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

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Abstract

This paper provides the first quantitative evidence on the causal effect of nature's wealth on human development. Focusing on the ocean's exploitation for food consumption, we study early-life exposure to exogenous shocks in the ocean's chemical composition, i.e., unobservable short-run changes in the wealth of species that can be locally harvested. Focusing on 36 low and middle income countries between 1972 and 2018, we estimate impacts up to 46 years post exposure analyzing information on 0.5 million adult women and 1.5 million births. Negative shocks have a significant effect on mortality early in life, especially where resources are overexploited. While mortality selection dominates scarring, we find long-lasting negative impacts on human capital and economic well-being among women. Effects are driven by unobserved nutritional deprivation during pregnancy. They operate in absence of any contemporaneous adaptation as no behavioral change or adjustment in consumption occur. We exclude the presence of income or price shocks using granular measures of resource exploitation, nightlight luminosity, and fish prices. Aggregate estimates reveal that persistent negative shocks lead to considerable life loss. (*JEL* I15, Q20, Q54, O10)

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

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For millennia, societies have exploited renewable natural resources as a source of food and energy. However, to make this exploitation sustainable, the resource's rate of reproduction needs to, at least, match that of consumption. While this condition has been discussed by economists since Malthus (1872), overexploitation has often prevailed, incentivized by the rivalrous and non-excludable essence of these resources (Ostrom, 2003). This applies to well-known issues like deforestation (Burgess et al., 2012; Jayachandran, 2013), overfishing and poaching (Kremer and Morcom, 2000; Stavins, 2011), or underground water exploitation (Hornbeck and Keskin, 2014; Blakeslee et al., 2020). The literature highlights the determinants of these phenomena, but there remains little understanding of their consequences for human development. To our knowledge, there exists no evidence on the impact of a reduced endowment of these resources.

This paper provides the first quantitative evidence on the causal effect of natural resource's abundance or scarcity on human development. Focusing on mortality early in life, human capital and economic well-being, we study these relationships in the context of the exploitation of the ocean for food consumption. This activity accounts for 1% of global GDP, relates to long-run economic development, and remains crucial for global food security (The World Bank, 2012; Dalgaard et al., 2020). The livelihood of more than 3 billion people depend on the consumption of fish, which provide nutrients that are both accessible in nature and essential for human health (United Nations, 2021). These populations are mostly living in low and middle income countries (L&MICs), where resources are limited, consumption is reliant on local harvest, and undernutrition and micronutrient-related malnutrition remain the most important risk factors for illness and death among pregnant women and children (Victora et al., 2021).

We uncover causality by exploiting early-in-life exposure to exogenous shocks in the ocean's chemical composition. We refer to these events as *resource shocks*: by altering marine habitats heterogeneously across space and time, they shift in the short-run the wealth of species that can be locally harvested and consumed. In particular, we focus on water acidity, a chemical property that lowers the availability of minerals needed by marine life to calcify bones and bleaches coral reefs (Doney et al., 2020). Recent evidence highlights how water acidity impacts the nutritional content of species that are commonly consumed (Maire et al., 2021).[1]

By affecting the returns to exploitation, the resource shock we study shares common features with exogenous inputs to labor or agricultural productivity, such as temperature and rainfall. However, two characteristics make it fundamentally different from previously-studied events. First, while a wide variety of events studied in the literature are either observable or have direct effects on health,[2] water acidity is unobserved: it 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). If at all, shocks can only be observed through the exploitation of the ocean's resources. Second, while most shocks to human development encompass changes in income (Adda et al., 2009; Banerjee et al., 2010) or prices (Cogneau and Jedwab, 2012), shocks to open access resources are unlikely to operate through market mediators in the short run, a hypothesis that we test in the paper. Fisheries are resilient with respect to income thanks to biodiversity and catch diversification, to the point that global fishing patterns show low sensitivity to environmental variation (Kroodsma et al., 2018; Bianchi et al., 2021). While scarcity is well reflected in markets for non-renewable natural resources, the prices of renewable resources are primarily driven by global demand (Stavins, 2011).

Exploiting these features, we test alternative mechanisms through which renewable resources' wealth operates using unique historical and geographical coverage. We analyze half a million adult women and 1.5 million live births in 36 L&MICs across Africa, Asia, and Latin America for the period 1972–2018. Exposure to shocks is computed by matching each individual's geolocation and date of birth with data on water acidity at a high spatial and temporal resolution. While we focus on exposure early in life, when human capital accumulation has the largest returns (Currie and Almond, 2011; Almond et al., 2018), we also study short- and long-run effects by covering impacts up to 46

[1] Acidity does not necessarily reduce the quantity of available resources. A large literature highlights how the ocean's chemical composition impact the reproductive behavior, size, chance of survival and spatial distribution of all marine species (Doney et al., 2020).

[2] The literature covers the effects of early-life exposure to atmospheric events (Heft-Neal et al., 2018; Geruso and Spears, 2018a; Adhvaryu et al., 2020), conflict (Wagner et al., 2018), macroeconomic fluctuations (Baird et al., 2011; Paxson and Schady, 2005; Bhalotra, 2010), political institutions (Kudamatsu, 2012), environmental contamination (Chay and Greenstone, 2003; Arceo et al., 2016; Isen et al., 2017; Geruso and Spears, 2018b), and radioactive exposure (Black et al., 2019).

years post exposure.

For identification, we exploit variation in water acidity that originates from two features. First, the ocean's chemical composition follows a natural cycle similar to weather systems: in a given spatial area, acidity and the availability of minerals needed by marine life to develop vary in the short-run as random draws from the long-run distribution. This plausibly random variation is similar to short-run variation in weather, which has been widely used in the literature (see, e.g., Corno et al., 2020 for a recent example). Second, the natural cycle of water acidity has been altered by climate change with exogenous and spatially-heterogeneous increases in acidity, a process known as *ocean acidification*. Exploiting these two features, we define shocks as short-run deviations in acidity levels from the spatially-specific (and seasonally-adjusted) long-run trend, an approach that makes relatively few identifying assumptions and allows unusually strong causative interpretation (Dell et al., 2014).

Deviations are obtained by capturing residual unobserved heterogeneity in the estimating equation using a multi-way fixed effects (FEs) model. The validity of identifying assumptions is supported by a series of results. First, observable characteristics are balanced with respect to the shock. Second, results are robust to varying the set of FEs and control variables, and altering the selection criteria for the population of interest. Third, following recent advances in the econometrics of multi-way FEs models (Miller et al., 2021), we show robustness to potential threats of non-random sample selection driven by overly-restrictive identifying assumptions. Fourth, results are robust to alternative assumptions related to statistical inference, such as using permutation-based inference to verify whether the results are driven by the specific pattern of shocks observed in the data (Chung and Romano, 2013). Finally, following an alternative identification strategy and focusing on extreme events leads to similar conclusions, as shown, for instance, in a binned analysis.

Resource shocks have a significant effect on mortality early in life. This effect is specific to negative shocks experienced *in utero*. A negative one standard deviation shock raises neonatal mortality–the probability of children to die during their first month of life–by approximately 0.5 deaths per 1,000 live births in communities living near the ocean's shore. The effect gradually converges to zero by the first year of life, supporting a death harvesting mechanism in the very first months of life–i.e., a displacement of mortality that is hastened by experiencing worse conditions.[3] In a counterfactual analysis, we show that these short-run effects can translate into large long-run aggregate effects of ocean acidification on neonatal mortality.

Resource shocks also have important consequences for human capital accumulation. By looking at anthropometric measurements, we show that, among children, mortality selection prevails over scarring, but we also highlight important differences depending on sex. On average, mortality is more prevalent among the weakest as living children who experienced negative shocks tend to have better health, especially in temporal proximity to birth. However, among female children, we observe a prevalence of a scarring effect, with a significant effect on stunting. This effect persists among adult women, among whom we can detect long-run consequences of the shock on economic well-being. Negative shocks lead to significant increases in fertility, and reductions in their probability to work and their wealth.

We highlight four main results documenting how these effects operate through unobserved (mild) nutritional deprivation induced by natural resource scarcity. First, the medical literature highlights that fetal growth restrictions–the main cause of neonatal deaths–are closely associated with maternal malnutrition, and in particular with micronutrient deficiencies (Black et al., 2013). In line, we show that the largest impacts are indeed recorded where fish is an essential nutritional source. Impacts on stunting, potentially induced by reduced growth while *in utero*, further support this channel.

Second, we exclude the presence of income shocks. Following Acemoglu and Robinson (2012), we test this channel by distinguishing between two alternative types of ocean's exploitation: *extractive* and *inclusive*. Extractive exploitation depletes fish resources and biodiversity without generating economic benefits for local communities, while inclusive exploitation redistributes the benefits among local populations in the form of consumption and/or income. Using geographically granular measures for the intensity

[3] This mechanism has been observed in relation to the COVID-19 pandemic. For weather-related shocks, evidence is mixed (Deschênes and Moretti, 2009; Heutel et al., 2017; Geruso and Spears, 2018a).

of these activities, we show that the effect on neonatal mortality is significantly larger in areas with a higher intensity of extractive exploitation. Because the effect is stable along the intensity of inclusive exploitation, these results rule out a channel driven by local income shocks. The consequences of short-run shocks are instead amplified by resource depletion driven by overexploitation.

Measures of economic well-being confirm this finding. We observe no effect on satellite-based nightlight luminosity, a proxy for economic productivity, growth and human development (Henderson et al., 2012; Bruederle and Hodler, 2018). In addition, estimates are unaffected by controlling for direct measures of (potentially-endogenous) pollution in coastal waters, which indicates the presence of human activity; conflict, which have been shown to respond to fishing income in coastal areas (Axbard, 2016); adverse weather events that could negatively impact income near the shore, such as typhons (Hsiang and Jina, 2014; Gröger and Zylberberg, 2016).

Third, the absence of any behavioral change contemporaneous to the shock confirms its unobservable nature. Parental investments on child health are unaffected, while the effect on early-life mortality is homogeneous by wealth and education of the household. Apart from indicating the absence of short-run impacts on household income, these results also exclude differential access to medical care and nutrient supplementation, two important correlates of neonatal death (Black et al., 2013). While prenatal health is only imperfectly observed in L&MICs, no postnatal response also excludes behavioral changes that can occur after observing child's health. Absence of adaptation further suggests that maternal stress, which has been found to impact child health in more traumatic events (Berthelon et al., 2021), does not play a role.

Fourth, we provide evidence against adjustments in consumption patterns through markets. Focusing on the Philippines, one of the most fish-dependent country in the world, we implement a highly geographically disaggregated analysis of the relationship between fish retail prices and neonatal mortality. Increases in (real) prices contribute to mortality, but resource shocks operate independently. This result reinforces the finding that nutrition is mildly affected in an unobservable way. In line with recent scientific evidence (Maire et al., 2021), the most plausible explanation is a reduced amount of nutrients contained in harvested resources, a subtle form of scarcity. Consumption patterns in a larger sample of countries at the time of the interview support this result, with no effect on the probability to consume fish or proteins from other sources.

These results contribute to three distinct strands of literature. We provide novel evidence on the role of natural resources for human development, further contributing to the nascent literature on the relationship between biodiversity and poverty. While a large literature studies the consequences of the extraction of subsoil assets, evidence on the exploitation of renewable natural assets and biodiversity remains limited (Van der Ploeg, 2011; Dasgupta, 2021). In particular, despite its global economic relevance, the role of the ocean remains understudied (Colt and Knapp, 2016). To our knowledge, this paper provides the first contribution on the mechanisms linking a shock associated with the ocean to human development, uncovering a novel channel explaining how nature's wealth determines human development and shedding light on mortality selection and scarring in L&MICs.

Secondly, as variation in the ocean's chemical composition is deeply affected by climate change, we contribute to the understanding of how natural resources shape its short-run effects, uncovering for the first time a channel that operates in absence of any contemporaneous adaptation. In response to rising temperatures and varying precipitations, households respond with a variety of coping strategies (Barreca et al., 2016; Burke and Emerick, 2016). In our setting, we do not observe any form of contemporaneous adaptation. We show instead that natural resources's wealth are a form of insurance against shocks independently from adaptation, to the extent that, where resources are more depleted, the consequences of shocks are significantly amplified. Current estimates of the effect of climate change might thus be under-estimating impacts on human development by excluding the role of these processes.

Thirdly, we uncover new evidence for the roots of childhood development in more deprived settings. We highlight that heterogeneity in development is in part due to chance, as parents do not compensate for unobserved shocks. Small decreases in nature's wealth at the time of gestation explains future differences in mortality rates, in development, and in long-term economic outcomes. These results are particularly important in light of the centrality of parental investments for early childhood development (Attanasio et al., 2020). In presence of nutritional deprivation, parental responses are in fact observed in a wide range of events, such as during famines and fasting (Razzaque et al., 1990; Almond and Mazumder, 2011; Majid, 2015), and in response to the supplementation of nutrients (Adhvaryu and Nyshadham, 2016).

1 Fish dependence and exploitation in L&MICs

The exploitation of the ocean is central for the economic development of L&MICs. Out of the 120 million workers employed worldwide in the marine capture sector, 116 million lives in L&MICs. Of these, more than 90% work in small-scale and artisanal fisheries, whose capture is almost entirely absorbed by local consumption (The World Bank, 2012). This has important consequences for nutrition, as fish is key thanks to its richness in macronutrients like proteins. Across the globe, 17% of all animal protein that is consumed is derived from fish. This contribution raises to 26% in L&MICs, with peaks of 50% or more in countries like Bangladesh, Cambodia, the Gambia, Ghana, Indonesia, Sierra Leone, and Sri Lanka (FAO, 2020). Fish is also crucial to tackle micronutrient deficiencies, which remain a public health concern in L&MICs (Hicks et al., 2019). Micronutrients contained in fish are highly bioavailable, i.e., a large fraction is absorbed by the body, and are particularly important for maternal health, and for fetal and child development (United Nations, 2021).[4] A reduced intake of nutrients derived from fish can result in malnutrition and have long-run consequences, especially where knowledge about appropriate food choices is limited (McGovern et al., 2017).

