FROM SEA TO SHORE: THE IMPACT OF OCEAN ACIDIFICATION ON CHILD HEALTH

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Abstract
Since the Industrial Revolution, ocean water acidity has risen by 26% due to anthropogenic emissions—a process known as *ocean acidification*—posing a risk for marine life and the communities depending on it. This paper examines the consequences of ocean acidification for child health, using data from coastal regions in 36 low- and middle-income countries from 1972 to 2018, encompassing 41% of the world's coastal population. Leveraging short-term exogenous shifts in ocean acidity near human settlements for identification, we find that prenatal exposure to higher water acidity significantly raises the risk of death in the first months of life and impacts early childhood development. We show evidence consistent with these effects being associated with maternal malnutrition, as increased acidity reduces catches for small-scale fisheries, increasing seafood prices and reducing consumption of crucial nutrients. Our findings indicate limited adaptation to these impacts. We estimate that, absent intervention, ocean acidification could contribute to as many as 77 million neonatal deaths in this region by 2100—a consequence that should not be ignored in the projected cost of climate change. (JEL: I15, Q20, Q54, O10)

Keywords: Climate Change; Ocean; Acidification; Health; Mortality; Development.

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1. Introduction

Since the Industrial Revolution, ocean water acidity has risen by 26%—a phenomenon known as *ocean acidification* (Doney et al. 2020). This outcome originates from the ocean's key role in regulating the climate by absorbing carbon dioxide from the atmosphere. Due to increased emissions from human activities, the amount absorbed has surged over the past two centuries, disrupting the ocean's chemical balance. The resulting increased acidity affects marine life and is likely endangering human communities whose economic development depends on marine resources (Dalgaard et al. 2020; IPCC 2022). Nevertheless, empirical evidence on these consequences remains limited, with most findings derived from economic or ecological models projecting the hypothetical effects of ocean acidification (see, e.g., Brander et al. 2012; Colt and Knapp 2016).

This paper investigates the consequences of ocean acidification for child health, focusing on the region where the impact is expected to be most pronounced—in low- and middle-income countries (L&MICs). These countries are home to most of the over 3 billion people worldwide who depend on ocean-harvested resources to survive (FAO 2022). In their coastal regions, seafood consumption forms a significant part of nutritional intake, predominantly supported by small-scale fisheries operating near human settlements (World Bank 2012). This form of dependency is particularly vulnerable to local disruptions to marine resources, such as those caused by acidification, with children being particularly at risk (see Section 2 for a detailed discussion of these processes).

We exploit local dependency on marine resources to analyse the effects of ocean acidification in the coastal areas of 36 L&MICs, spanning large regions of Africa, Asia, and Latin America from 1972 to 2018. In 2020, these countries accounted for 39% of the world's population, rising to 41% when focusing on coastal areas (United Nations 2024). Our approach compares individuals and communities over time by matching their locations to temporal variation in the acidity of the nearest waters, as measured by pH—a logarithmic scale where lower values indicate the higher acidity of a solution. For identification, we focus on short-term exogenous changes in pH at these locations. In the short run, and similarly to weather patterns, pH in a specific point in the ocean deviates exogenously around a long-run (decreasing) trend, with waters being relatively more (or less) acidic.[1] Exploiting this property, we capture deviations using a linear framework accounting for unobserved heterogeneity through multi-way fixed effects (FEs). We support this approach with several checks described in Sections 4 and 5.

Following this approach, we first establish a link between ocean acidity and child health. Comparing marine catches in coastal areas over time, we show that higher acidity reduces the quantity and value of seafood caught by small-scale fisheries, suggesting a net negative effect of water acidity on species harvested in proximity

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[1] Ocean pH is affected by wind, temperature, sea ice, precipitation, runoff, and ocean circulation (Feely et al. 2008). As such, its local variation is analogous to weather patterns (Online Appendix B.1), whose short-run deviations have been used in the literature to identify climatic shocks (Dell et al. 2014).

to coastal settlements. At the same time, higher acidity does not impact the catch of commercial fisheries or the overall economic activity in the coastal area. Our findings indicate that the negative shocks to small-scale fisheries increase local prices for seafood, translating into a diminished probability of seafood consumption and increased malnutrition for local populations, particularly affecting pregnant women. Maternal malnutrition is a critical risk factor for children's health, and can lead to developmental deficits and even to death (Victora et al. 2021).

Motivated by this link, we study the consequences of early-life exposure to varying degrees of ocean acidity. We use data from up to 1.5 million live births from 1972 to 2018, leveraging individuals' geolocation and month and year of birth to compute exposure. Comparing children (or siblings) born in the same location, but at different points in time, we reveal that experiencing higher acidity in nearby waters while *in utero* leads to increased mortality in the first months of life. A 1% increase in acidity raises neonatal mortality (death during the first month of life) by approximately 1.5 deaths per 1,000 live births in coastal communities. This effect represents a 5% increase relative to the sample average of neonatal mortality in the period of study. The largest impacts are observed in areas with a higher dependence on seafood and in regions where forms of fishing that deplete marine biodiversity are prevalent, in line with evidence on the cascading effects of over-exploitation (see, e.g., Frank and Wilcove 2019). Experiencing higher acidity while *in utero* has instead no effect on mortality beyond the first months of life.

The increase in neonatal mortality following ocean acidification confirms a mechanism rooted primarily in changes in maternal health. However, investments in maternal and child health are unaffected, suggesting the lack of adaptation. Our results indicate that differential access to medical care and nutrient supplementation, as well as behavioural changes that could occur after parents observe their child's health, are unlikely to be at play.[2] The results also confirm the absence of significant income changes at the household level, as such changes would typically prompt adjustments in investment (see, e.g., Baird et al. 2011).

Finally, exposure to ocean acidity *in utero* not only impacts mortality rates, but also influences infants' development. Objective anthropometric measurements indicate that mortality due to prenatal exposure to ocean acidity is more common among children who would have otherwise had worse health outcomes. On average, children who survive past their first month of life have slightly better health indicators and thus represent a positively selected group. However, when examining gendered effects, we observe a significant increase in stunting among female children, which outweighs this positive selection. We present evidence consistent with these negative effects lasting into women's adulthood, accompanied by worse economic outcomes.

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[2] We lack direct measures of maternal stress. However, evidence indicates that maternal stress plays a significant role in response to traumatic events (see, e.g., Aizer et al. 2016; Persson and Rossin-Slater 2018; Menclova and Stillman 2020; Berthelon et al. 2021), as opposed to the relatively mild changes in maternal health that we examine in later sections.

These results enable projections of the aggregate effects of ocean acidification in the future. By combining the estimated effect of *in-utero* exposure to ocean acidity with various emissions and adaptation scenarios, we project neonatal mortality rates in the study area through 2100. Continued carbon dioxide emissions are projected to lower average surface ocean pH by as much as 0.38 units by 2100, compared to 1975 levels (Tagliabue et al. 2022). Under a high-emissions scenario with no adaptation, the cumulative neonatal deaths attributable to ocean acidification could reach 77 million for the period 1975–2100. This outcome equates to an average neonatal mortality rate of 23 per 1,000 live births, similar to the rates seen in Northern Africa and Western Asia in 1990 or Southern Asia in 2020 (UNICEF 2024). The introduction of adaptation measures could significantly dampen these estimated consequences. However, given the limited adaptation to ocean acidification observed from 1972 to 2018, our findings underscore the importance of shifting away from high-emissions pathways.

