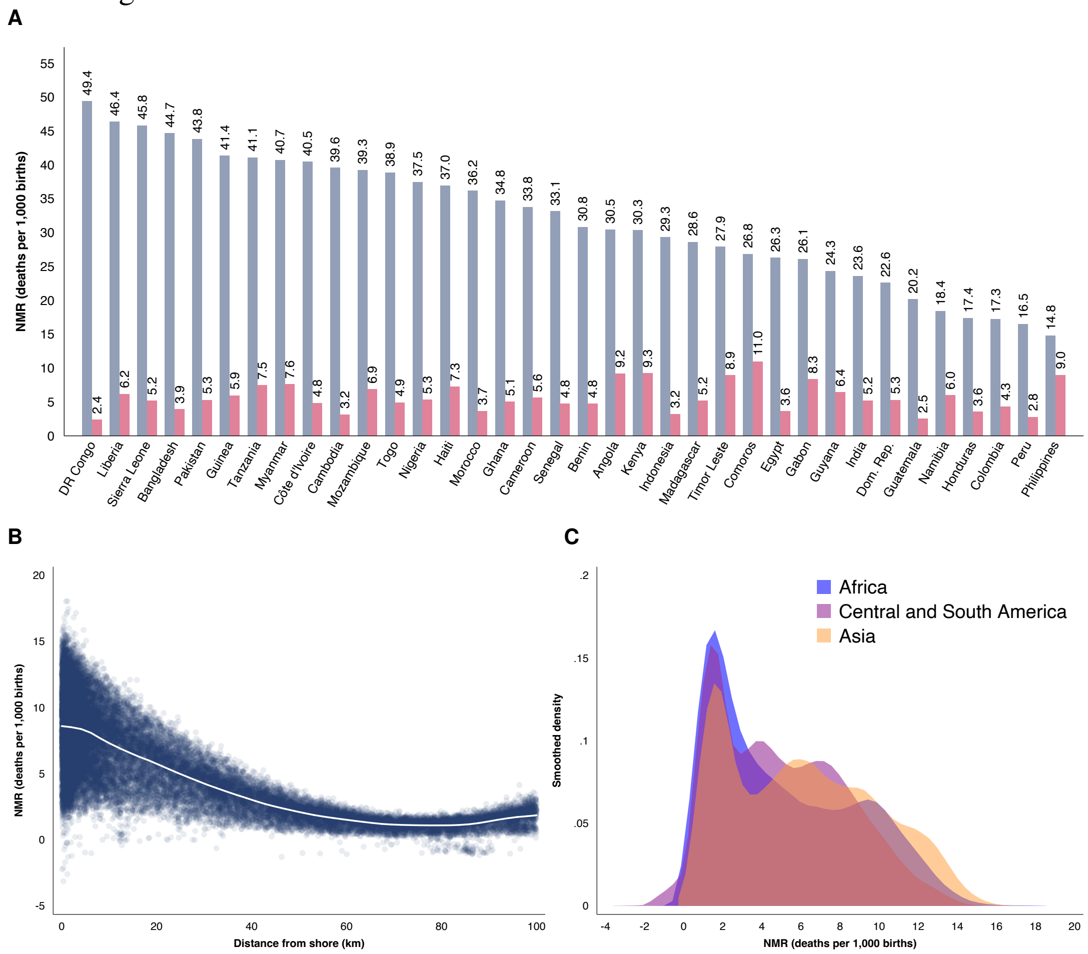


Note. Evolution over time of the province-level average seafood price (*Panel A*) and spatial distribution of the 1990 – 2018 median seafood price (*Panel B*). Prices are obtained for the following species: indian mackerel, milkfish, threadfin bream, blue crab, caesio, anchovies, frigate tuna, tilapia, 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 3 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)
In-utero 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]
$\times$ 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	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. *In-utero 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. *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 $5° \times 5°$ 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.

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