In L&MICs, studying the consequences of the dependence on renewable resources requires considerations over the magnitude of overexploitation. In L&MICs' coastal waters, only half of the total catch is made by small-scale and artisanal fisheries, while the other half is predominantly characterized by extractive forms of fishing. In the

[4] *Iron* and *iodine* support brain development and help preventing stillbirth. *Zinc* and *vitamin A* support childhood survival and promote growth. *Calcium* and *vitamin D* prevent preterm delivery, *vitamin B12* is essential for a healthy pregnancy and for the health of the nervous system and brain in children, and *essential fatty acids* help prevent preeclampsia, preterm delivery, low birth weight, and support cognitive development in children.

face of more stringent regulations, the demand for fish in richer countries has been satisfied by an increase of industrial fishing in the waters of L&MICs, also taking advantage of a worse natural resource governance. Marine capture fishery production in richer countries is about half its 1980s level, while in L&MICs has increased steadily since the 1950s (Ye and Gutierrez, 2017). This practice is largely responsible for the greater biodiversity declines in these areas, but with limited economic benefits for local communities as a positive trade balance for seafood correlates with undernourishment (Golden et al., 2016; Sala et al., 2021).[5]

2 Data

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

Mortality, human capital and adaptative behavior. We collate and homogenize 95 household surveys from 36 countries collected by the Demographic and Health Surveys (DHS) Program in the period 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 indicators of child development and nutrition, such as height and weight. The program surveys women aged 15–49 and includes information about their demographics, including wealth and human capital accumulation. Each surveyed woman's birth history is recorded and includes information on the children's year and month of birth, sex, birth order, whether they are twins, and the date of death when it applies.[6]

The primary sampling unit is a cluster, which represents the community (a village or a neighborhood). Our dataset includes all available surveys with coordinates at the cluster level and only considers countries with direct access to the ocean, thus excluding land-

[5] For anecdotal evidence, see, e.g., The Guardian's *UK steps in to help West Africa in fight to overturn EU fishing abuses* (18/03/2012).

[6] While stillbirths are not recorded, we assume measurement error is minimal because the death of a child is a tragic event. Appendix B.4 shows evidence against recall bias.

locked countries and those that only have access to a sea. Appendix A.1 provides the full list of countries and surveys included in the study. We use all available surveys and re-weight observations to correct for oversampling of countries with multiple surveys.

Geolocation of communities allows for restricting the sample to households living in coastal areas; by definition, these are the ones with the highest dependence on the ocean. Following the United Nations (2003), a *coastal area* is defined as the buffer extending landward from the ocean's shore up to a distance of 100 km. Distances from shore are computed as the minimum straight distance from the community to the shoreline of continental landmasses and ocean islands (see Appendix A.2 for details about the procedure). Panel A in Figure 1 shows the geographical coverage of the study area, and Table 1 presents descriptive statistics for the sample. While individual characteristics tend to be comparable in magnitude between communities in the coastal and inland areas, households in proximity with the ocean are slightly richer and present lower mortality rates (Appendix Table A4). Appendices B.1, B.3 and B.5 discuss potential issues associated with the definition of coastal area.

Ocean's chemical composition. We focus on the degree of water acidity at the surface measured by pH, i.e., a logarithmic scale indicating at lower values the acidity of an aqueous solution. For seawater, pH typically ranges between 7.5 and 8.4. Chemical features of the ocean in open waters are obtained from the Hadley Global Environment Model 2 - Earth System provided by the European Space Agency (ESA) Pathfinders-OA project (Sabia et al., 2015).[7] Data are provided as monthly global raster data at the $1° \times 1°$ resolution for the period 1972–2018. We match this information with DHS data using a proximity criteria: each community is matched with a data point in the ocean using the shortest straight-line distance between geo-coordinates.

We supplement information about water acidity with other climatic variables. First, we gather information about another vital input to marine life by building concentrations of dissolved oxygen at the surface using the HadGEM2-ES model and adopting the same

[7] The produced series from the model match 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).

Table 1: Descriptive statistics

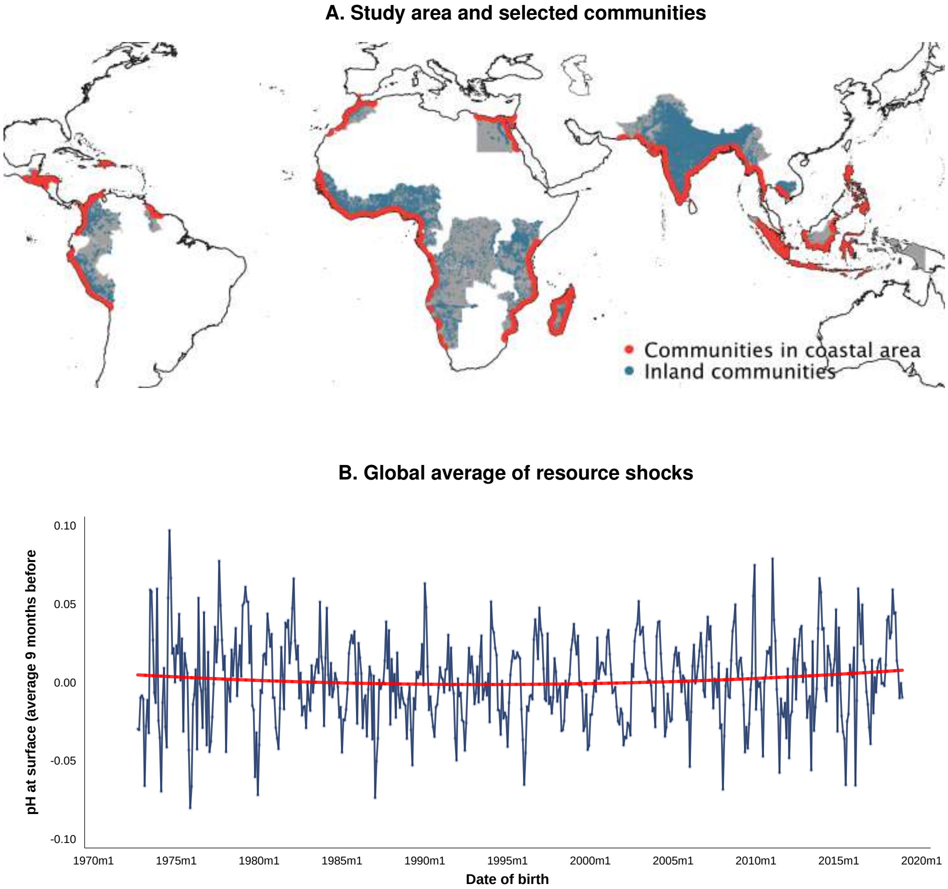
	Mean	Std. dev.	Percentiles			N
			1st	Median	99th	
	(1)	(2)	(3)	(4)	(5)	(6)
A. Children						
Child is alive	0.92	0.27	0.00	1.00	1.00	1,587,285
Child is female	0.48	0.50	0.00	0.00	1.00	1,587,285
Birth order	2.54	1.81	1.00	2.00	9.00	1,587,285
Number of twins born with the child	0.03	0.23	0.00	0.00	2.00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

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

resolution used for water acidity.[8] Second, we supplement data with a direct measure of ocean warming and other meteorological characteristics from the ERA5 database, and time-varying average rainfall and temperature at community-level from the PRIO-GRID database. Finally, we compute chlorophyll concentration in coastal waters, a

[8]This chemical feature has also been impacted by climate change as increased water temperature reduces oxygen content. Global sea surface temperature (SST) increased by 0.7 °C since the end of the 19th century, and is predicted to rise an additional 3.1 °C by 2100 (Keeling et al., 2010).

Figure 1: Coastal area and resource shocks



Note. Geographical distribution of selected communities in coastal areas (*Panel A*), and evolution over time the average deviation in acidity levels from spatially-specific (and seasonally-adjusted) long-run trends (*Panel B*). In Panel A, 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. Appendix A.2 details the procedure followed to compute distance from shore. In Panel B, variation is restricted to cells matched to the sample using the nearest cell in the open waters. The solid red line shows the quadratic trend over the period.

proxy for water contamination based on satellite data obtained from the GlobColour project. Appendix B.7 provides descriptive statistics for these variables.

Ocean's exploitation. We supplement information with geographically-granular data about natural resource exploitation. The aim is to distinguish between coastal areas that have been characterized by a varying degree of extractive versus intensive exploitation. Extractive exploitation harvests marine resources with a high depletion of resources, including a large cost in terms of biodiversity, and with limited economic benefits for local communities. For L&MICs, industrial fishing is widely recognized as a form of extractive exploitation (Section 1). We measure it using the Global Fishing Watch dataset, which provides data on the hours industrial fishing vessels spend at specific geo-locations. Because data are available only for the period 2012–2016, we build a global grid at the 1°×1° resolution summing fishing hours within each cell over the available period. It is unlikely that this type of variation captures short-run responses to changes in the ocean's health because global fishing patterns have low sensitivity to economic and environmental variation and are stable over time (Kroodsma et al., 2018), and dependency on fish for nutrition is also highly stable over time (Appendix B.2). We thus rely on time-invariant heterogeneity not only due to the availability of data only for more recent years, but also to capture longer-run patterns.

Inclusive exploitation harvests marine resources by generating income for local populations. We measure this activity using the Automatic Boat Identification System for VIIRS Low Light Imaging Data (Elvidge et al., 2015). This algorithm detects boat presence using nightlight measured from satellite imaging and provides the time and geolocation of each detection. Because it focuses on boats that use lights to attract fish, which are expected to operate on a small scale and on a local basis, it indicates dependency of the local economy on fishing. Similar to the measure of extractive exploitation, we build a global grid at the 1°×1° resolution with the sum of all detected boats for the period in which data are available (2017–2019). We normalize intensity from both activities to be between 0 (no presence) and 1 (high intensity). Appendix Figure B11 shows an example of the geographical distribution.

Economic well-being. We proxy well-being with the average nighttime light emission from the calibrated DMSP-OLS Nighttime Lights Time Series 4. Yearly data are available for the period 1992–2012. We normalize luminosity by population in the grid cell using the PRIO-GRID database., performing the analysis using nightlight luminosity per 100,000 inhabitants in a gridded dataset at the 0.5°×0.5° resolution, selecting only grid cells where at least one observation used in the main analysis is present.

Prices. We cannot rely on fish prices at the geographical and temporal scale of our analysis because data are generally scarce. We restrict our analysis to the Philippines, for which we gather monthly retail fish prices at the province level for the period 1990–2018 from the Philipppine Statistics Authority. Prices are spatially heterogeneous and their pattern over time is in line with the global trend (Appendix Figure B12).

3 Empirical strategy

Focusing on water's acidity allows exploiting two features for identification. First, because acidity is affected by winds, temperature, sea ice, precipitation, runoff, and ocean circulation, natural variation presents a short-term component that is randomly drawn from the long-run distribution, a standard feature of weather systems (Feely et al., 2008). Summary statistics for matched raster points confirms this property as variation around a global trend with within-year seasonality is common to other weather variables, such as air temperature and rainfall (Appendix B.7). 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. Variation in pH originates from both the time and geographic dimensions with comparable contributions of its between and within components (Appendix B.6).

Second, local variation has been altered by climate change. The ocean's absorption of anthropogenic CO_2 has led to an increase in the global average of water acidity by 26% since the Industrial Revolution (Doney et al., 2020). Overall, in the sample of children, average *in-utero* exposure to pH is equal to 8.05 (Table 1), and decreased from 8.08 to 8.02 in the considered time frame. Because acidification is determined at a global scale, but with spatially-heterogeneous effects, it introduces further exogenous variation in the local trend and seasonality of pH: some regions exhibit steeper trends than others, in addition to amplified or compressed within-year variation.

We denote as $R_{vc,mt}$ the open water's acidity of the ocean in the nearest point from the community v of macro-region c measured at time m, t (where m indicates the month and t the year). Acidity is reported in pH and multiplied by 100 to relate coefficients to an increase of 0.01 units in pH (roughly one third of a standard variation in the sample). Individual exposure to water acidity early in life is then computed by matching individual information about children and adult women with $R_{vc,mt}$ using their date and location of birth.[9] When exposure is computed over multiple months, we average acidity over the period. For instance, when we refer to exposure *in utero*, we average $R_{vc,mt}$ during the 9 months preceding the date of birth.

For identification, we follow a standard approach in the literature on the effects of weather shocks (see, e.g., Dell et al., 2014), and define a *resource shock* as the short-run deviation in water acidity levels from the spatially-specific long run trend (corrected for seasonality) at the location of birth. This approach relies on the inclusion of a set of FEs, $\Omega_{vc,mt}$, in the estimating equation. First, to remove spatially-specific seasonality in both the ocean's chemical composition and in outcome variables, we include macro-region by birth month FEs, $\mu_{c,m}$. Second, to remove spatially-specific trends, we include community FEs, θ_{vc}, which capture fixed (observed or unobserved) spatial characteristics, and macro-region by birth year FEs, $\phi_{c,t}$, which captures unobserved variation in trends among areas affected by faster or slower rates of acidification. Finally, time FEs, η_{mt}, remove unobserved characteristics of the date of birth by controlling for year by month of birth indicators. Panel B in Figure 1 shows the evolution of the average shock in the sample over time.

In our *benchmark* specification, the set of FEs is defined by $\Omega_{vc,mt} = \eta_{mt} + \theta_{vc} + \phi_{c,t} + \mu_{c,m}$. Because unobservable characteristics of mothers could threaten identification in the benchmark specification, in what we label as *within-sibling* specification, we replace community FEs with mother-specific FEs, τ_k. This strategy restricts the analysis to siblings and allows controlling for mothers and households' time-invariant characteristics.

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

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

where y_{ikvym} is the outcome of interest for individual i born from mother k in month m of year t in community v of macro-region c, $\mathbf{X}_{ikvc,mt}$ is a vector of control variables, and

[9] We assume that the location of surveying correspond to the location of birth. We do not highlight potential issues associated with selective migration (Appendix B.5).

$\epsilon_{ikvc,mt}$ are idiosyncratic errors assumed to be clustered at the ocean raster data point. For child-level regressions, *demographic controls* include the child's gender and birth order, the number of twins born with the child, mother's age at birth (including a square term), mother's age at the time of the interview (including a square term), mother's years of education, the household head's gender and age, and household size. For adult-level regressions, 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 (both measured inland), and dissolved O_2 concentration in the same location and temporal granularity of the resource shock.[10]

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

Second, we present estimates using alternative identifying assumptions, varying the set of FEs in equation (1), thus altering the definition of a shock. We control for alternative sets of control variables, including the exclusion of $\mathbf{X}_{ikvc,mt}$ from equation (1), and for different time FEs, including year and month indicators separately. Further, we consider different geographical areas to remove seasonality and trend, varying the definition of macro-regions. We consider administrative indicators, such as the country or the district of the community, which is a standard approach in the literature, and global grids at different resolutions, which dissuade concerns about the potential endogeneity of administrative bounds. In the latter, the macro-region is defined by the grid cell that contains the community v. To guarantee sufficient variation in ocean acidity, we use as main reference a global grid with a latitude-longitude resolution of $5°\times5°$ per grid cell.