Our findings contribute to different strands of the literature. First, we further our understanding of the current and future effects of climate change. By providing evidence on the consequences for coastal communities of altering ocean acidity and projecting them to the future, our results contribute to the emerging literature on the impacts of ocean acidification on human communities (see, e.g., Colt and Knapp 2016), an essential dimension to integrate into the general literature measuring the costs of climate change (see, e.g., Auffhammer 2018). While many studies have explored the impact of climate change on human behaviour—focusing on issues like rising temperatures and shifting rainfall patterns (Deschênes et al. 2009; Deschênes and Moretti 2009; Barreca et al. 2016)—the ocean has received far less attention. In addition, due to the open-access nature of ocean resources, changes in their productivity are not comparable to changes in land and agricultural productivity (see, e.g., Collier 2010), which have been more extensively studied in relation to climate change.

Second, we provide new evidence regarding the early stages of children's development. Numerous studies have examined shocks that are either directly observable or have direct effects on health, thus leading to adaptation or avoidance behaviour (Almond et al. 2018 provides a review of this literature).[3] Ocean pH is not directly observed or felt by individuals (e.g., it is not reported in weather forecasts or newspapers), it has no direct effect on health, and public awareness about its changing nature is highly limited.[4] Our results suggest that shocks with these characteristics—being largely imperceptible, lacking direct health impacts, and receiving minimal public attention—generate a limited behavioural response, contrasting with evidence

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[3] Studies related to our setting cover atmospheric events (Maccini and Yang 2009; Heft-Neal et al. 2018; Geruso and Spears 2018a; Adhvaryu et al. 2024) and environmental contamination or degradation (Chay and Greenstone 2003; Arceo et al. 2016; Isen et al. 2017; Geruso and Spears 2018b; Black et al. 2019; Berazneva and Byker 2024). On avoidance behaviour, see Moretti and Neidell (2011) on air pollution.

[4] The tangible effects of ocean pH could be discerned from seafood catch. However, awareness among the general public of a link between water acidity and fisheries is severely limited. Surveys conducted in richer countries suggest that only a tiny segment of the population is aware of this influence (Gelcich et al. 2014; Lotze et al. 2018).

on adaptation following nutritional shocks such as famines and prolonged fasting (Razzaque et al. 1990; Almond and Mazumder 2011; Majid 2015), or nutrient supplementation (Adhvaryu and Nyshadham 2016). In our setting, parents are likely either unaware of the consequences of altering their diets, or their health is not sufficiently affected to induce behavioural changes. These findings align with evidence on the limited knowledge of dietary consequences in poorer settings (see, e.g., Hirvonen et al. 2017) and with the high prevalence of micronutrient deficiency in L&MICs (Lowe 2021). Such deficiency can occur without deficits in caloric intake, making detection difficult for non-experts.

Finally, this study provides new evidence on the importance of wildlife for human and economic development (Michalopoulos and Papaioannou 2013; Bowles and Choi 2019; Dalgaard et al. 2020; Mayshar et al. 2022). Our findings complement the recent literature on biodiversity and poverty (see, e.g., Dasgupta 2021) and on the role of overly exploitative practices such as deforestation (Burgess et al. 2012; Jayachandran 2013), overfishing (Stavins 2011), and poaching (Kremer and Morcom 2000). Closely related to our study is the work of Frank and Sudarshan (2024), which highlights the role of the functional extinction of vultures in India on human mortality, and that of Feir et al. (2024), which shows how the loss of the bison in North America led to persistent negative consequences for Native Americans.

2. Background

This section summarises how ocean acidity can impact marine life and human behaviour, while we test these channels in Section 5.1. Concerning marine life, the scientific literature highlights two channels.

First, water acidity directly affects the physiology of marine species: at lower pH levels, many organisms must invest additional energy to maintain their metabolic processes and biological functions, with consequences for their survival, growth, development, and reproduction (Gattuso and Hansson 2011). Although these effects are heterogeneous across and within species, biological effects are generally large and negative (Kroeker et al. 2010; Alter et al. 2024). Laboratory experiments indicate negative responses to acidity in approximately 50% of species tested (Wittmann and Pörtner 2013).

Second, water acidity degrades key marine habitats such as coral reefs and macroalgal forests. These areas serve as crucial feeding grounds for fish, making them important catchment areas for subsistence and artisanal fisheries (Doney et al. 2020). Degradation of these ecosystems disrupts marine food chains, not only reinforcing the direct effects of pH on the physiology of marine species, but also altering competition for food across species (Sunday et al. 2017). Scientific evidence indicates that commonly-consumed species, which typically boast better nutritional content, are more vulnerable to these effects, particularly in the presence of overfishing (Jones and Cheung 2018; Hicks et al. 2019; Maire et al. 2021).

The overall net effect of these two channels on marine life is uncertain (IPCC 2022). Some species might benefit from the consequences of acidic conditions, resulting in compositional changes (i.e., an increase in the quantity or quality of some species and a reduction in others) rather than reduced seafood stock.[5] Nevertheless, any change in species occurrence can impact harvest composition and, consequently, human nutrition and health. The reduced availability of commonly harvested species could result in income deterioration (Colt and Knapp 2016), potentially reducing investments in health and nutrition among those relying on fisheries as a source of income, and in dietary shifts driven by price adjustments or changes in seafood quality.[6]

The resulting effects on nutrition are expected to be more pronounced in vulnerable coastal and island communities in L&MICs. In these countries, seafood is a crucial source of nutrients, providing 26% of all consumed animal proteins, as compared to the global average of 17% (FAO 2022). Countries such as Bangladesh, Cambodia, the Gambia, Ghana, Indonesia, Sierra Leone, and Sri Lanka reach peaks of at least 50% reliance on seafood for protein. In addition, most of this nutrient intake is supported by small-scale fisheries, definitionally more vulnerable to local shocks as compared to larger fisheries (FAO 2023). L&MICs host 97% of all workers employed in marine capture, and more than 90% of them are engaged in small-scale fisheries supporting local consumption (see, e.g., Simmance et al. 2022). The ability to balance changes in local supply with imports is limited because L&MICs tend to export higher-quality seafood caught in their waters and supplement local demand with imports of lower-quality fish (McCauley et al. 2018).

Children, particularly, are at risk. Because nutritional alternatives and access to micronutrient supplementation are limited, seafood is recognised as an important source of macronutrients, such as proteins, and micronutrients, such as iron, iodine, zinc, vitamin A, vitamin D, vitamin B12, calcium, and essential fatty acids (United Nations 2021). These nutrients are essential for maternal health and for fetal and child development.[7] Early-life deficiencies in these nutrients can lead to severe health consequences, even including death (Victora et al. 2021).

3. Data

We collate myriad data sources. Online Appendices A.1–A.2 further detail the variables and data sources. Figure 1 shows the geographical coverage of the study.

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[5] Online Appendix B.1 discusses variables with a more direct effect on quantity, such as rising global sea surface temperatures (Keeling et al. 2010).

[6] The biological changes to marine life induced by water acidity are expected to result in reduced protein intake and compromised seafood quality (Falkenberg et al. 2020).