Third, the identifying assumptions in equation (1) can lead to non-random selection when, within the groups defined by FEs, the variance of the resource shock is limited. In our setting, this can occur from the loss of groups with only one observation and can

[10]To control for O_2 concentration, we include the residual variation that is unexplained by pH because of its highly correlation with pH. This control is computed as the residual of a linear regression of dissolved O_2 concentration on pH. Appendix B.7 provides further details for this procedure.

lead estimates to differ from the population-wise average effect if impacts are heterogeneous (Cameron et al., 2011; Miller et al., 2021). For example, the within-sibling identifying assumptions require restricting the sample to mothers having at least two live births, who are generally older, have fewer years of education, had a younger age during first birth, and live in poorer households and communities (Appendix B.6). Threats from this form of selection are limited by the resource shock being not only continuous, but also presenting a high degree of variation as 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, to correct for this potential threat, Appendix B.6 provides estimates using the Miller et al. (2021) re-weighting procedure and, following Alesina et al. (2021), estimating the benchmark specification using the identifying sample of the within-sibling specification.

Finally, we present results using alternative assumptions related to statistical inference. We show robustness not only to alternative assumptions about standard errors (Appendix B.8), but we also implement permutation-based inference by artificially varying the resource shock. Section 4 details the procedure.

When analyzing outcome variables in a (balanced) panel form, such as the case of nightlight luminosity, we follow a similar approach achieving identification from deviations from spatially-specific long-run trends. We estimate the following specification:

$$nlight_{ic,t} = \beta\, R_{i,t} + \mathbf{X}_{ic,t}\gamma + \delta_i + \eta_{c,t} + \epsilon_{ic,t} \tag{2}$$

where $nlight_{i,ct}$ is nightlight luminosity in the grid cell i of macro-region c at time t, $R_{ic,t}$ is the (average) open water's acidity of the ocean at year t in the nearest point from the grid cell i, $\mathbf{X}_{ic,t}$ is a vector of time-varying controls, δ_i are cell-specific time-invariant unobservable characteristics, and $\eta_{c,t}$ capture local trends. $\epsilon_{ic,t}$ are idiosyncratic errors assumed to be clustered at the grid cell.

4 Results

4.1 Mortality and human capital accumulation

Mortality. We begin by focusing on the effect of a resource shock on mortality in temporal proximity with birth. To isolate a channel operating through maternal health, we begin by studying exposure to shocks while *in utero*. Table 2 presents estimates of the effect on the Neonatal Mortality Rate (NMR)–the number of deaths in the first month of life per 1,000 live births. Panel A uses the benchmark specification, while Panel B uses the within-sibling specification. All specifications include community FEs, birth year by birth month FEs, and to control for local trends include country by birth year FEs. 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, while columns (3) and (6) further add demographic controls.

Resource shocks experienced *in utero* have a substantial impact. A 0.01 decrease significantly increases NMR by 1.42–2.12 deaths per 1,000 live births in our benchmark specification. 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 (Appendix Table B7). Point estimates are larger in magnitude when local seasonality is captured at grid cell level. Adding control variables has a limited effect on the estimates of the effect, providing further evidence in support of the exogeneity of the shock. Significant effects are also found when varying the definition of coastal area.[11] In Section 5, we discuss how these short-run effects translate into long-run aggregate effects of ocean acidification.

Impacts are driven by the specific pattern of resource shocks observed in the data. Statistical inference is robust to permutation-based inference, which artificially varies the exposure in both space and time to the shock. We focus on the specification in column (3) of Table 2 and implement three different tests producing 1,000 iterations each. In

[11] 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.3).

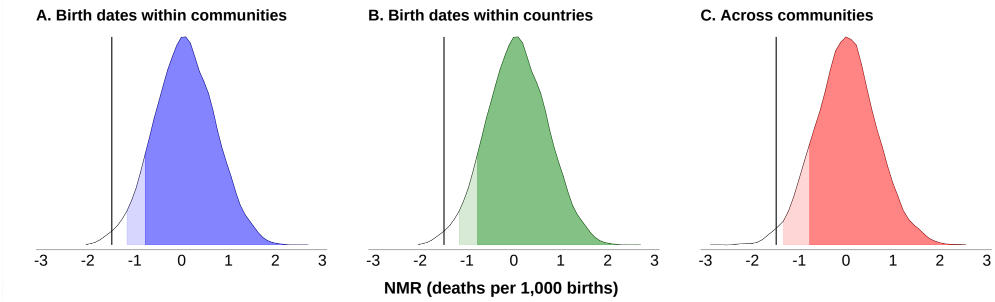
Table 2: The effect on neonatal mortality

Dependent variable:	Neonatal Mortality Rate (deaths per 1,000 births)					
	(1)	(2)	(3)	(4)	(5)	(6)
A. Benchmark specification						
Resource shock	-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 (min)	1972	1972	1972	1972	1972	1972
Birth year range (max)	2018	2018	2018	2018	2018	2018
B. Within-sibling specification						
Resource shock	-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 (min)	1972	1972	1972	1972	1972	1972
Birth year range (max)	2018	2018	2018	2018	2018	2018
Weather controls	-	Yes	Yes	-	Yes	Yes
Demographic controls	-	-	Yes	-	-	Yes
Seasonality	Country	Country	Country	Cell	Cell	Cell

Note. Estimates based on equation (1). The dependent variable is a dummy variable equal to 1 if the child died within the first month of life and 0 if the child survived, multiplied by 1,000. The *resource shock* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. The sample is restricted to coastal areas (see Section 2). 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. Sseasonality 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 3. Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

a first test, birth dates are randomly reassigned within each community. In a second test, birth dates are randomly reassigned within each country, independently from the community and the survey. In a third test, mothers (and their children) are randomly allocated to different communities, independently from the country and the survey. Figure 2 plots the distribution of marginal effects in the permutation samples. For all tests, the 1st percentile of the distribution in the permutation samples lies to the right of our estimate, therefore rejecting the null hypothesis of a nil effect.

Figure 2: The effect on neonatal mortality: permutation-based inference

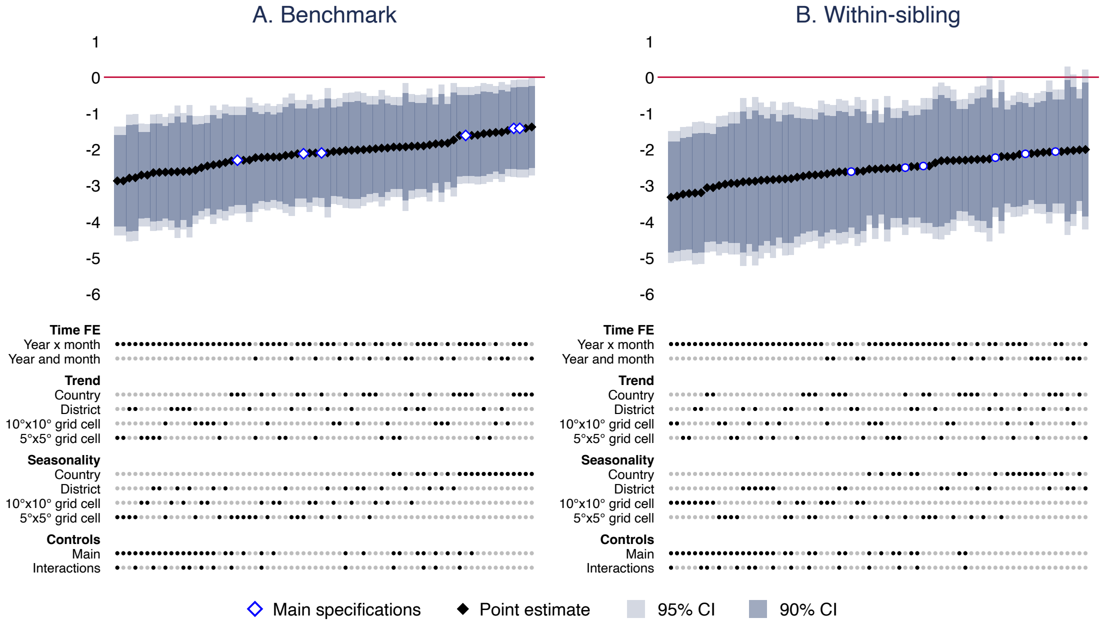


Note. Distribution of marginal effects of the resource shock on NMR when birth dates are randomly reassigned within each community (*Panel A*), when birth dates are randomly reassigned within each country (*Panel B*), and when mothers are randomly allocated to different communities (*Panel C*). Each test is based on 1,000 iterations. In each iteration, the *resource shock* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. The light-shaded and dark-shaded areas highlight the 1^{st}–5^{th} percentiles and the area beyond the 5^{th} percentile of the distributions. The vertical lines indicate the estimate in column (3) of Table 2. In each iteration, marginal effects are estimated using equation (1) including community FEs, birth year by birth month FEs, country by birth year FEs, country by birth month FEs, and control variables (see Section 3). The sample is restricted to the coastal area (see Section 2). Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

Results are robust to a wide variety of specification checks. First, estimates using the within-sibling specification are not highly dissimilar to the benchmark specification (Panel B of Table 2), suggesting that family-specific unobserved heterogeneity is not diving identification. A one-standard-deviation shock leads to 0.53-0.67 deaths per 1,000 live births. Even though the share of singleton observations increases to roughly 7% in this specification, selection into identification does not drive these results. Estimating the effect using the reweighting procedure proposed by Miller et al. (2021) and the benchmark specification restricting the sample to the identifying sample of the within-sibling specification as in Alesina et al. (2021) highlight similar estimates and conclusions. Second, Figure 3 shows how these estimates vary using alternative specifications. While we expect some degree of variation in the estimates, because changing the set of FEs alters our identifying assumptions and our measure of shock, we highlight a high stability of the estimates. At standard confidence levels, estimates are always negative and significantly different from zero.[12]

[12]Results are also robust to including interactions between the birth year and the birth month of the child with the time-invariant average across the study period of the following variables: intensity of extractive and inclusive exploitation; the gross cell product, the population living in the cell, and the average nightlight luminosity. Results available upon request.

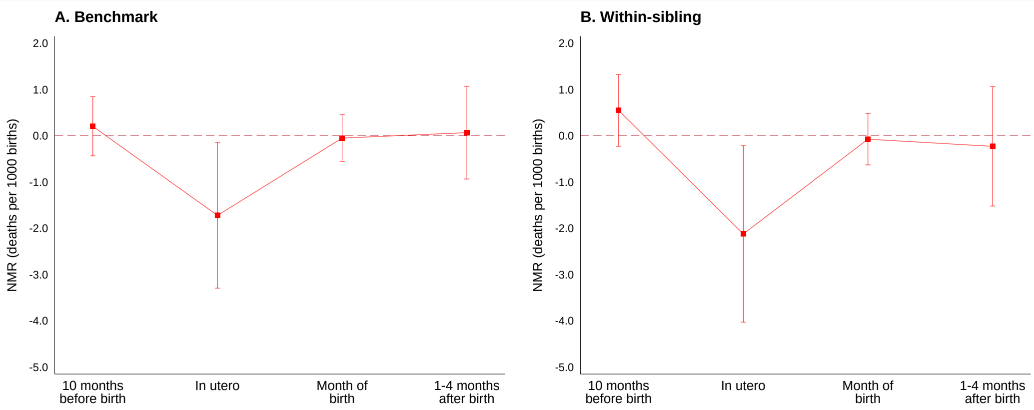
Figure 3: The effect on neonatal mortality – alternative specifications



Note. Marginal effect of the resource shock 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. The *resource shock* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. Marginal effects are estimated using equation (1) with the set of FEs and controls reported in the bottom panel. *Main specifications* are the ones used in Table 2. The sample is restricted to coastal areas (see Section 2). 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 3). *Interactions* are interaction terms between the birth month and indicator variables for different oceans.

While we began by focusing on exposure to resource shocks while *in utero*, we are interested in understanding whether exposure of shocks in periods in proximity to gestation can also explain mortality. We estimate 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 since it is posterior to the period considered for the death). Figure 4 shows the marginal effects. For both the benchmark and the within-sibling specifications, impacts are driven by the specific exposure to shocks during the gestation, reinforcing the role of maternal health during pregnancy and excluding channels operating through direct effects on children.

Figure 4: The effect on neonatal mortality, by timing of exposure to the ocean's acidity



Note. Marginal effects of resource shocks by timing of exposure (reported in the horizontal axis) estimated using the benchmark specification (*Panel A*), and the within-sibling specification (*Panel B*). *Resource shocks* are 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. The sample is restricted to the coastal area (see Section 2). In Panel A, the 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 3). In Panel B, the specification adds mother-specific FEs. Standard errors are clustered at the ocean raster data point. Confidence intervals at 90% level. Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

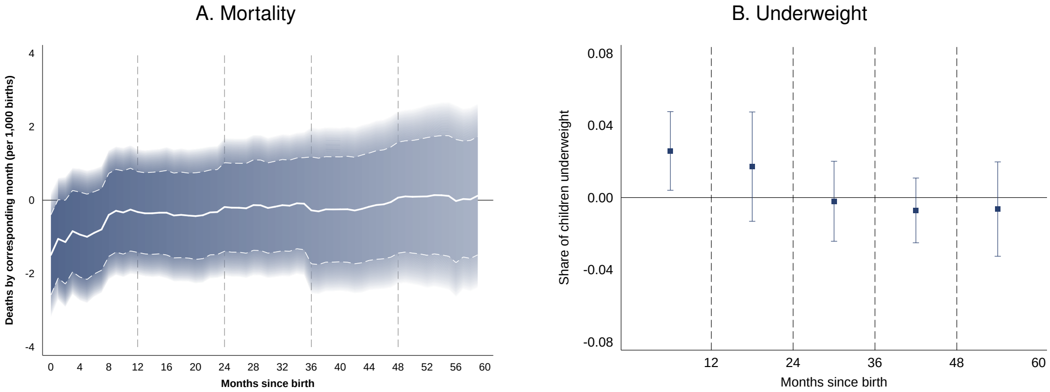
We then look at how resource shocks experienced *in utero* impact the probability of death for each month of life up to age 5. We focus on the probability of death at the monthly level to avoid potential issues related to the heaping of self-reported date of death.[13] We estimate the probability of 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). We select the sample based on time from birth, rather than age, to avoid selecting children alive and younger than x (because at the time of the interview it is uncertain whether they will survive up to x). We repeat the same specification for x ranging from 1 month to 60 months. The dependent variable, updated in every iteration, is an indicator variable equal to one if the child is not alive at time x from birth, and 0 otherwise, and is multiplied by 1,000 to relate coefficients to changes in deaths per 1,000 live births. We present results for mortality rates at standard times in Appendix B.9.