[7] *Iron* and *iodine* support brain development and help prevent stillbirth. *Zinc* and *vitamin A* promote childhood survival and growth. *Calcium* and *vitamin D* reduce the risk of preterm delivery, while *vitamin B12* is vital for a healthy pregnancy and the development of the nervous system and brain in children. *Essential fatty acids* help prevent preeclampsia, preterm delivery, and low birth weight, and support children's cognitive development.

Mortality, Human Capital, And Adaptive Behaviour. We collate and homogenise 92 household surveys from 36 countries collected by the Demographic and Health Surveys (DHS) from 1990 to 2018. Individual surveys provide nationally representative data on health and population in L&MICs, with a particular focus on maternal and child health, and they have been widely used to calculate mortality rates among children. The dataset is supplemented with objective measurements of human development and nutrition, such as height, weight, and hæmoglobin concentration in blood samples. The programme 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 their children's year and month of birth, sex, birth order, whether they are twins, and the date of death when applicable. We assume measurement error related to mortality is minimal, as the timing of a child's death, being a tragic event, is unlikely to be forgotten.[8]

The primary sampling unit is a community (or cluster), representing a village or neighbourhood. Our dataset includes all available surveys with geographical coordinates and considers only countries with direct access to the ocean. We use all available surveys and re-weight observations to correct for oversampling of countries surveyed multiple times. Online Appendix A.1 provides the full list of countries and surveys. Results are robust to different selection criteria. For questions omitted in specific survey rounds, we re-compute weights to account for this selection.

We restrict the sample to coastal areas. Using geolocation for communities, we compute the minimum straight distance to the shoreline, and following United Nations (2003), we define a *coastal area* as the buffer extending landward from the ocean's shore up to a distance of 100 km. Individual characteristics tend to be comparable in magnitude between communities in the coastal and inland areas, but households in proximity to the ocean are slightly richer and exhibit lower mortality rates (Online Appendix A.2).

Ocean Acidity. We capture this chemical feature of the ocean using water pH—a logarithmic scale that indicates the acidity (basicity) of an aqueous solution at lower (higher) values—measured at the surface. Measurement of ocean pH using satellites for our time-space dimension is currently unavailable (Land et al. 2019). We therefore obtain the chemical features of the ocean from the Hadley Global Environment Model 2 – Earth System or HadGEM2–ES, developed by Collins et al. (2011) and Jones et al. (2011), which combines historical climate data, physical equations, and simulations to reconstruct past climate conditions, extrapolating from observations where observed

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[8] The history of terminated pregnancies (i.e., pregnancies that did not result in a live birth regardless of the cause) is not recorded. Online Appendix B.3 shows that ocean acidity in nearby waters does not affect the probability of experiencing a terminated pregnancy and that results are robust to accounting for recall bias in the reporting of a child's death.

data are incomplete.[9] Section 5 discusses estimates controlling for confounders that could influence the pH measurement, such as anthropogenic waste.

Data are monthly global raster data at the 1°×1° resolution for the period 1972–2018.[10] We match raster points to communities or coastal areas using a proximity criterion (see Section 4 for details about the matching procedure). Summary statistics for matched points highlight that pH varies locally both within and across years around its long-run level, showing a high similarity to weather systems (Online Appendix B.1). Variation in pH originates from both the time and geographic dimensions, with comparable contributions from its between and within components.

We supplement our data with other variables that could jointly determine ocean acidity and outcomes in the coastal areas. First, we gather information about additional chemical features of the ocean with the same source used for pH. Second, we draw on the ERA5 database to supplement the data with other meteorological features in the same location in the ocean where pH is measured, including temperature and wind speed. Third, to control for weather characteristics inland, we include yearly rainfall and temperature data at the community level from the PRIO-GRID database.

Ocean Exploitation. Data about seafood catch at the temporal and geographical resolution of the DHS data is unavailable, forcing us to work with data aggregated at the country level or for a restricted temporal horizon.

First, we gather data about quantity, price, and landed value of catches within the exclusive economic zones (EEZs) of each country in our sample from the Sea Around Us initiative (Pauly et al. 2020). An EEZ is a sea zone prescribed by the United Nations Convention on the Law of the Sea (UNCLOS) extending up to 200 nautical miles from the coast. Within this zone, the coastal state has special rights over the exploration and use of marine resources. Figure 1 shows the geographical coverage of these zones.

Data are disaggregated at the levels of fishing sector (industrial or small-scale), seafood group (defined by 11 commercial categories), and destination of use (direct human consumption or other uses). Quantities are reported in kilotons (kt), while landed values are computed using nominal ex-vessel prices in local currency and converted into 2010 US$ real equivalents. Using ex-vessel species-level prices, we build yearly median prices for each commercial group.

We include catches whose destination of use is direct human consumption and distinguish between two sectors of activities: the *industrial sector* is large-scale and commercial, and it includes catch from large motorised vessels that is overwhelmingly

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[9] Although the series matches well the available information from observational data of ocean features (see, e.g., Totterdell 2019), our estimates might suffer from measurement error due to extrapolation. The possibility that such measurement error is correlated with unobservable determinants of local development or health is minimised by the climatology-based framework of the data (i.e., by construction, data cannot capture pH at the coast, where it may be influenced by local human activity). While there may be unobserved factors that influence both the outcome variables analysed in the paper and pH, we interpret our results assuming measurement error is uncorrelated with both. Regarding the use of climatology-based data in economics, see, e.g., Carleton et al. (2022); Adhvaryu et al. (2024); Matranga (2024).

[10] Data in this format was provided by the European Space Agency (ESA) Pathfinders–OA project.

sold commercially; the *small-scale fishing sector* comprises artisanal and subsistence fishing and includes vessels that primarily supply local consumption.[11] The resulting dataset is a yearly time series at the seafood group–country level covering the full period under analysis (1972–2018). In our selected group of countries, both quantities and landed values have been steadily increasing for both small-scale and industrial fishing (Online Appendix B.4).

Second, for heterogeneity analyses, we supplement these data with more geographically granular data about exploitation intensity and type, but restricted to a shorter time period due to data availability. We consider a form of *extractive fishing* by focusing on industrial fishing. The Global Fishing Watch dataset provides us data on the hours industrial fishing vessels spend at specific geolocations. Because data are available only for 2012–2016, we build a global grid at the 1°×1° resolution summing fishing hours within each cell over the available period.

In addition, we define *night-time fishing* using the Automatic Boat Identification System for VIIRS Low Light Imaging Data (Elvidge et al. 2015). This system provides the time and geolocation of boats using nightlight as measured from satellite imaging. Because only 16% of fishing detected with this algorithm is also captured by industrial fishing (Kroodsma et al. 2018), night-time fishing tends to capture boats operating on a smaller and local scale, thus potentially contributing to the local economy. As with the measure of extractive fishing, 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 normalise intensity from both activities to be between 0 (no presence) and 1 (high intensity). These measures aim to capture longer-run fishing patterns by averaging daily information over the full period in which data are available. However, if patterns of fishing were very different in the past, we would be capturing heterogeneity specific to exploitation in the period for which we have data availability. At least for extractive fishing, which tends to have low sensitivity to economic and environmental variation (Kroodsma et al. 2018), time-invariant heterogeneity is likely capturing suitability for industrial fishing. Online Appendix B.4 shows that fishing patterns are primarily driven by differences in geography, while individual characteristics are comparable in areas with high versus low intensities of both types of fishing. The intensity of night-time fishing is comparable in areas with varying intensities of extractive fishing. Dependency on fish for nutrition is also highly stable over time.