Panel A of Figure 5 shows how this probability is affected by shocks experienced during the gestation period. The pattern is consistent with a death harvesting mechanism–a

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

displacement of mortality that is hastened by a shock. 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. However, a smaller net effect is observed beyond the first month of life, with convergence to zero within the first year of life. In presence of harvesting, short-run effects would slowly disappear as the initial increase in mortality is offset by later decreases.

Figure 5: Mortality and child development



Note. Marginal effect of the resource shock experienced *in utero* on the probability to die (*Panel A*), and on the probability of the child to be underweight (*Panel B*). In Panel A, 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). In Panel B, the dependent variable is an indicator variable equal to 1 if the child is underweight, and 0 otherwise. Confidence intervals at 90% level. In both panels, 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 3). 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.

Human capital. Table 3 shows the effects of resource shocks experienced *in utero* on nutritional indicators built upon anthropometry, whose relation with long-term human capital accumulation is well established in the literature (McGovern et al., 2017). Panels A and B focus on short-run effects by analyzing measurements for children, while Panel C presents long-run effects among adult women. Column (1) focuses on whether the individual is *underweight*, which highlights an abnormally low weight-for-age among children or body mass index (BMI) among adults. To study insufficient food intake or a high incidence of infectious diseases in temporal proximity with the measurement, columns (2)–(3) focus on weight-for-height (z-score) and for wasting, an indicator variable for an abnormally low weight-for-height. Finally, to measure the effect on the past or cumulative effects of under-nutrition and infectious diseases since conception, columns (4)–(5) report effects on height-for-age (z-score) and on stunting, an indicator variable for an abnormally low height-for-age.[14] 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 moment of the interview, and therefore need to be interpreted in light of the results on mortality.

Living children that experienced a negative shock tend to have slightly better indicators (Panel A). A 0.01 negative shock decreases the probability of the child to be underweight by 1.2 percentage points. Panel B in Figure 5 shows that this effect is specific to the first months of life and converges to zero over time.[15] This effect is partially reflected in weight-for-height, especially in relation to wasting. We do not observe any significant effect on height-for-age and stunting among children.

The pattern of the effects observed among children is driven by male children in the sample. Among male children the effect of the resource shock on early-life mortality is slightly larger, even though the male-female difference is not statistically significant (Appendix B.11). In Panel B, for comparability with Panel C, we restrict the sample to female children. While we do not observe any significant effect on variables associated with weight, we record a significant effect on stunting. A 0.01 negative shock increases the probability of the child to be stunted by 1.3 percentage points. This effect is persistent, as we observe a significant effect on height-for-age and stunting among adult women (Panel C). A 0.01 negative shock increases the probability of adult women to be stunted by 0.7 percentage points. The magnitude of the effect is smaller among adults, possibly due to further mortality selection or partial adaptation at later ages.

Table 3 highlights that the shock operates with two distinct channels. On one hand, it induces *mortality selection*, which leads children to have on average better indicators in presence of negative shocks. This channel, characterized by death harvesting among the weakest children, is the prevalent in our setting. This result is in line with the negative relationship between mortality and anthropometrics for L&MICs (Deaton, 2007).

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

[15]Among children, we do not observe any significant effect on morbidity and on an objective measurement of micronutritional deficiency (i.e., anemia) at the time of the interview (Appendix B.10). These results suggest that differences in anthropometrics are not associated with contemporaneous nutrition.

Table 3: The short- and long-run effect on nutritional indicators

Dependent variables:	**Underweight**	**Weight-for-height**	**Wasted**	**Height-for-age**	**Stunted**
	(1)	(2)	(3)	(4)	(5)
A. Short-run effects					
Resource shock	0.012	-0.021	0.006	-0.012	0.004
	(0.005)	(0.016)	(0.003)	(0.015)	(0.004)
	[0.017]	[0.191]	[0.091]	[0.407]	[0.285]
Mean (dep.var.)	0.198	-0.309	0.080	-0.984	0.234
Identifying observations	230,037	232,339	232,339	232,575	232,575
Singleton observations	1,119	1,106	1,106	1,124	1,124
Communities	24,808	24,824	24,824	25,110	25,110
Countries	33	33	33	33	33
Birth year range (min)	1985	1985	1985	1985	1985
Birth year range (max)	2018	2018	2018	2018	2018
B. Short-run effects (female)					
Resource shock	-0.004	-0.014	-0.004	0.024	-0.013
	(0.011)	(0.019)	(0.007)	(0.020)	(0.006)
	[0.699]	[0.446]	[0.595]	[0.227]	[0.037]
Mean (dep.var.)	0.197	-0.285	0.076	-0.942	0.227
Identifying observations	109,940	111,095	111,095	111,157	111,157
Singleton observations	3,544	3,508	3,508	3,577	3,577
Communities	20,784	20,843	20,843	21,052	21,052
Countries	33	33	33	33	33
Birth year range (min)	1985	1985	1985	1985	1985
Birth year range (max)	2018	2018	2018	2018	2018
C. Long-run effects (female)					
Resource shock	0.001	0.011	0.000	0.010	-0.007
	(0.002)	(0.007)	(0.001)	(0.005)	(0.003)
	[0.664]	[0.133]	[0.988]	[0.069]	[0.022]
Mean (dep.var.)	0.138	-0.310	0.082	-1.386	0.301
Identifying observations	298,436	324,160	324,160	327,124	327,124
Singleton observations	757	554	554	683	683
Communities	22,613	22,635	22,635	22,848	22,848
Countries	32	32	32	32	32
Birth year range (min)	1972	1972	1972	1972	1972
Birth year range (max)	2003	2003	2003	2003	2003

Note. Estimates based on equation (1). Dependent variables are reported in the column's header. *Underweight* is an indicator variable equal to 1 if the child has an abnormally low weight-for-age (Panels A and B) or the adult has an abnormally low body mass index (Panel C), and 0 otherwise. *Weight-for-height* and *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. *Stunted* is an indicator variable equal to 1 for an abnormally low height-for-age, and 0 otherwise. The *resource shock* 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 2). 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, mother's birth year by mother's birth month FEs, country by mother's birth year FEs, country by mother's birth month FEs, and control variables (see Section 3). 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.

On the other hand, a *scarring effect*, i.e., a worsening of indicators in response to a shock. This channel is more prevalent among female children and persists into adulthood. Overall, the magnitude of effects remains relatively small, making it likely that these small differences would remain unobserved by parents.

To understand further the long-run effect of the shock among adult women, Table 4 focuses on other adult-level outcomes that are directly or indirectly related with human capital accumulation. We focus on fertility (reported as number of births), years of schooling, cognitive skills (determined by the ability to read a sentence). In addition, while income is not available at our level of analysis, we also look at economic well-being by focusing on whether the woman is working at the time of the interview, and on wealth, measured with an asset-based index known to be capturing household's longer-run economic well-being (Jean et al., 2016). Columns (1)–(4) refer to the full sample of women aged 15–49. To avoid issues with family heterogeneity and study household-level outcomes like wealth, columns (5)–(6) select only women that are either a household head or their partner (labeled as *main*).

Table 4: The long-run effects on fertility, schooling and economic well-being

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

Note. Estimates based on equation (1). The dependent variables are reported in the column's header. *Number of children* 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. *Work* is an indicator variable equal to 1 if the respondent is working at the time of the interview, and 0 otherwise. *Wealth* is a household-level asset-based index which ranges from 1 (poorest) to 5 (richest). The *resource shock* 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 2), 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, mother's birth year by mother's birth month FEs, country by mother's birth year FEs, country by mother's birth month FEs, and control variables (see Section 3). 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.

Resource shocks have long-run consequences that are not limited to anthropometrics. A negative shock leads to a significant increase in fertility, relatively small in magnitude as a 0.01 negative shock causes a decrease in the number of births per woman of 0.01 children. This is possibly associated with a decrease in schooling, even though this effect is not statistically significant and we do not observe any impact on cognitive ability. More importantly, resource shocks have a significant impact on economic well-being: a 0.01 negative shock causes a decrease by 1.4 percentage point in the probability of the main woman in the household to work and by 1.6 percentage points in the wealth index. From the sample means, these effects corresponds to a decrease by 2.7 percent in the share of main women working and a 0.5 percent decrease in wealth.

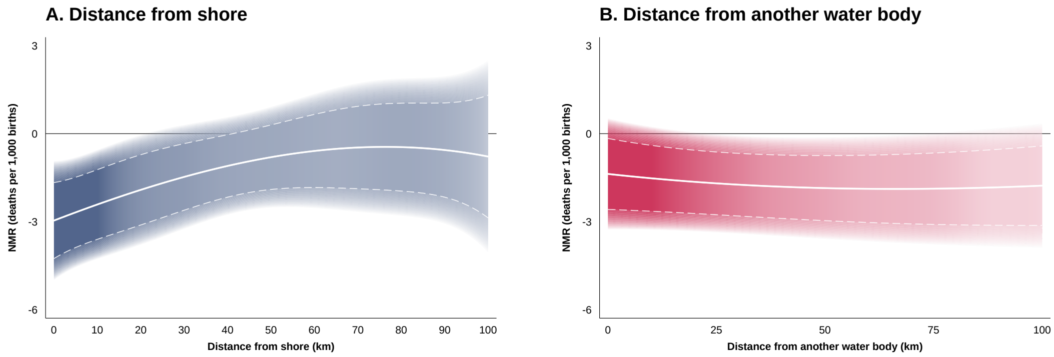
4.2 Resource exploitation and mortality: mechanisms

Section 4.1 provides evidence in favor of a mortality selection mechanism centered around maternal health, as the main effects operate through exposure while *in utero*. This section tests alternative mechanisms that could explain this results.

Income shocks. Dependency on the exploitation of fish can be identified purely out of distance from water bodies, with proximity with the ocean's shore and with estuaries indicating higher dependency (FAO, 2020). Figure 6 shows estimates of the effect of resource shocks on neonatal mortality allowing the effect to vary flexibly with distance from water bodies. Panel A focuses on distance from the ocean's shore, and Panel B on distance from other water bodies (lakes, ponds in islands within lakes, and all rivers).[16] The largest effect on neonatal mortality is observed at the shore, while the estimate converges to zero as distance increases. On the contrary, the effect is homogeneous with respect to distance from other water bodies. These results confirms that impacts are concentrated in communities that rely more heavily on ocean's resources. Areas in high proximity to the ocean–within 10 km from the shore–are also areas with higher population densities. Estimates are robust to potential sources of measurement error associated with distances (Appendix B.1).

[16] Freshwater ecosystems are also acidifying, but proximity to the shore is negatively correlated with proximity to other water bodies. Estimates are robust to excluding estuaries (Appendix B2).

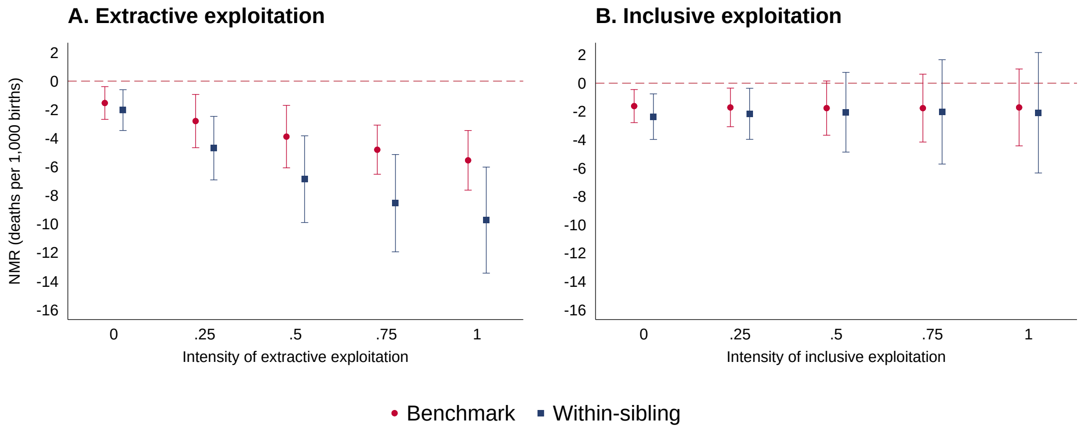
Figure 6: Early-life mortality and dependence on water bodies



Note. Marginal effect of the resource shock 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. The *resource shock* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. 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 3). The sample is restricted to the coastal area (see Section 2). 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.

While these findings highlight the importance of marine resources, they do not exclude whether the shock operates as an income shock. We thus turn our attention to heterogeneity with respect to resource exploitation. Figure 7 plots the marginal effects on neonatal mortality at different intensities of extractive (Panel A) and inclusive exploitation (Panel B). Areas characterized by high intensity of extractive exploitation presents a significantly larger effect as compared to areas where extractive exploitation is absent. On the contrary, the effect is homogeneous along the intensity of inclusive exploitation. Formal tests of heterogeneous impacts confirm these results. We estimate equation (1) using both the benchmark and the within-sibling specifications and adding interaction terms between the resource shock and a function of the intensity of exploitation. We perform three tests assuming a linear, quadratic and cubic functions, and computing p-values for the joint tests of equality to 0 of the coefficients on the interaction term(s). For extractive exploitation, p-values are always smaller than 0.01, while for inclusive exploitation they are in the range of 0.68–0.97.

Figure 7: Early-life mortality and resource exploitation



Note. Marginal effect of the resource shock on NMR as function of intensity of extractive exploitation (*Panel A*), and of inclusive exploitation (*Panel B*). Intensities range between 0 (no presence) and 1 (high). Estimates based on equation (1) introducing interaction terms between the resource shock and a quadratic polynomial in the corresponding intensity. 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. The *resource shock* 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 2). 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 3). Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures. We exclude surveys for Peru as information for the intensity of inclusive exploitation is not available (see Appendix A.1).

As extractive exploitation depletes resources with limited redistribution of income among local populations, these results exclude a channel associated with fishing-related income and corroborate the importance of overexploitation as a factor amplifying short-run resource shocks. To confirm this result, we perform additional checks. First, we look at satellite-based nightlight luminosity. We use panel data for the coastal area covered by DHS at the yearly temporal resolution and at the $0.5°\times0.5°$ spatial resolution. Table 5 presents estimates of the effect of the shock on average nightlight using equation (2). Columns (1)–(4) includes all cells, while columns (5)–(8) restrict the sample to cells with positive luminosity. Not only estimates are very small, but they are also never significantly different from zero. While we cannot exclude that climate change and ocean acidification influence aggregate income in the long run, we exclude that in the short run resource shocks have an impact on economic well-being.