Economic Activity. We complement the data with the average night-time light emission from the calibrated DMSP-OLS Night-time Lights Time Series 4. Night-time luminosity measured by satellite images is a widely used proxy for economic activity and human development (see, e.g., Bruederle and Hodler 2018). Yearly data are available for the period of 1992–2012. We normalise luminosity by population in

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[11] Catch from small-scale fisheries is notoriously under-reported in national statistics (Pauly and Zeller 2016). The Sea Around Us explicitly accounts for this limitation, and it applies under-reporting adjustments to better reflect actual catches. Any measurement error related to under-reporting is not expected to correlate with local changes in ocean acidity.

the grid cell using the PRIO-GRID database, performing the analysis using night-time luminosity in a gridded dataset at the 0.5°×0.5° resolution, selecting only grid cells in the coastal area of sampled countries.

4. Empirical Strategy

To estimate the impact of ocean acidification, we exploit temporal and geographical variation in ocean pH to compare communities as they face varying degrees of ocean acidity near their locations. We match communities with ocean pH using the nearest data point in the ocean. This point is likely the fishing ground of small-scale fisheries based in or near the community. Available evidence highlights that 84% of all small-scale fisheries operate within 20 km from the shoreline (FAO 2023).

We denote as $R_{c,mt}$ the ocean pH (multiplied by 100 to focus on changes of 0.01 units) matched to community or country c and measured at time mt, where m indicates the month and t the year. To match geographical and temporal variation in the unit of analysis with $R_{c,mt}$, we follow two approaches. First, contemporaneous exposure is computed by matching $R_{c,mt}$ either with the location and time of observation of the outcome variable. Second, early-life exposure is computed by matching $R_{c,mt}$ with an individual's location, month, and year of birth. As is standard in the literature, we assume that the survey location corresponds to the location of birth, also supported by the evidence suggesting the absence of selective migration in our setting (Section 5.2). When exposure is computed over multiple months, we average pH over that period. For instance, exposure *in utero* is the average $R_{c,mt}$ during the nine months preceding the date of birth.

Because pH is a logarithmic scale, we can interpret a decrease of 0.01 units as approximately a 1% increase in acidity. In our sample, 0.01 units correspond to the median within-year variation that a specific location experiences (i.e., the difference between the minimum and maximum pH in a specific year is on average 0.01), and to one-third of a standard deviation in *in-utero* exposure to pH.[12] To better understand the magnitude of the estimated effects, we also quantify the historical change in pH in the sampled area. The average reduction in pH from 1972 to 2018 was 0.075 units (0.016 units per decade). Therefore, the unit we analyse corresponds to the average reduction in pH experienced over approximately 6.25 years. Considering future projections of ocean acidity, the Intergovernmental Panel on Climate Change (Tagliabue et al. 2022) predicts, under a business-as-usual emissions scenario, an average reduction of approximately 0.31 units of pH between 2018 and 2100 (0.037 units per decade). Under this scenario, a 0.01 decrease in pH would occur in just 2.67 years. See Section 6 for a detailed discussion of future projections.

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[12] The standard deviation of pH is amplified by the large geographical area we cover. Conditional on FEs, a change of 0.01 in pH is roughly three standard deviations of residual variation (Online Appendix B.1).

For identification, we exploit short-run exogenous deviations in pH levels from the spatially specific long-run trend (correcting for seasonality if the unit of analysis varies within year). Deviations are computed by capturing unobserved heterogeneity in the estimating equation using a set of FEs, which allows the isolation of deviations from the raw variation in pH. These FEs capture the time-invariant characteristics of the location of birth or observation (*location effects*); the common characteristics at the time of birth or observation (*non-spatial time effects*); and the trends and seasonality components of the ocean pH and the outcome variable of interest that are specific to a geographical region (*spatially specific time effects*). The latter are particularly important for identification because ocean acidification is spatially heterogeneous, with some regions experiencing faster or slower acidification, and more amplified or compressed within-year variation than others. The nature of abnormal deviation in the pH of our main independent variable is reinforced by the evolution over time of the sample average short-run deviation (Online Appendix Figure B1). Exogeneity is supported by the balance of observable characteristics in areas affected by different deviations (Online Appendix B.6).

We adapt this approach based on the geographical and temporal variation of the unit of analysis. When analysing data about seafood catch, the unit of analysis is at the seafood group–country–year level. We therefore estimate the effect of ocean pH in the nearest area of the ocean using the following specification:

$$y_{ic,t} = \beta R_{c,t} + \mathbf{X}_{c,t}\gamma + \Omega_{c,t} + \varepsilon_{ic,t} \tag{1}$$

where $y_{ic,t}$ is the catch in the seafood group i fished in the EEZ of country c in year t. Because the unit of analysis covers an area of ocean larger than the resolution at which pH is observed, to compute $R_{c,t}$, we average all data points within the EEZ of country c in a year t. We label this variable *pH in proximity to the coast*. The specification includes a vector of weather control variables, $\mathbf{X}_{c,t}$, and the set of FEs that defines the identifying variation in terms of deviations from long-run patterns, $\Omega_{c,t}$.[13] Location effects are captured by seafood group by country FEs; non-spatial effects by year of observation FEs; and spatially specific time effects by fishing area by year FEs. Fishing areas are geographical regions used for fisheries management and reporting, grouping multiple countries together (FAO 2020). Finally, the idiosyncratic errors, $\varepsilon_{vc,t}$, are assumed to be clustered at the EEZ level.

When analysing data about children and women, the unit of analysis is at the individual level. We estimate the effect of ocean pH in the nearest area of the ocean using the following specification:

$$y_{ic,mt} = \beta R_{c,mt} + \mathbf{X}_{ic,mt}\gamma + \Omega_{c,mt} + \varepsilon_{ic,mt} \tag{2}$$

where $y_{ic,mt}$ is the outcome of interest for individual i at time mt in community c.

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[13] Controls include the average temperature and rainfall (and their interaction) of coastal areas, and the average oxygen concentration in the EEZ, another chemical feature of the ocean that is strongly correlated with ocean temperature (Free et al. 2019).

Because the geographical area of a community is smaller than the resolution at which pH is observed, $R_{c,mt}$ is the pH corresponding to time mt at the closest data point in the ocean, matched using the shortest straight-line distance. We label this variable as *pH in the nearest waters*. The specification includes a vector of demographic and weather control variables, $\mathbf{X}_{ic,mt}$, and the set of FEs that defines the identifying variation in terms of deviations from long-run patterns, $\Omega_{c,mt}$.[14] Non-spatial time effects are captured by controlling for (interview or birth) month by year FEs. Spatially specific time effects are captured by macro-region by (interview or birth) year FEs, capturing local trends and, when within-year variation is observed, by macro-region by (interview or birth) month FEs, capturing local seasonality. A macro-region is a geographical area including multiple communities. We consider alternative definitions, such as administrative units like the district or the country of the community, and grid cells of different resolutions.[15] Location effects depend instead on whether we are focusing on contemporaneous or early-life exposure. For contemporaneous impacts, we cannot exploit within-community variation because almost every individual in the community is interviewed in the same month. In this case, the *benchmark* specification includes location FEs, grouping multiple communities using grid cells. For early-life exposure, the *benchmark* specification includes community FEs, leveraging within-community temporal variation originating from birth dates. In this scenario, we can further exploit within-family variation by adding mother-specific FEs, controlling for mothers' time-invariant characteristics (*within-sibling* specification). Finally, the idiosyncratic errors, $\varepsilon_{ic,t}$, are assumed to be clustered at the ocean raster data point (see Section 3).