Second, we test whether our main estimates are affected by including (potentially-endogenous) controls capturing income processes at the time in which resource shocks are measured. We control for the chlorophyll concentration in coastal waters, a proxy

Table 5: The effect on nightlight luminosity

Dependent variable:	**Nightlight luminosity (per 100,000 inhabitants)**					
Sub-sample:		*All cells*			*Cells with positive values*	
	(1)	(2)	(3)	(4)	(5)	(6)
Resource shock (yearly)	0.017	0.021	0.022	0.030	0.033	0.034
	(0.078)	(0.079)	(0.079)	(0.079)	(0.080)	(0.080)
	[0.824]	[0.789]	[0.786]	[0.703]	[0.676]	[0.673]
Mean (dep.var.)	0.080	0.080	0.080	0.082	0.082	0.082
Identifying observations	30,864	30,864	30,864	30,421	30,421	30,421
Singleton observations	229	229	229	238	238	238
Grid cells	1,470	1,470	1,470	1,470	1,470	1,470
Year range (min)	1992	1992	1992	1992	1992	1992
Year range (max)	2012	2012	2012	2012	2012	2012
Weather controls	-	Yes	Yes	-	Yes	Yes
Demographic controls	-	-	Yes	-	-	Yes

Note. Estimates based on equation (2). The dependent variable is the satellite-based nightlight luminosity at year t in the corresponding grid cell i. Luminosity ranges between 0 (lowest) and 1 (highest), and is normalized by population in the cell. The *resource shock* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the grid cell i. All specifications include grid cell FEs and $5°\times5°$ cell by year FEs. *Weather controls* include rainfall, temperature and the interaction between rainfall and temperature, (residual) dissolved oxygen concentration, while *demographic controls* include dpopulation size and its square value. We include only cells in coastal areas where at least one DHS community is found (see Section 2). Appendix A.1 provides further information on the variables, and the list of surveys included in the study.

for the presence of nutrients release linked with economic activity.[17] In addition, we include controls for the presence and intensity of conflict. Finally, we control for other adverse weather events which are experienced more frequently in communities living on the shore and that could negatively impact their income, such as heat and storms. The inclusion of these controls does not affect our main estimates, further confirming the absence of an income shock in the short run (Appendices B.7 and B.12).

Evidence on the importance of fish-dependence to explain the effect on early-life selection, in absence of any effect on income, supports a channel that is exclusive to the nutritional content of fish which is harvested and used for consumption. This mechanism is further supported by evidence of larger effects in areas with overall greater dependency on fish for nutrition: where fish represent a higher percentage of total animal proteins consumed, and where artisanal fisheries are a central activity, such as in proximity to reefs (Appendix B.2).

Behavioral adaptation. While income remains unaffected by the shock, it is important to study behavior to understand not only whether adaptation limits or amplifies the

[17] In presence of economic activity, coastal waters get contaminated from pollutants deriving from fossil fuels and industrial production, and nutrients from agriculture. Higher concentrations favor algae abundance, which negatively impacts marine life. Resource shocks are measured in open ocean's waters rather than coastal waters to avoid this confounding effect.

magnitude of the effects, but also whether lack of adaptation confirms that shocks are unobserved. Table 6 looks at adaptation contemporaneous to the shock using birth-level information on parental health investments. Antenatal investments refer to attendance to health visits during pregnancy and to the presence of health professionals during these visits. Delivery investments refer to the presence of health professionals during the delivery and to whether delivery is performed in a health center. Both variables range from 0 (no investment) to 2 (high investment). Appendix B12 provides evidence on the individual indicators composing these variables. For postnatal care, we look at attendance to postnatal health checks and the completion of the cycle of basic vaccinations according to the World Health Organization (WHO). In addition, because sub-optimum breastfeeding is recognized as a primary cause of neonatal mortality (Black et al., 2013), we focus on whether the child has ever been breastfed.[18]

Table 6: Behavioral adaptation

Dependent variables:	**Antenatal investment**	**Delivery investment**	**Postnatal investment**		
			Healthcare	Breastfed	Vaccinated
	(1)	(2)	(3)	(4)	(5)
Resource shock	0.004	-0.004	0.004	0.001	-0.005
	(0.007)	(0.004)	(0.009)	(0.003)	(0.005)
	[0.590]	[0.374]	[0.630]	[0.691]	[0.317]
Mean (dep.var.)	1.698	1.299	0.441	0.972	0.293
Identifying observations	263,697	256,548	101,075	206,350	210,372
Singleton observations	1,100	1,191	3,078	2,336	2,212
Communities	29,942	29,822	18,445	28,029	27,964
Countries	36	36	34	36	36
Birth year range (min)	1985	1985	2002	1987	1987
Birth year range (max)	2018	2018	2018	2018	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 WHO, and 0 otherwise. The *resource shock* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. The sample is restricted to coastal areas (see Section 2). 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 3). 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.

For both antenatal and delivery investments, we do not observe any significant effect.

[18] For cross-survey comparability, the sample for variables relative to antenatal and delivery investments and to postnatal visits 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.

The effect is also homogeneous in the birth order and gender of the child, two predictors of differential parental investments in 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. In addition, we do not observe any effect on postnatal care, which indicates that, during the period in temporal proximity to birth, parental adaptation following the observation of child health is limited.

Adjustments in consumption. In response to shocks, individuals can also change their consumption patterns by reverting to markets, especially if the relative prices of fish or nutritious food are impacted. In L&MICs, this possibility is somehow limited because these countries tend to export high-quality fish caught in their waters and supplement local demand with imports of low-quality fish (Pauly and Zeller, 2016). In fact, we highlight larger effects on neonatal mortality in countries with positive trade balance for fish products (Appendix B.2). However, higher ability to purchase more nutritious food has only a minor contribution in explaining the main effect: poorer households exhibit a slightly larger effect in terms of neonatal mortality, but we cannot identify any statistically significant heterogeneous effect with respect to wealth.[19]

To verify this channel, we look at fish markets and study the effect of exposure to higher or lower fish prices while *in utero*. Focusing on markets allows testing not only the role of prices, but also the role of aquaculture and of other local market imperfections (see, e.g., Jensen, 2007). For this analysis, we restrict our analysis to the Philippines, a unique setting in our context: its coastline is the 5$^{\text{th}}$ largest in the world, it is home to 9% of global coral reef, and depends highly on fish. Using retail fish prices at the province level, we compute the average fish price while *in utero* for each birth using dates of births and matching DHS communities with the provinces where prices are recorded. Table 7 presents estimates of equation (1) using the benchmark specification and controlling for the *in-utero* exposure to average retail fish (log-)prices.

First, the effect of the resource shock on NMR is significant for the Philippines. Re-

[19]The effect is homogeneous across a wide array of individual characteristics, such as the sex of the child, the birth order and the year of birth (Appendix B.11). Higher (but not statistically significant) vulnerability is observed among male children, children born from younger and less educated mothers living in poorer households.

Table 7: Fish prices and early-life mortality

Dependent variable:	Neonatal Mortality Rate (deaths per 1,000 births)				
	(1)	(2)	(3)	(4)	(5)
Resource shock	-4.887		-4.997	-4.643	-4.728
	(2.620)		(2.630)	(2.629)	(2.685)
	[0.064]		[0.059]	[0.079]	[0.080]
Fish price (*in utero*)		7.274	7.361	7.243	7.580
		(3.445)	(3.443)	(3.436)	(3.368)
		[0.036]	[0.034]	[0.036]	[0.026]
Mean (dep.var.)	15.410	15.410	15.410	15.410	15.412
Identifying observations	82,739	82,739	82,739	82,739	82,730
Singleton observations	9	9	9	9	9
Communities	2,751	2,751	2,751	2,751	2,751
Countries	1	1	1	1	1
Birth year range (min)	1990	1990	1990	1990	1990
Birth year range (max)	2017	2017	2017	2017	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. The *resource shock* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. Fish price (*in utero*) is the average fish price (including all available prices and reported in logarithms) in the province of birth of the child during the 9 months before birth. The sample is restricted to communities in the coastal area of the Philippines (see Section 2) and to the period 1990–2018 (due to data availability; see Appendix B.14). 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 3. Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

sults correspond to approximately 0.75 deaths per 1,000 live births in response to a one-standard-deviation negative shock. At the same time, a 1 percent increase in fish prices while *in utero* leads to an increase in NMR by 0.07 per 1,000 live births. As higher prices capture the capacity of households to purchase and consume it, a positive estimate on NMR is a clear indication of the link between fish consumption and maternal health. However, conditional on the set of FEs, the two channels operate independently on mortality: estimating equation (1) with both the resource shock and the average fish price *in utero* as independent variables does not have a major influence on the estimates of both effects. The presence of a channel for the resource shock that is independent from market mechanisms reinforces the finding of an unobservable deterioration of natural resource quality, i.e.,the nutritional content of fish. While recorded information about maternal nutrition during each pregnancy is not available, in periods with negative shocks in the ocean's acidity, women's probability of consuming fish is in fact unaffected, further supporting this channel (Appendix B.13).

5 The aggregate effect of ocean acidification

The ocean's chemical composition is influenced by climate change, which characterizes the long-run process of acidification. While we cannot identify the causal effect of ocean acidification directly, we provide evidence using counterfactual estimates and focusing on long-run adaptation. Appendix C details the results for this analysis.

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

Second, to understand whether acidification shocks drives our results, similar to Deschênes and Greenstone (2011), we implement an analysis based of binned variation of pH rather than continuous. We estimate 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 in a specific range during their gestation period. The effect is driven by exposure to pH in the bottom part of the distribution, confirming that our findings are indeed related with negative shocks in water acidity.

Finally, following Dell et al. (2014), we focus on long-run adaptation estimating equation (1) and 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 data point. The effect of resource shocks 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.

6 Conclusions

Climate change is putting under severe pressure animal species that already suffer from human overexploitation. Because biodiversity provides a source of insurance, we must prioritize its conservation. Our results show that this is particularly important for the communities that are more dependent on natural resources for survival, and therefore more vulnerable to variation in nature's wealth. United Nations (2012) highlight as priorities to 'regulate the industrial fishing sector to protect the access rights of traditional fishing communities' and 'introduce exclusive artisanal fishing zones and user rights for small-scale and subsistence fisheries'. However, the weak natural resource governance in L&MICs complicates the feasibility of these goals.

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

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FOR ONLINE PUBLICATION

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

Alex Armand, Ivan Kim Taveras

A Data and methodological procedures

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

Variable	Description
Altitude	Communities' elevation in meters from the SRTM–Digital Elevation Model for the specified coordinate location. The variable is available in the DHS surveys (ICF, 2019).
Basemaps	Basemaps were created using ArcGIS® software by Esri®. Basemaps are used in line with the Esri Master License Agreement, specifically for the inclusion of screen captures in academic publications. We use the *World Topographic Map*.
Behavioral adaptation	Information is based on parental health investments obtained from the DHS Program (ICF, 2019). We homogenize information across surveys and make use of the following variables: *Antenatal investment* is equal to 0 if no antenatal visit is completed, 1 if at least one visit is completed but without health professional, 2 if at least one visit is completed with a health professional. In Appendix B.10, this indicator is split into individual variables. *Any visit* is an indicator variable equal to one 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 one 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.10, this indicator is split into individual variables. *In health center* is an indicator variable equal to one if the mother gave birth in a health center, and 0 otherwise. *With health professional* is an indicator variable equal to one 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 having never breastfed the child. For cross-survey comparability, the sample is restricted to children who live with their mother and are alive, and are less than three years old. *Vaccinated* is an indicator variable equal to 1 if the mother reports or shows a vaccination card for the following doses: BCG, 3 doses of DPT-containing vaccines, 3 doses of polio vaccine (excluding polio vaccine given at birth), and 1 dose of MCV. The sample is restricted to children under three years old for comparability (Croft et al., 2018).
Child mortality	Information is based on the DHS Program surveys (ICF, 2019). DHS surveys collect respondents' full birth history and includes information on all children's year and month of birth, sex, birth order, whether they are twins, and the date of death when it applies. Note that only live births are recorded. This information is also used to create *age at first delivery*, and *fertility* (the number of live births at the time of the interview). We build mortality rates by multiplying the following indicators by 1,000 (the variables are set to missing if the date of the interview is before the end of the period considered for defining mortality): *Neonatal (NMR)*: indicator equal to 1 if the child died before their first month of life, and 0 otherwise. Note that the DHS Program reports two ages of death. The first is self-reported, while the second gives a calculated age from reported information. When dates of birth are not disclosed, these are imputed by the DHS Program (Croft et al., 2018). We also use 67 special cases of self-reported age of death (198 and 199, which indicate that age at death was reported as a number of days and that the exact number is unknown), but results are robust to dropping these cases. *Post-neonatal (PMR)*: indicator equal to 1 if the child died between the ages of 1–11 months, and 0 otherwise. *Child (CMR)*: indicator equal to 1 if the child died between the ages of 12–59 months, and 0 otherwise. *Infant (IMR)*: indicator equal to 1 if the child died between the ages of 0–11 months, and 0 otherwise. *Under-5 (U5MR)*: indicator to 1 if the child died between the ages of 0–59 months, and 0 otherwise.