We support the validity of the identifying assumptions in equations (1) and (2) with a variety of tests discussed in Section 5. In particular, we address issues related to non-random selection driven by FEs, which occurs from the loss of groups with only one observation and can lead estimates to differ from the population-wise average effect (Cameron et al. 2011). For example, the within-sibling identifying assumptions restrict the sample to mothers with at least two live births, who are generally older, have fewer years of education, were younger at the time of their first birth, and live in poorer households and communities (Online Appendix A.2). Threats from this form of selection are limited by our measure of shocks being not only continuous, but also exhibiting a high degree of variation (the within-community variance in the identifying sample used by the benchmark specification is always positive). Nevertheless, in all estimation tables, we report the number of observations used in the

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[14] When the outcome variable refers to children, *demographic controls* include the child's gender and birth order, the number of twins born with the child, mother's age at birth and at the time of the interview (including their square terms), mother's years of education, the household head's gender and age, and household size. When the outcome variable refers to adult women, these controls are limited to mother and household head characteristics. *Weather controls* are the same as in equation (1). In Section 5, we discuss the sensitivity to estimates of adding additional controls.

[15] Grids allay concerns about the potential endogeneity of administrative boundaries. To guarantee sufficient variation in the measurement of ocean pH, which varies at the 1°×1° resolution, we consider grids at 5°×5° and 10°×10° resolutions.

estimation (*identifying observations*), and the number of observations dropped due to the identifying restrictions (*singleton observations*).

5. Results

We apply the methodology presented in Section 4 to estimate the impact of ocean pH on child health. Section 5.1 begins by discussing the causal pathway between ocean acidity and child health, focusing on the impact of contemporaneous exposure on fishing and on human nutrition. Section 5.2 presents results on the effect of early-life exposure on child mortality and development, and on health investments. Section 5.3 analyses how these effects vary according to the prevalent method of marine resource exploitation near the community.

5.1. Defining the Causal Pathway of Ocean Acidity

We begin by looking at the impact of contemporaneous ocean pH on fisheries. Table 1 shows estimates of equation (1) of the impact of ocean pH in the EEZ on the quantity and value of seafood catch, on the median price of seafood, and on aggregate economic activity proxied by satellite-based night-time luminosity. Dependent variables are reported using an inverse hyperbolic sine transformation to account for zero values. Results are robust to alternative transformations (Online Appendix B.4).

We begin by focusing on small-scale fishing in columns (1)–(2). This activity primarily serves local consumption, and impacts the nutrition of coastal communities, as confirmed by a positive correlation between seafood catch derived from this activity and better nutritional indicators among women (Online Appendix B.4). We observe that a decrease of 0.01 in pH leads to a significant decline of 0.13 log-points in the quantity caught and 0.20 log-points in the landed value. These results highlight that, at least for species harvested by small-scale fisheries, ocean acidification has a net negative effect (see Section 2). Effects are larger for seafood with a lower price, whose primary nutrient is essential fatty acids, and with a lower resilience to ocean acidification, but not statistically different (Online Appendix B.4).

In columns (3)–(4), we focus instead on industrial fishing. Neither the quantity of seafood caught nor its value is influenced by ocean pH in the EEZ. These results highlight the resilience of industrial fishing to the shock and is consistent with evidence showing this sector's ability to absorb shocks by diversifying catch or relocating fishing activities outside EEZs (see, e.g., Anderson et al. 2017), a possibility that is more limited for small-scale fishing.

Column (5) provides estimates on the effect on the overall median price of seafood. We observe that a decrease of 0.01 in pH leads to a significant increase of 0.09 log-points in the media price of seafood. Overall, these results suggest that the effects on small-scale fishing are enough to influence the median price of seafood, thus potentially influencing consumption choices.

Because fishing is an important economic activity in coastal areas, we want to exclude any income changes that occur alongside price changes. In column (6), we test whether ocean pH induces a short-term deterioration in the overall economic activity of coastal areas. We look at the effect of ocean pH on the average satellite-based night-time luminosity in the coastal area of each selected country. For this analysis, and for comparison with estimates in columns (1)–(5), we average night-time luminosity according to the definition of the coastal area of a country (see Section 3) and estimate equation (1) at the country level.

We find no effect on night-time luminosity. While we cannot exclude the possibility that ocean acidification may eventually influence the overall economic activity, these results suggest that the consequences of short-run variations in ocean pH are not driven by changes in aggregate income. One possibility is that the effects on fishing, which are specific to small-scale fisheries, are too small to influence the whole economy or are specific to regions where night-time luminosity is not very responsive to changes in economic activity, such as poorer areas. Another alternative is that night-time luminosity responds to these shocks only over the long term.

Online Appendix B.7 shows that these results are not specific to coastal areas. We show that a drought in the coastal area, a shock to agricultural productivity known to generate income changes (see, e.g., Barrios et al. 2010), leads to significant reductions in night-time luminosity. In addition, the lack of changes in labour supply induced by ocean acidity further suggests the absence of short-term impacts on the aggregate economic activity.

In the absence of income changes, the effects on seafood prices should reflect on consumption choices. We examine whether ocean acidity induces responses in nutrition by estimating the contemporaneous effect on women's fish consumption. With a limited number of surveys and respondents, the DHS programme asked whether a mother consumed different kinds of food in the 24 hours prior to the interview. Columns (1)–(2) in Table 2 show that a decrease in ocean pH lowers the probability of seafood consumption by 2.6 percentage points (or 8.8% over the sample mean of 29.6%). This reduction is specific to the consumption of seafood, as we observe no significant effect on the probability of consuming other food items (Online Appendix B.8). These results suggest that adults do not compensate by adapting their diets.[16]

Columns (3)–(5) in Table 2 focus instead on malnutrition among women. For women who are not pregnant, we measure malnutrition using an indicator variable for whether the respondent is underweight, defined as having a body mass index (BMI) below 18.5. We supplement this measure with micronutrient deficiency, a direct measure of malnutrition for all women and for pregnant women. We proxy deficiency using objective measurements of anæmia, performed by the DHS enumerators on a random subset of women in the sample. Anæmia is characterised by low levels of

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[16] The DHS provides only information on whether the respondent consumed a food item, but not the quantity consumed. We cannot exclude the possibility that respondents adapt their diets by increasing/decreasing the quantities consumed.

hæmoglobin, a protein in red blood cells that carry oxygen in the blood, and is often caused by iron deficiency.

In line with the evidence discussed in Section 2, the results indicate a pattern in which ocean acidification leads to changes in fish harvesting that impacts nutrition. A 0.01 decrease in ocean pH in nearby waters increases the probability of nearby women being underweight by 0.4 percentage points (or 3.3% over the sample mean of 12.0%). In addition, it leads to a higher prevalence of anæmia, but only among pregnant women. The existence of an effect specific to this vulnerable population is unsurprising because, during pregnancy, the human body requires more iron to supply the growing fetus, and with limited nutritional alternatives, seafood is an important source of iron (US Institute of Medicine 1990; FAO 2023). A 0.01 decrease in pH at the time of the measurement leads to an increase in anæmia prevalence of 1.7 percentage points among pregnant women (or 3.7% over the sample mean of 45.4%).

5.2. *The Effect Of Early-Life Exposure*

This section focuses on the effect of being exposed early in life to varying degrees of ocean acidity in nearby waters. We analyse relevant effects on mortality, parental adaptation, and child development.

Mortality. To investigate the effect on early-life mortality and to isolate a channel operating through maternal malnutrition, we begin by studying *in-utero* exposure to varying degrees of ocean acidity in the waters nearest to people's places of birth.[17] We estimate impacts on the likelihood of mortality at age x (in months). For each age x ranging from 1 month to 60 months, we estimate equation (2), restricting the sample to children who, at the time of the interview, were born at least x months before (independently from being alive). We select the sample based on time from birth to avoid selecting children who are alive and younger than x.[18] The dependent variables are indicator variables equal to 1 if the child has died by age x from birth, and 0 otherwise (multiplied by 1,000 to relate coefficients to changes in deaths per 1,000 live births).

Figure 2 plots the coefficients. We observe that experiencing higher degrees of ocean acidity while *in utero* has a substantial impact on mortality. The effect peaks in the first month of life (corresponding to neonatal mortality), and remains significant across the very first months of life. A smaller net effect is observed beyond the first months of life, while the effect is not statistically different from zero after the first year of life. Because the initial increase in mortality is offset by later decreases, the

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[17] We approximate the actual gestation period assuming a gestation period of nine months. Estimates assuming a gestation period of eight months, which can be interpreted as a lower bound of the effect, remain negative and statistically significant in most specifications (Online Appendix B.9).

[18] The heaping of deaths at 1 year of age is common, while mortality at ages 2, 3, 4 and 5 is hardly affected by heaping (Croft et al. 2018). We observe no effect on the estimates due to these potential issues. Online Appendix B.10 presents estimates of the effect on mortality rates at standard times.

pattern is consistent with a displacement of mortality hastened by experiencing worse conditions *in utero*—a mechanism known in the literature as *death harvesting* (see, e.g., Heutel et al. 2021).

Given the results on mortality, we focus on neonatal mortality. Table 3 presents estimates of the effect on the neonatal mortality rate (NMR)—the number of deaths in the first month of life per 1,000 live births. Panel A uses the benchmark specification, while Panel B uses the within-sibling specification. Columns (1)–(3) remove seasonality at the country level, while columns (4)–(6) remove seasonality at the grid cell level. Columns (1) and (4) do not include any control variables, columns (2) and (5) add weather controls, and columns (3) and (6) further add demographic controls. Figure 3 shows estimates using alternative specifications, including alternative sets of control variables, different time FEs, and different definitions of macro-regions.

A 0.01 decrease in pH significantly increases NMR by 1.42–2.12 deaths per 1,000 live births in our benchmark specification (panel A). Estimates using the within-sibling specification are similar (panel B). In terms of standardised effects (conditional on FEs), a one-standard-deviation negative shock leads to an increase in NMR of 0.53–0.56 deaths per 1,000 live births in the benchmark specification and 0.53–0.67 deaths per 1,000 live births in the within-sibling specification (Online Appendix Table B1).[19] Adding control variables has a limited impact on the estimates of the effect, providing further evidence in support of the exogeneity of short-run deviations in pH. Significant effects are also found when varying the definition of coastal area, with the most affected communities living within 40 km from the shore (Online Appendix B.2).

Estimates in Table 3 are robust to a wide variety of checks. First, while changing the set of FEs alters our identifying assumptions and our definition of deviation, estimates are always negative and significantly different from zero at standard confidence levels (Figure 3). Second, in Appendices B.1, B.2, and B.7, we show that estimates are robust to adding controls for (potentially endogenous) confounders in both the location of birth and the location where pH is measured, such as adverse weather events (see, e.g., Gröger and Zylberberg 2016), the presence of human activity proxied by pollution in coastal water, and the presence of conflict (see, e.g., Axbard 2016), or to excluding areas that are generally subjected to vast anthropogenic waste, such as estuaries (see, e.g., Kennish 2017). Third, selective migration does not drive estimates, as restricting our sample using information on whether the mother was living in the same location of the interview before the gestation period does not affect our conclusions (Online Appendix B.5). Fourth, results are not driven by selection into identification and are robust to potential sources of measurement error associated with distances from the shore (Online Appendix B.6). Finally, statistical inference is robust to alternative clustering assumptions about standard errors in equation (2) and to permutation-based inference,

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[19] The magnitude of these point estimates is smaller compared to interventions providing medical services to pregnant women. Nyqvist et al. (2019) show that introducing community health promoters in Uganda reduced neonatal mortality by 28%. Lazuka (2023) shows instead that introducing maternity wards in Sweden reduced neonatal mortality by 56%. Note, however, that the historical reduction in pH in the study period is seven times larger than the deviation in pH described by the estimate.

which artificially varies the exposure to the shock in both time and space (Online Appendix B.11). The latter allows a rejection of the null hypothesis of a nil effect at the 5% significance level for all estimates in Table 3.

Figure 4 presents a heterogeneity analysis of the effect on neonatal mortality, distinguishing by exposure type. We highlight two main features. First, evidence suggests that the effect is driven by exposure during gestation to lower levels of pH. Panel A presents a binned analysis rather than a continuous one, displaying estimates from equation (2), where ocean pH while *in utero* is replaced by the share of gestation time during which children were exposed to ocean pH levels within specific ranges. These ranges are computed using the quartiles of the 1972–2018 pH distribution in the nearest waters. The effect is significantly different from zero only for exposure to lower levels of pH, indicating that accelerated acidification has a stronger negative impact than the potential positive effect of slowed acidification. Panel B shows the estimates of equation (2) by adding ocean pH in the nearest waters one month before conception (10 months before birth), the month of birth, and 1–4 months after birth (a placebo period posterior to the period considered for the death). Effects are specific to the gestation period, reinforcing the role of maternal malnutrition. Further, we find no evidence of short-term responses in fertility or in the probability of a mother experiencing a terminated pregnancy (Online Appendix B.3).