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Variable	Description
Chlorophyll	Concentration in coastal waters is measured in mg/m^3 (AWV weights). We use data from the GlobColour project (d'Andon et al., 2009), which provides monthly global rasters for the period 1997–2018 at the 25-meter resolution by merging satellite imaging from five different sources made available by the European Space Agency and NASA.
Conflict	Number of violent events (and fatalities) in each cell for a specific year. The data are obtained from the Uppsala Conflict Data Program (UCDP) (Sundberg and Melander, 2013).
Distances	For shorelines, distance (in 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 straight line) between the DHS cluster and the closest coral reef. Geographical distribution of warm-water coral reefs is obtained from UNEP-WCMC (2018).
Fish dependency	Average fish protein supply as proportion of all animal protein supply. The data are obtained from the FAOSTAT database (FAO, 2019).
Fish prices	Monthly retail price for fish at the province level from 1990 to nowadays. The series is provided by the Philippine Statistics Authority (2020) provides. See Appendix B.14 for details.
Extractive exploitation	Total number of hours from industrial fishing activities in the cell built using data from the Global Fishing Watch (Kroodsma et al., 2018), which tracks more than 70,000 industrial fishing vessels from 2012 to 2016. Because variation is available only for the period 2012–2016, we first compute total fishing hours in a global grid at $1°\times1°$ resolution and then average each cell over the available period.
Inclusive exploitation	We use Automatic Boat Identification System for VIIRS Low Light Imaging Data (Elvidge et al., 2015) to identify detections. The algorithm detects boats using nightlight captured from satellite imaging (Visible Infrared Imaging Radiometer Suite (VIIRS) day/night band). Using individual daily detections (which include geolocation), we build a $1°\times1°$ global grid with the sum of detections for the period 2017–2019. We select as boats only strong detections (quality flag rating equal to 1). To avoid false positives, data are not available over the South Atlantic Anomaly, and are therefore missing for DHS surveys for Peru.
Human capital	We make use of *schooling*, i.e., the number of completed years of education based on the respondent's self-reported highest level of education (comparable across countries), and of *cognitive skills*, i.e., an indicator variable of whether the respondent is able to read a whole sentence in her native language (as observed by enumerators) or has, at least, completed secondary schooling.
Marriage	DHS surveys collect respondents' civil status, date of birth and, when available, their partner's age in years. We make use of the following variables. *Married* is an indicator variable equal to 1 if the respondent is currently married or living in an union, and 0 otherwise. *Age difference with partner* is the difference in years between the respondent and her partner.
Nightlight	Average nighttime light emission from the $0.5°\times0.5°$ DMSP-OLS Nighttime Lights Time Series Version 4 calibrated (Elvidge et al., 2014). Values range between 0 (lowest luminosity) and 1 (highest observed value). The times-series are available from 1992–2012 from the PRIO-GRID database (Tollefsen et al., 2012). Data are spatially merged to DHS clusters using their geolocation.
Nutritional indicators	The DHS records objective measurements performed by the DHS data collection team. Standardized distributions are the CDC Standard Deviation-derived Growth Reference Curves (Croft et al., 2018). The following indicators are used: *Underweight* is, for chidren, an indicator variable equal to 1 if the weight-for-age z-score is smaller than 2 (for children) or the BMI is lower than 18.5 (for adults), and 0 otherwise. *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. *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.
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 raster data at the $1°\times1°$ resolution for a series of chemical features of the ocean in open waters. We use two variables: pH at surface and dissolved O_2 concentration.
Ocean's features	We obtain 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 $0.5°\times0.5°$ covering all terrestrial areas of the world, and spatially merged to DHS clusters using their geolocation.

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Variable	Description
Protein consumption	Information is based on the DHS Program surveys (ICF, 2019). DHS surveys collect respondents' food consumption for a variety of items. This information is available only for a restricted number of surveys: Cambodia (2005), Dominican Republic (2007), Egypt (2008), Ghana (2008), Guatemala (2015), Guyana (2009), Haiti (2006), Liberia (2007), Madagascar (2008), Namibia (2006), Nigeria (2008), Philippines (2008), Sierra Leone (2008), and Timor-Leste (2009 and 2016). We focus on two indicator variables: *fish* is an indicator variable that equals 1 if the female respondent ate fresh or dried fish or shellfish, or foods containing those ingredients, during the day previous to the interview, and 0 otherwise.; *meat and dairy* is an indicator variable that equals 1 if the female respondent ate any meat (beef, pork, lamb, or chicken), eggs, dairy products (cheese, yogurt, or other milk products), or foods containing those ingredients during the day previous to the interview, and 0 otherwise.
Trade balance	Sum of exports and re-exports of fish products, minus the sum of imports of fish products. The data are obtained from the FAOSTAT database (FAO, 2019). In the analysis of heterogeneity of the effect of the ocean's acidity, we opt for a time-invariant version for the period 1976-2017.
Wealth	The DHS records information on asset ownership and provide an asset-based wealth index ranging from 1 (poorest) to 5 (richest).
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 $0.5° \times 0.5°$ 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 so-called *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 survey selected:	*All*	*Latest*	*Largest*	*Random*
	(1)	(2)	(3)	(4)
Resource shock	-1.491	-1.420	-1.803	-1.609
	(0.664)	(0.701)	(0.654)	(0.675)
	[0.025]	[0.043]	[0.006]	[0.018]
Mean (dep.var.)	30.474	26.601	27.328	29.036
Identifying observations	1,581,815	794,713	861,938	757,132
Singleton observations	25	32	35	30
Communities	31,380	17,389	18,476	16,416
Countries	36	36	36	36
Birth year range (min)	1972	1972	1972	1972
Birth year range (max)	2018	2018	2018	2018

Note. Estimates based on equation (1). The dependent variable is a dummy variable equal to 1 if the child died within the first month of life and 0 if the child survived, multiplied by 1,000. The *resource shock* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. 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 3). 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

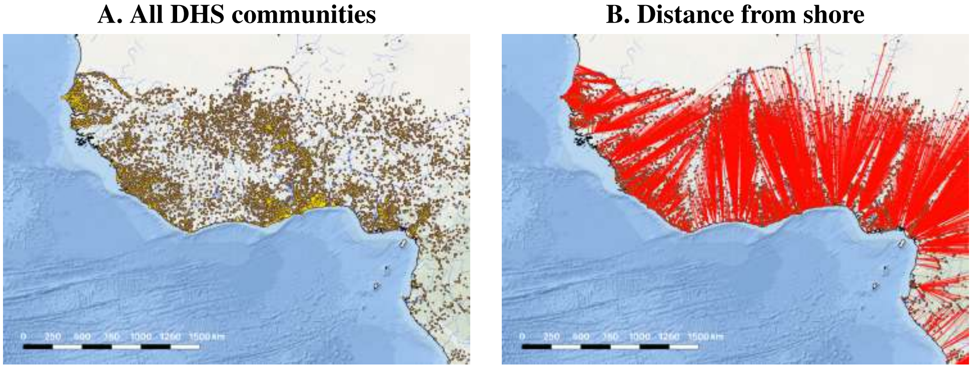
The computation of distances are based on the geocoding of DHS clusters. For each household, distance is the minimum straight distance to the coast and closest alternative water source computed using *v.distance* function in GRASS. Table A4 presents descriptive statistics for households living within 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.1.

Table A4: Descriptive statistics for coastal and inland areas

	Coastal area		**Inland area**		
	Mean (1)	Std. dev. (2)	Mean (3)	Std. dev. (4)	Observations (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 exploitation	0.06	0.20	0.05	0.13	1951250
Intensity of inclusive exploitation	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 2). Inland area includes all communities that are farther away than 100 km from the ocean's shore. Means are reported in columns (1) and (3), standard deviations are reported in columns (2) and (4). Column (5) presents the total number of observations. *Years since birth* is measured at the time of the interview and is independent from the child being alive. *Mortality rates* are relative to 1,000 live births. *Ocean's pH (in utero)* is the average pH in the ocean's cell closest to an individual's community during the 9 months before birth; it refers to the date of birth of the child in Panel A and to the date of birth of the woman in Panel B. Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

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



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

A.3 Coloring of shaded graphs

In selected graphs, the color intensity is reflecting the share of observations at a specific distance (or time). For Figures 5 and B4, 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 6 and B5, 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 Falsification and placebo tests

Balance across mother characteristics. Table B1 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.

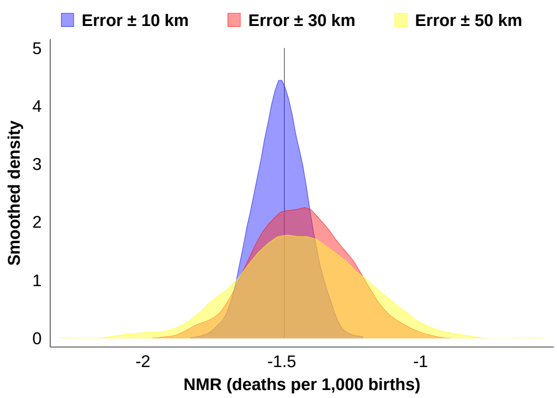
Table B1: Placebo test: balance on observable characteristics

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

Note. Estimates based on equation (1) without control variables. The dependent variable is a dummy variable equal to 1 if the child died within the first month of life and 0 if the child survived, multiplied by 1,000. The *resource shock* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. The sample is restricted to coastal areas (see Section 2). 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 B1 shows the distribution of the coefficients in all iterations.

Figure B1: The effect on neonatal mortality, by magnitude of measurement error

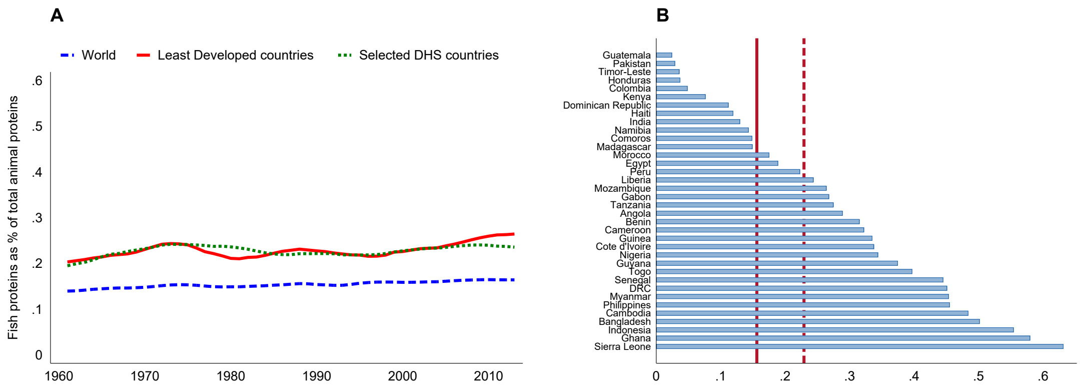


Note. Distribution of the marginal effect of a resource shock on NMR, estimated using (1) and introducing measurement error in the distance from the ocean. The procedure performs 1,000 iterations. The vertical line represents our benchmark point estimate (column 3 in Table 2). The distribution fits are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

B.2 Fish dependency

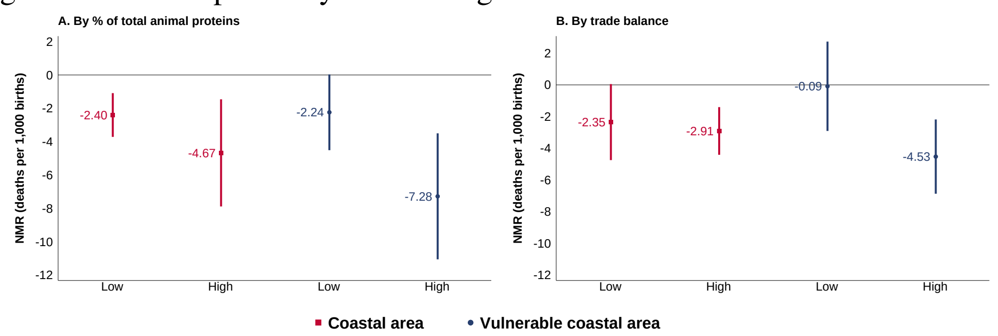
Figure B2 presents descriptive statistics for fish dependency, defined as the share of total proteins of animal origin coming from fish. Figure B3 presents the estimates of the heterogeneous effect of the resource shock on neonatal mortality distinguishing by a country's fish dependency in Panel A, and by trade balance for fish products from the FAOSTAT database (FAO, 2019) in Panel B.

Figure B2: Fish dependency amd trade balance for fish products



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

Figure B3: Fish dependency and heterogeneous effect of resource shocks on NMR

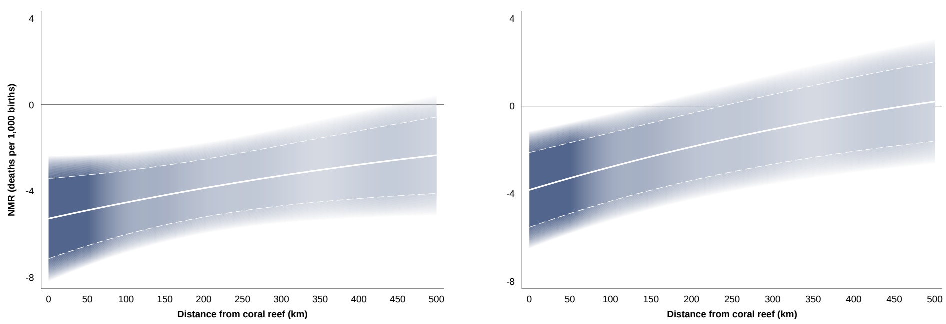


Note. Heterogeneous effect by dependency on fish proteins as a % of total animal proteins (*Panel A*), and by trade balance for fish products (*Panel B*). Marginal effects are estimated using equation (1) restricting the sample to the corresponding group. In Panel A, dependency is *high* if the country is in the top tercile of the sample distribution of the 1960–2013 average fish dependency. In Panel B, 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. 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 3). Section 2 provides definitions of coastal and vulnerable coastal areas. Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

As a separate measure of fish dependency, we focus on proximity to coral reefs, a proxy for dependency on artisanal fishing. Figure B4 shows marginal effects of a resource shock on neonatal mortality as a function of distance from the closest coral reef. Distance (in straight line) between the community and the closest coral reef obtained from UNEP-WCMC (2018), subtracting the distance from the ocean's shore. Panel A shows the marginal effects assuming a zero distance from the ocean's shore, while Panel B assumes a distance of 40km.

Figure B4: *In utero* exposure, NMR and distance to coral reefs

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



Note. Marginal effect of a resource shock 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. The *resource shock* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. 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 3). The sample is restricted to the coastal area (see Section 2). 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.3 Robustness to alternative definitions of coastal area

Table B2 shows how estimates of the effect of the resource shock on NMR vary under different criteria for defining coastal areas.

Proximity. We define coastal area using a proximity criteria based on 100km from the ocean's shore. Panel A of Figure B5 shows that the total number of live births considered is clearly affected by the distance bound. Panel B shows estimates of the effect of the resource shock on neonatal mortality by varying the distance bound from 20 to 250 km, allowing x to increase by 1 unit after each iteration. The largest magnitude is observed when distance is constrained at 40 km, which we label as the *vulnerable coastal area*. The *less vulnerable* areas is the one extending 40–100 km from the shore. Panel A of Figure B6 maps communities according to this criteria.

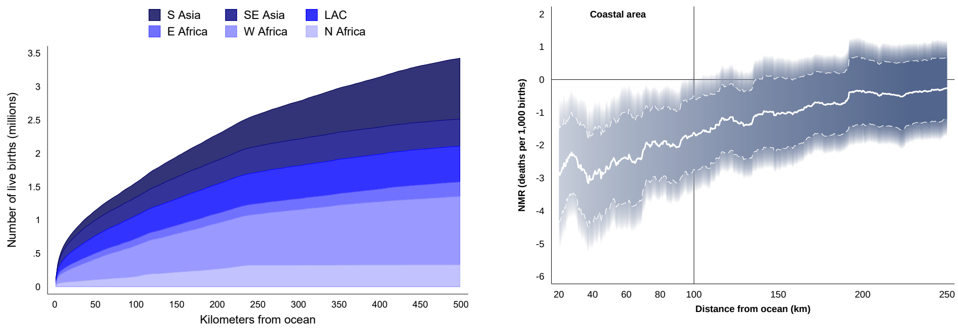
Table B2: The effect on neonatal mortality: varying sample selection criteria

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

Note. Estimates based on equation (1). The dependent variable is a dummy variable equal to 1 if the child died within the first month of life and 0 if the child survived, multiplied by 1,000. The *resource shock* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. The sample is restricted to coastal areas (see Section 2) 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 the 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 3). 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 B5: Sample selection by distance from shore

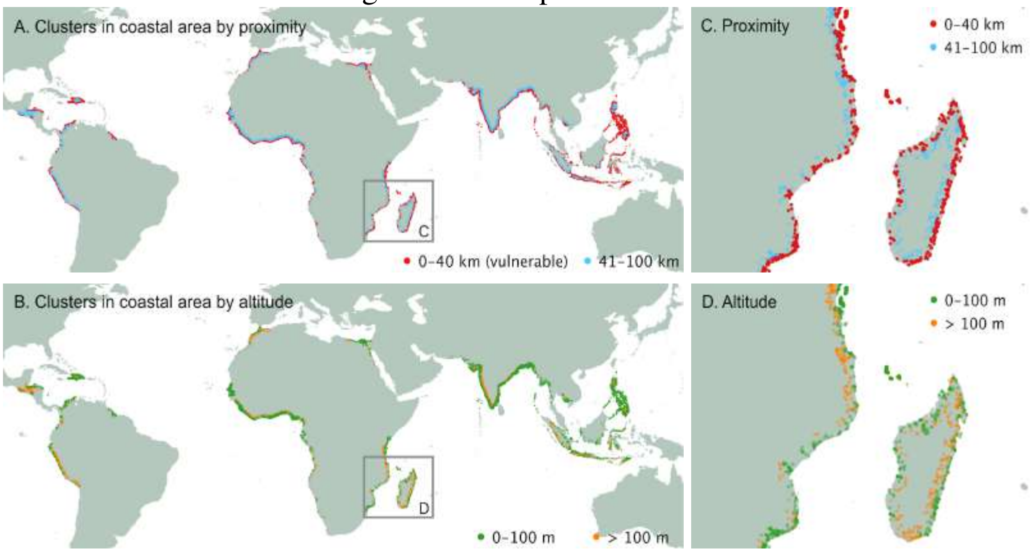
A. Number of live births B. Effect of pH (*in utero*)



Note. Number of live births (decomposed by region) included in the dataset by distance from the shore (*Panel A*), and marginal effects of the resource shock 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 3). The 90% confidence interval is indicated by dotted lines, beyond which the intervals are progressively shaded up to the 99% level. Within confidence bounds, darker colors indicate a larger number of observations (see Appendix A.3). Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

Altitude and estuaries. Panel B of Figure B6 shows communities in coastal areas according to the criteria of Christian and Mazzilli (2007), who select the land margin within 100 km of the coastline or less than 100 meters above the mean low tide. In addition, we can include or exclude areas where the ocean's chemical composition has a higher probability of human contamination, such as estuaries.

Figure B6: Sample selection



Note. Communities in coastal areas distinguished by vulnerability (*Panel A*), or by altitude (*Panel B*), and corresponding examples (*Panel C* and *Panel D*). The full list of countries and surveys included in the study is reported in Appendix A.1. See Section 2 for a definition of coastal area.

B.4 Recall bias

Table B3 replicates Table 2 by restricting the sample to recent births (at most 10 years prior to the interview.) Estimates are robust to restricting the sample to more recent births, such as within 5 years.

Table B3: The effect on neonatal mortality: restricting the sample to recent births

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

Note. Estimates based on equation (1) restricting the sample to births within 10 years of the interview. The dependent variable is a dummy variable equal to 1 if the child died within the first month of life and 0 if the child survived, multiplied by 1,000. *Resource shock* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. The sample is restricted to the coastal area (see Section 2). All specifications include community FEs, birth year by birth month FEs, country by birth year FEs, and control variables (see Section 3). Controls for local seasonality are either country by birth month FEs or $5°\times5°$ 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.5 Selective migration

Table B4 shows estimates of the effect of resource shocks on the probability that the mother migrated to the community of the interview within the first five years following delivery. This period corresponds to the time period considered for under-5 mortality.

Table B4: Post-delivery selective migration

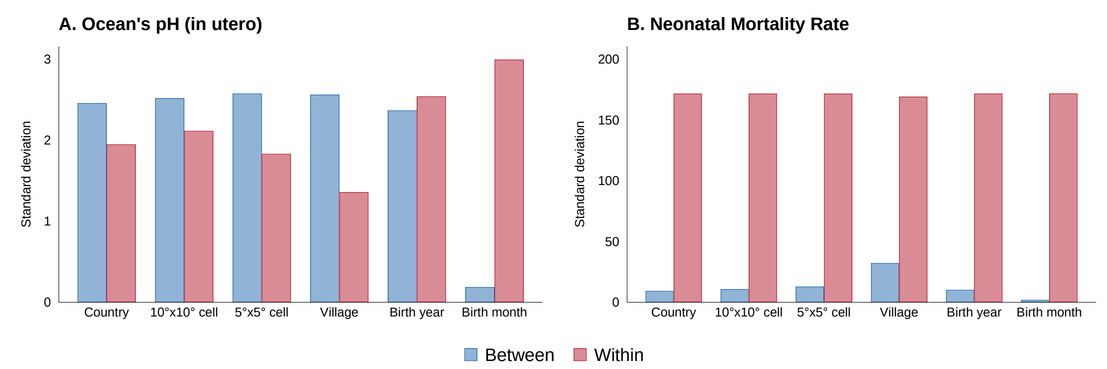
Dependent variable:	**Mother migrated to community 0-4 years after delivery of child**					
	(1)	(2)	(3)	(4)	(5)	(6)
Resource shock	-0.000	-0.000	-0.000	0.001	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
	[0.958]	[0.908]	[0.988]	[0.840]	[0.612]	[0.627]
Mean (dep.var.)	0.112	0.112	0.112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

Note. Estimates based on equation (1). The dependent variable is a dummy variable equal to 1 if the mother of the child migrated to the community of the interview in the first 5 years of life of the child, and 0 otherwise. *Resource shock* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. The sample is restricted to the coastal area (see Section 2). All specifications include community FEs, birth year by birth month FEs, country by birth year FEs, and control variables (see Section 3). 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.6 Issues related to identification

Figure B7 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.

Figure B7: 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 2). 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.

The identifying assumptions in 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 shocks 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 in the within-sibling specification. Columns (4)–(6) provide estimates of the effect using the identifying sample of the within-sibling specification and re-weighting as in Miller et al. (2021) to recover the overall effect on the population of interest (mothers with at least one birth). The re-weighting procedure is based on observable characteristics. To estimate the probability to be in the identifying sample of the within-sibling specification, we use a probit model and include mother and weather characteristics.

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 exploitation	0.06	0.20	0.06	0.19	495310
Intensity of inclusive exploitation	0.09	0.19	0.09	0.20	495310

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

Table B6: The effect on neonatal mortality: identification checks

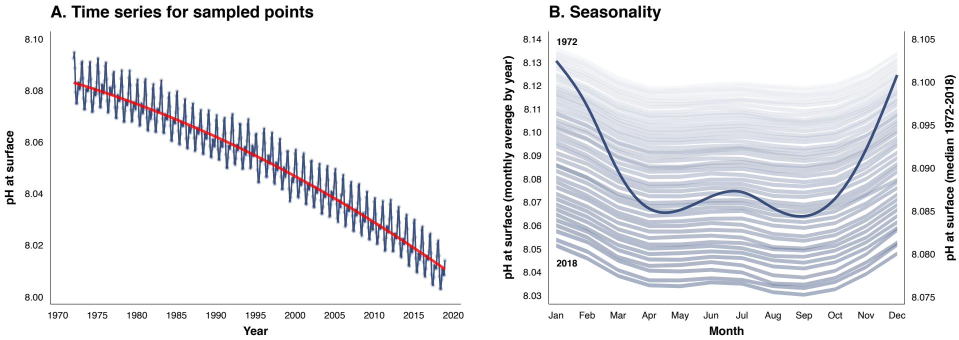
Dependent variable:	**Neonatal Mortality Rate (deaths per 1,000 births)**					
Check:	*Benchmark specification with within-sibling identifying sample*			*Re-weighting procedure*		
	(1)	(2)	(3)	(4)	(5)	(6)
Resource shock	-1.939	-1.950	-2.000	-2.740	-2.785	-2.883
	(0.792)	(0.790)	(0.776)	(0.996)	(1.001)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

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

B.7 Climate- and weather-related variables

Ocean's acidity. Figure B8 shows descriptive statistics of pH at surface averaged at global level. Table B7 shows descriptive statistics of the measure of shock under the different specifications presented in Table 2, and the correspondent standardized effect.

Figure B8: Variation in the ocean's acidity for communities in the coastal area



Note. 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.

Other ocean's characteristics. First, because the process of changing ocean biochemistry is not uniquely characterized by pH, we also focus on the role of dissolved O_2 concentration at the ocean's surface. To isolate the effect of the ocean's pH in equation

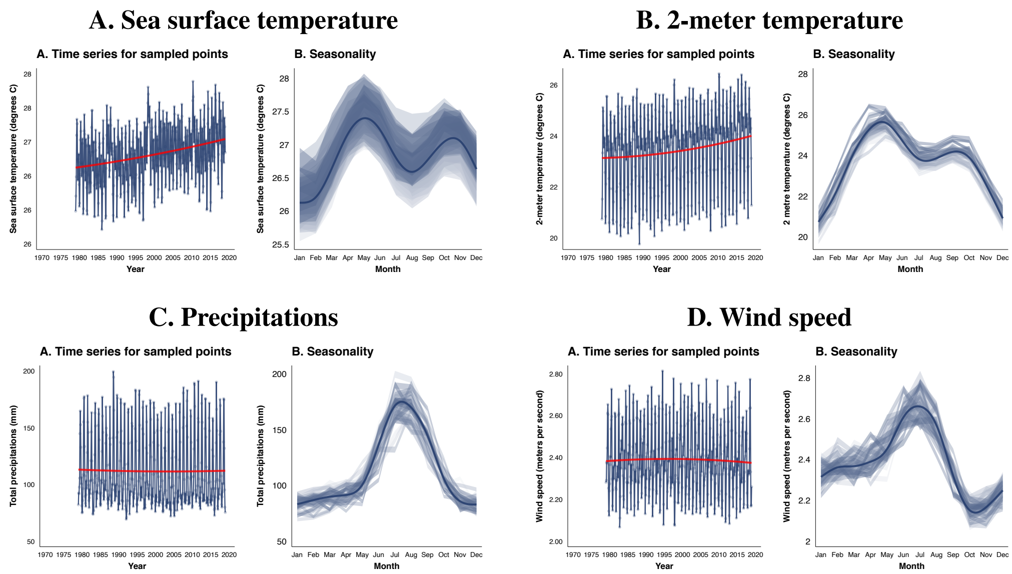
Table B7: Resource shocks and standardized effects

	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 the resource shock under the benchmark and the within-sibling specifications. Columns (3) and (7) refer to the point estimates in Table 2. The standardized effect is rescaling point estimates in terms of standard deviations in the residual variation of the resource shock. 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.

(1), we include the estimated residuals of a linear regression of dissolved O_2 concentration (multiplied by 1,000, so that coefficients relate to an increase of 0.001 μmol/kg), oxy_{mtvc}, on pH. Second, Figure B9 presents the time series and the seasonality component for a variety of ocean's characteristics obtained from the ERA5 dataset. Table B8 presents estimates of the effect of the resource shock on NMR using equation (1) and controlling for these additional variables.

Figure B9: 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. 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. Information is obtained from the ERA5 and is available for the period 1989–2018. Appendix A.1 provides further information on the variables.

Table B8: NMR, ocean's characteristics *in utero* and weather in the location of birth

Dependent variable:	**Neonatal Mortality Rate (deaths per 1,000 births)**						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Closest point in the ocean							
Resource shock	-2.034		-2.192		-2.140		-2.084
	(0.745)		(0.744)		(0.741)		(0.743)
	[0.007]		[0.003]		[0.004]		[0.005]
Sea surface temperature (*in utero*)	1.467	1.695					1.549
	(0.925)	(0.918)					(1.064)
	[0.113]	[0.066]					[0.146]
Wind speed (*in utero*)			1.752	1.596			2.159
			(1.510)	(1.505)			(1.547)
			[0.247]	[0.290]			[0.164]
Total precipitations (*in utero*)					0.008	0.007	0.009
					(0.008)	(0.008)	(0.008)
					[0.289]	[0.351]	[0.265]
2-meter temperature (*in utero*)					0.674	0.902	0.040
					(0.898)	(0.892)	(1.039)
					[0.453]	[0.312]	[0.969]
Residual dissolved O2 (*in utero*)							-0.069
							(0.306)
							[0.822]
Location of birth							
Temperature (*year of birth*)							-0.121
							(0.427)
							[0.778]
Total precipitations (*year of birth*)							-0.003
							(0.002)
							[0.126]
Mean (dep.var.)	29.645	29.645	29.645	29.645	29.645	29.645	29.645
Identifying observations	1,518,357	1,518,357	1,518,357	1,518,357	1,518,357	1,518,357	1,518,357
Singleton observations	23	23	23	23	23	23	23
Communities	31,380	31,380	31,380	31,380	31,380	31,380	31,380
Countries	36	36	36	36	36	36	36
Birth year range (min)	1979	1979	1979	1979	1979	1979	1979
Birth year range (max)	2018	2018	2018	2018	2018	2018	2018

Note. Estimates based on equation (1). The dependent variable is a dummy variable equal to 1 if the child died within the first month of life and 0 if the child survived, multiplied by 1,000. The *resource shock* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. The sample is restricted to coastal areas (see Section 2). 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, $5° \times 5°$ grid cell by birth month FEs, and demographic controls (see Section 3). Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

Quality of coastal water. Table B9 shows estimates of equation (1) controlling for the (potentially-endogenous) quality of coastal waters, proxied by the chlorophyll concentration in the closest ocean data point from the community. We do not use coastal water quality in the main text due to the potential endogeneity of chlorophyll concentration with idiosyncratic shocks related to child mortality.