Second, impacts are concentrated in communities relying more heavily on the ocean's resources. Panel C of Figure 4 shows estimates of the effect on NMR, allowing estimates to vary flexibly with distance from the ocean's shore, and from other water bodies, like lakes and rivers. The largest effect is observed at the shore, while the estimate is not statistically different from zero at higher distances. On the contrary, the effect is homogeneous with respect to distance from other water bodies. In line with these results, effects are larger where seafood represents a higher share of total animal proteins consumed, in countries with a positive trade balance for fish products, and where small-scale fisheries are central, such as in proximity to reefs (Online Appendix B.4).[20]

Adaptation in Health Investments. Section 5.1 highlighted limited adaptation to ocean acidity in terms of dietary choices. In Table 4, we examine whether a mother alters health investments (before and after a child's birth) in response to experiencing varying degrees of ocean acidity during gestation. Columns (1)–(2) examine birth-level information regarding investments in antenatal care (attendance to health visits during pregnancy and the presence of health professionals during these visits) and care at the time of delivery (presence of health professionals during delivery and whether delivery was performed in a health centre). Both variables range from 0 (no) to 2 (high investment). Columns (3)–(5) focus on investments after the birth: postnatal healthcare,

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[20] In Online Appendix B.4, we show that *in-utero* exposure to higher seafood prices in the local market significantly contributes to the probability of neonatal death. Due to data limitations, we limit the analysis to the sample of the Philippines, one of the most fish-dependent countries globally.

the completion of the cycle of basic vaccinations, and whether the child has ever been breastfed.[21] Estimates are based on equation (2).

For both antenatal and delivery investments, we do not observe any significant effect. In line with these results, the effect on neonatal mortality is homogeneous in the birth order and sex of the child—two predictors of differential parental investments (Baird et al. 2011)—and across a wide array of individual characteristics (Online Appendix B.12). Given that antenatal care is closely linked with nutrient supplementation plans during pregnancy, we also exclude this pathway. The lack of observable effects on postnatal care suggests limited adjustments in response to their child's health. We observe no effect on morbidity and anæmia prevalence among children at the time of the measurement (Online Appendix B.12), suggesting no dietary changes among living children, and no evidence of adaptation through post-delivery migration (Online Appendix B.5).

Online Appendix B.12 provides further evidence suggesting the absence of adaptation. First, the effects on health investments are homogeneous with respect to the ability to purchase more nutritious food, as measured by household's wealth, and the marital status and education of the mother. Second, following Dell et al. (2014), we estimate equation (2) by interacting the ocean pH in the nearest waters while *in utero* with the 1972–1975 average pH in the same location. The larger effect on NMR in areas historically exposed to more acidic waters suggests an absence of long-run adaptation, despite the extended time these regions have had to adjust to acidification.

Child Development. Table 5 shows the effects of *in-utero* exposure to varying degrees of ocean acidity on early-life physical development, as assessed through anthropometric measurements—an important form of human capital accumulation. Columns (1)–(2) focus on the effects on weight-for-height (w/h), which captures insufficient food intake or high incidence of infectious diseases in temporal proximity to the measurement, and on height-for-age (h/a), which captures the past or cumulative effects of under-nutrition and infectious diseases since conception. Estimates in columns (3)–(4) focus instead on indicator variables for abnormally low values of w/h (*wasting*) and of h/a (*stunting*). All measures rely on objective measurements performed by the DHS enumerators on a random subset of children alive at the time of the interview, and they therefore need to be interpreted in light of the results on mortality. Panel A estimates the overall effects using equation (2), while panel B looks at heterogeneity by sex, introducing in equation (2) an interaction term between the ocean pH and an indicator variable for whether the child is female.[22]

Among all children (panel A), we do not highlight any significant effect on w/h, h/a, or the prevalence of stunting, but we do observe a significant effect on the prevalence

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[21] Because information on parental investments is not recorded for all children, but only for a subset within the household (generally the youngest child), we cannot estimate the effect on adaptation using the within-sibling specification.

[22] Online Appendix B.13 provides estimates of equation (2) splitting the sample into male and female children and shows results trimming z-scores at the 1st and 99th percentiles.

of wasting. A 0.01 decrease in pH in nearby waters reduces the probability of being wasted by 0.6 percentage points, or 7.5% over the sample mean of 8%. This effect is also captured by examining the probability of being underweight in the first months of life, which potentially indicates differences in birth weight (Online Appendix B.12). While only the effect on wasting is statistically significant, the coefficients in panel A suggest that mortality selection prevails over a scarring effect, as living children who experienced higher degrees of water acidity tend to have better, rather than worse, indicators.[23]

Although the effect on neonatal mortality is not heterogeneous by sex, when looking at heterogeneity by sex in the effect on child development (panel B), we highlight that the effects in panel A are driven primarily by male children. Among female children, results suggest the prevalence of a scarring effect (i.e., living children who experienced higher degrees of water acidity tend to have worse as compared to those that experienced lower degrees), concentrated in measures associated with height. Among boys, a 0.01 decrease in pH increases h/a by 0.03 standard deviations and the probability of being stunted by 1.1 percentage points (with a p-value of 0.15). Among girls, these outcomes are statistically different from those of boys. A 0.01 decrease in pH decreases h/a by 0.06 standard deviations and increases the probability of being stunted by 2.3 percentage points, as compared to boys. The effect on stunting is not only statistically different between male and female children, but it is significantly negative for girls (Online Appendix B.13).

To understand whether these effects persist into adulthood, in Online Appendix B.13 we examine these indicators for adult women, building their *in-utero* exposure to ocean pH in nearby waters by exploiting their month and year of birth, and the location of the interview. Because the temporal distance between exposure and the date of measurements is much larger than that of Table 5, these estimates implicitly assume no migration. While female migration in poorer settings is expected to occur within limited geographical distances (see, e.g., Rosenzweig and Stark 1989; Mbaye and Wagner 2017; Corno et al. 2020), we cannot exclude this possibility.

The results suggest that the scarring effect on girls is persistent in the long run. A 0.01 decrease in pH significantly decreases h/a by 0.1 standard deviations and increases the probability of being stunted by 0.7 percentage points. Adaptation at later ages could also play a role as the magnitude of the effect is smaller among adults than children. We also consider the impacts on women's economic well-being. A 0.01 decrease in pH significantly decreases adulthood wealth by 0.5% relative to the sample mean. This impact is accompanied by statistically significant decreases in the number of births per woman and the probability of working of 0.01 children and 1.4 percentage points, respectively. We do not observe any effect on schooling and cognitive skills.

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[23] Refer to Deaton (2007) for a discussion on adult height and childhood mortality in poorer countries.

5.3. *Heterogeneity by Resource Exploitation*

Due to the centrality of ocean exploitation for nutrition in coastal areas, we turn our attention to the heterogeneity of the effects discussed in Section 5.2 with respect to the type and intensity of fishing activities (see Section 3 for definitions and limitations related to this measure). For comparability, we quantify the effect of a one-standard-deviation decrease in nearby waters' pH that is experienced while *in utero* (labelled as an *acidity shock*), and we report estimates in terms of a percentage change with respect to the sample mean. Figure 5 plots the estimated effects at different intensities of night-time fishing (panel A), capturing the activity of boats operating on a smaller and more local scale, and of extractive fishing (panel B), which captures the activity of industrial fleets. In terms of outcomes, we consider impacts on NMR and an index of physical development among children, built by averaging available z-scores for w/h and h/a to capture multiple anthropometric insufficiencies. By averaging z-scores, our approach is similar to the multiple-inference approach of Anderson (2008), using as a control group the reference population used by DHS to compute z-scores.