Table B9: The effect on neonatal mortality: control for quality of coastal waters

Dependent variable:	**Neonatal Mortality Rate (deaths per 1,000 births)**					
Sub-sample	*Coastal area*			*Vulnerable coastal area*		
	(1)	(2)	(3)	(4)	(5)	(6)
Resource shock	-1.568	-1.747	-1.809	-2.791	-2.982	-3.218
	(1.017)	(1.151)	(1.093)	(1.295)	(1.451)	(1.375)
	[0.124]	[0.130]	[0.099]	[0.032]	[0.040]	[0.020]
Chlorophyll concentration	0.487	0.599	0.406	0.293	0.404	0.281
	(0.521)	(0.521)	(0.520)	(0.548)	(0.546)	(0.551)
	[0.351]	[0.252]	[0.435]	[0.593]	[0.459]	[0.611]
Mean (dep.var.)	25.497	25.497	25.502	24.735	24.733	24.740
Identifying observations	780,920	780,904	779,925	523,719	523,710	522,989
Singleton observations	470	486	487	350	359	361
Communities	28,670	28,670	28,669	19,838	19,838	19,837
Countries	36	36	36	36	36	36
Birth year range (min)	1998	1998	1998	1998	1998	1998
Birth year range (max)	2018	2018	2018	2018	2018	2018
Weather and demographic controls	-	-	Yes	-	-	Yes
Seasonality	Country	Cell	Cell	Country	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. The *resource shock* and *chlorophyll concentration* are the average acidity (reported in pH and multiplied by 100) and the average chlorophyll concentration 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 in columns (1)–(3) and to the vulnerable coastal area in columns (4)–(6) (see Section 2). Due to data availability, the sample is also restricted to children born between 1998 and 2018. All specifications include community FEs, birth year by birth month FEs. Controls for local seasonality are either country by birth month FEs or 5°×5° cell by birth month FEs. The full list of controls is presented in Section 3. 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 Robustness to alternative assumptions about standard errors

Table B10 shows estimates of equation (1) for NMR using different assumptions for the clustering of standard errors (reported in column).

Table B10: Robustness to assumptions about standard errors

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

Note. Estimates based on equation (1). The dependent variable is a dummy variable equal to 1 if the child died within the first month of life and 0 if the child survived, multiplied by 1,000. The *resource shock* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. The sample is restricted to the coastal area (Section 2). 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 3). 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.

B.9 Early-life mortality

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

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

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

Note. Estimates based on equation (1). The dependent variables are reported in the column's header. The *resource shock* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. The sample is restricted to coastal areas (see Section 2). 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 3. Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

B.10 Detailed parental investments and postnatal outcomes

Table B12 shows estimates of the effect of resource shocks on parental health investments and on health outcomes associated with poor contemporaneous nutrition.

Table B12: Parental investments and postnatal nutritional outcomes

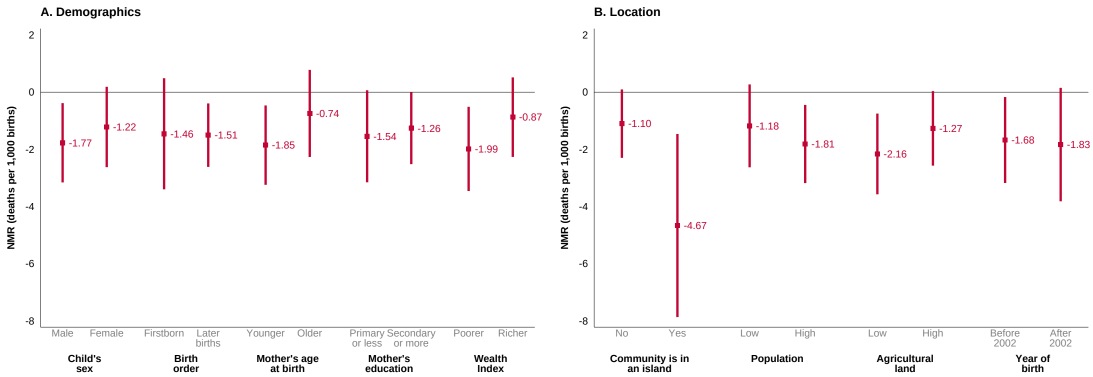
	ANTENATAL		DELIVERY		NUTRITION	
Dependent variables:	Number of visits	w/ health professional	In health center	w/ health professional	Morbidity	Anemia
	(1)	(2)	(3)	(4)	(5)	(6)
Resource shock	-0.001	0.004	0.003	-0.003	-0.002	0.002
	(0.009)	(0.002)	(0.002)	(0.003)	(0.004)	(0.006)
	[0.940]	[0.025]	[0.067]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

Note. Estimates based on equation (1). The dependent variables are reported in the column's header. *Morbidity* is an indicator variable equal to one if the child has experienced fever, cough or diarrhea in the weeks previous to the interview, and 0 otherwise. *Anemia* is an indicator variable equal to one if the child has haemoglobin levels below 110 g/L, and 0 otherwise. *Resource shock* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. The sample is restricted to coastal areas (see Section 2). 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 3). Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

B.11 Heterogeneous effects

Figure B10 presents estimates of heterogeneous effects for children and mothers' demographics (Panel A) and for location characteristics (Panel B).

Figure B10: Heterogeneous effect of the resource shock 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 effect 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 3). Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

B.12 Adding controls for the presence 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 B13 presents estimates of the effect on NMR. Due to data availability, the birth year range is reduced to children born after 1984. For comparability, columns (3) and (6) are therefore restricted to the sample included in column (1) and (4), respectively.

Table B13: Comparing the effect size of ocean acidification and conflict

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

Note. Estimates based on equation (1). The dependent variable is a dummy variable equal to 1 if the child died within the first month of life and 0 if the child survived, multiplied by 1,000. The *resource shock* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. The sample is restricted to coastal areas (see Section 2). 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 3). Controls for local seasonality are either country by birth month FEs or 5°×5° cell by birth month FEs. Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

B.13 Protein consumption: fish versus meat and dairy

Table B14 shows the effect of the resource shock on the female respondent's consumption of animal proteins. Data are available for a subset of surveys (see Appendix A.1).

Table B14: Protein consumption at the time of the interview

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

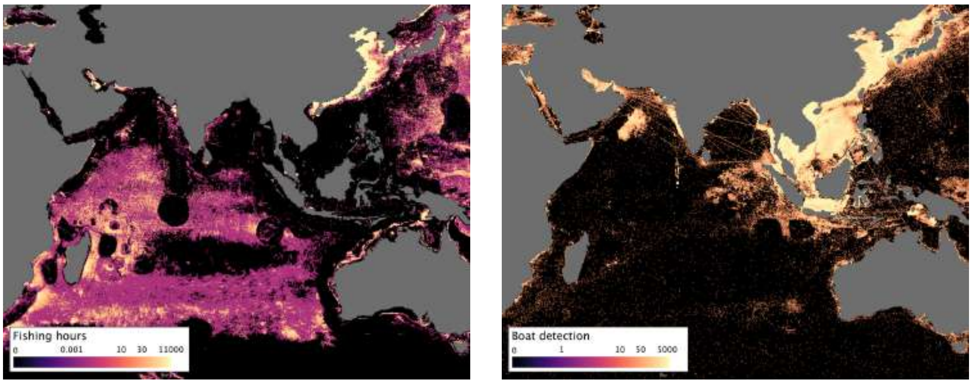
Note. Estimates based on equation (1). The *resource shock* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the female respondent's community in the month of the interview. The sample is restricted to coastal areas (see Section 2) and in columns (5)–(8) to households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

B.14 Fishing and fish prices

For **extractive and inclusive exploitation**, Figure B11 shows an example of the geographical variation. For **fish prices**, the Philippine Statistics Authority (2020) provides monthly retail prices at the province-species level. Figure B12 shows the evolution of prices and spatial distribution of the median fish price for the period 1990 – 2018.

Figure B11: Geographical distribution of extractive and inclusive exploitation

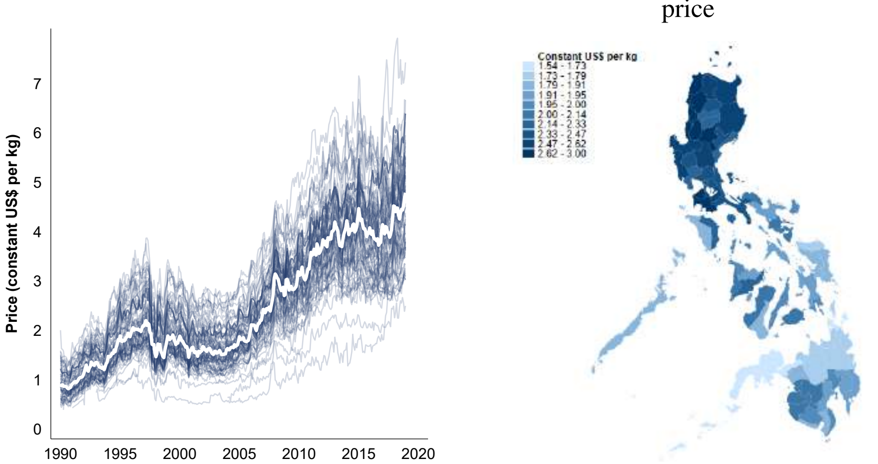
A. Extractive exploitation **B. Inclusive exploitation**



Note. Example of the geographical distribution of the intensity of extractive (*Panel A*) and inclusive exploitation (*Panel B*). The resolution is $0.25° \times 0.25°$ in Panel A and $0.1° \times 0.1°$ in Panel B. Color scales are based on quantiles. Appendix A.1 provides further details about the variables.

Figure B12: Time series and spatial distribution of retail price for fish

A. Time series B. Spatial distribution of the median price

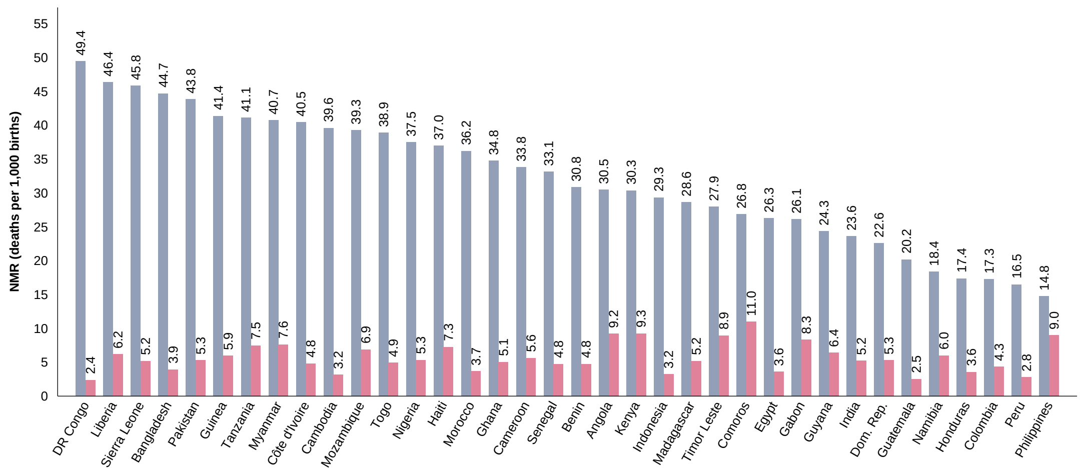


Note. Evolution over time of the province-level fish prices (*Panel A*) and spatial distribution of the 1990 – 2018 median fish price (*Panel B*). Prices are obtained for the following species: indian mackerel, milkfish, threadfin bream, blue crab, caesio, anchovies, frigate tuna, tilapia, tiger prawn,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

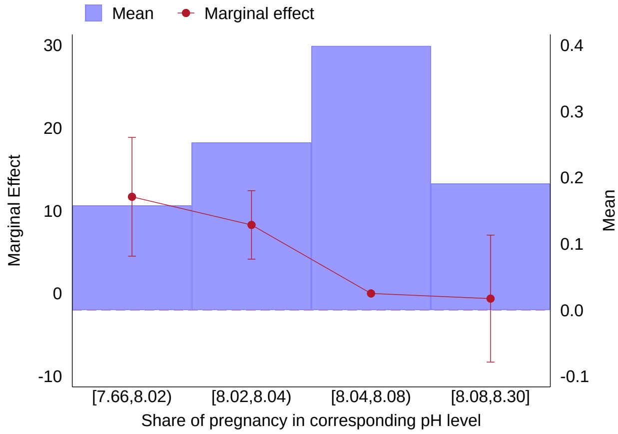
Figure C1: Counterfactual estimates of NMR attributed to acidification



Note. Country-level average NMR in the coastal area (left bar) and average NMR attributed to acidification (right bar).

Acidification shocks and adaptation. Figure C2 presents 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 in a specific range during their gestation period. The effect is mainly driven by exposure to pH in the bottom part of the distribution, suggesting our findings relate to an increase in acidity. In addition, to test for adaptation, Table C1 re-estimates Table 2 interacting the ocean's ph while *in utero* with a location's initial conditions, namely the (standardized) average ocean's pH from 1972–1975.

Figure C2: Resource shocks and neonatal mortality: binned analysis



Note. Estimates based on equation (1) where the resource shock 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 (presented in the horizontal axis). The excluded category is the third bin, which includes the historical median and mean of the resource shock in sampled areas. The lowest and highest values in the range are the historical minimum and maximum in the sample. 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. The right vertical axis presents the average share of time of exposure *in utero* for each bin. The 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 3). The sample is restricted to coastal areas (see Section 2). Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

Table C1: The effect on neonatal mortality: initial conditions

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

Note. Estimates based on equation (1). The dependent variable is a dummy variable equal to 1 if the child died within the first month of life and 0 if the child survived, multiplied by 1,000. *Resource shock* is the average pH (multiplied by a factor of 100) in the ocean's cell closest to the child's community during the 9 months before birth. *Initial conditions* refer to a location's (standardized) average between 1972–1975. The sample is restricted to coastal areas (see Section 2). Standard errors (in parenthesis) are clustered at the ocean raster data point, p-values are reported in brackets. All specifications include community FEs, birth year by birth month FEs, country by birth year FEs. Controls for local seasonality are either country by birth month FEs or 5°×5° cell by birth month FEs. The full list of controls is presented in Section 3. Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

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