Extractive fishing significantly reduces the ability to counteract shocks, amplifying their impacts. The effects on both NMR and physical development are homogeneous along the intensity of night-time fishing. Conversely, we observe heterogeneous effects by intensity of extractive fishing. Areas characterised by high intensity present a significantly larger effect on NMR compared to areas without extractive fishing. An acidity shock leads to a 1.4% increase in NMR in areas where extractive fishing is absent and a 5.0% increase in areas where extractive fishing is largest. The mortality selection induced by these effects is captured in the heterogeneity of the impact on physical development. An acidity shock leads to an improvement in physical development by 0.7% in areas where extractive fishing is absent and by 4.3% in areas where extractive fishing is largest. Formal tests of heterogeneous impacts confirm these results (Online Appendix Table B11). Online Appendix B.13 shows a similar analysis for outcomes among adults by focusing on economic well-being and on the physical development index among adult women, highlighting a similar pattern for the persistence of the effects presented in Figure 5.

6. Projections on the Effect of Ocean Acidification

The results in Section 5 have highlighted the magnitude and the mechanisms through which ocean acidification impacts coastal areas in L&MICs, emphasizing the significant role of neonatal mortality. We use these estimates to compute the aggregate number of neonatal deaths attributable to ocean acidification from 1975 to 2100. It is important to note that our estimates are based on short-term deviations in ocean pH, whereas the projections used in this exercise reflect long-term trends in ocean acidification. Therefore, projections should be interpreted under the assumption that the mechanisms linking acidity to neonatal mortality are similar across different temporal scales. For this exercise, we focus on the coastal area of the sample of L&MICs used in the paper. Online Appendix C details this procedure, including further descriptive statistics.

To develop these projections, we decompose the time series of NMR for a country into two additive components: a counterfactual measure of NMR in the absence of ocean acidification (NMR^{CF}), reflecting broader trends such as economic development, and a component attributable to ocean acidification (NMR^{OA}), which is driven by variation in ocean acidity near human settlements. We compute NMR^{CF} estimating equation (2) in our sample of births, predicting NMR while holding ocean acidity and oxygen levels at their 1975 values, and averaging these predictions at the country–year level. This step allows us to obtain the series for the period 1975–2018, from which we extrapolate values until 2100 fitting an exponential decay curve. We then compute NMR^{OA} combining the estimated effect of experiencing varying degrees of ocean acidity in nearby waters while *in utero* on NMR (discussed in Section 5) with the 1975–2100 series for ocean pH obtained from the IPCC's Sixth Assessment Report (Tagliabue et al. 2022). We consider two emission trajectories: a low-emissions scenario targeting global warming limits of around 1.5°C–2°C by 2100 through strong mitigation efforts (RCP2.6) and a worst-case high-emissions scenario leading to increases in temperatures by 4°C–5°C or more by the end of the century (RCP8.5).

Computing NMR^{CF} and NMR^{OA} under these emission scenarios and population growth projections for coastal areas, we obtain the cumulative number of neonatal deaths attributable to ocean acidification under different assumptions concerning adaptation to ocean acidification. First, we consider *no adaptation*, assuming that the effect of ocean acidification on NMR is constant over time and equal to the value reported in column (3) of Table 3. This assumption, combined with the high-emissions scenario, can be considered the worst-case hypothesis. Second, we consider alternative types of adaptation. We introduce the possibility of internal migration, assuming that the coastal population decreases linearly by 20% between 2024 and 2100 (*migration away from coast—low*) or by 50% (*migration away from coast—high*).[24] We also consider alternative forms of adaptation, such as changing diets or increasing health investments, assuming the effect on NMR decreases over time. Because there is limited evidence on the rate and the functional form of adaptation (see, e.g., Moore and Diaz 2015), we assume that the effect diminishes linearly over time, halving in 2100 (*decreasing effect—slow*), or reaching a nil effect in 2100 (*decreasing effect—fast*). Finally, we consider *optimistic adaptation* by combining the assumptions in *migration away from coast—high* and *migration away from coast—low*. We report the evolution over time of the cumulative number of deaths attributable to ocean acidification in Figure 6. Online Appendix C provides estimates, confidence intervals, and the evolution of NMR^{CF} and NMR^{OA} for each case.

The total number of births in our study area from 1975 to 2100 is estimated at 3.28–3.29 billion. In the same period, we estimate that counterfactual neonatal deaths

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[24] For some countries, like the Philippines, this assumption is not relevant because the whole or most of the country is considered coastal area.

account for 31.1 million, corresponding to an average NMR over the whole period of 9.45–9.48. Absent any form of adaptation, the cumulative number of neonatal deaths from ocean acidification could reach 77.2 million by 2100 under the high-emissions scenario, as compared to 38.0 million under the low-emissions scenario. Uncertainty about the effect of ocean acidity on NMR generates wide confidence intervals for these estimates. Using the 90% confidence interval for the effect of ocean acidification on NMR is 20.5–133.8 million under the high-emissions scenario, and 10.1–65.8 million under the low-emissions scenario.

Introducing migration away from coastal areas as a form of adaptation has limited effects. Under the low-emissions scenario, the cumulative number of deaths decreases to 34.5 million if migration is relatively small, and to 30.0 million if a larger share migrates. Introducing adaptation measures that reduce the effect of ocean acidification over time is more effective, with the cumulative number of deaths reducing to 14.6–26.3 million in the low-emissions scenario. Under optimistic adaptation, the number is further reduced to 12.9 million under the low-emissions scenario, as compared to 18.1 under the high emission scenario. These statistics correspond to an average NMR attributable to ocean acidification for the period 1975–2100 ranging from 11.58 (low-emissions) to 23.47 (high-emissions) when assuming no adaptation, and from 3.92 (low-emissions) to 5.51 (high-emissions) when assuming optimistic adaptation.

Overall, these projections highlight the importance of considering adaptation measures in conjunction with reduced emissions when analysing deaths induced by climate change. Reducing emissions leads to a reduction in cumulative deaths from ocean acidification by 50.8% in the case of no adaptation, but in presence of optimistic adaptation the returns from reduced emissions are lower, at 29.1%. Because we observe limited adaptation to ocean acidification (Section 5), these results highlight the importance of reducing emissions to minimise neonatal deaths in the future.

7. Conclusions

Small changes in the ocean's chemical composition can have significant impacts on coastal communities. Our research demonstrates that increased ocean acidity negatively affects local fishing, in turn compromising nutritional quality in these areas. Deteriorating conditions in people's early lives raise neonatal mortality rates and influences mortality selection. Accordingly, in the absence of emissions-reduction strategies, the Tagliabue et al. (2022) predicts further significant increases in ocean water acidity by 2100. We should be cautious about the substantial mortality effects of ocean acidification, even with improvements in mitigation efforts due to economic development.

Our findings highlight the need for future research in two key areas. First, studies on climate change impacts should probe various alternative channels that have not yet been thoroughly investigated, through which climate-related shifts influence human and economic development. For instance, evidence concerning the ocean's role in these dynamics remains limited. While our research focuses on water acidity and its effects on marine life, this represents only one dimension of how a changing ocean could impact communities, especially those heavily reliant on marine resources. Gaining a deeper understanding of these mechanisms would enhance the design and targeting of policies to support vulnerable communities as they cope with climatic risks.

Second, by illustrating that wildlife serves as a crucial buffer against negative shocks, we emphasise the importance of research not only on policies promoting wildlife conservation, but also on strategies to mitigate the effects of reduced biodiversity. For instance, prioritising regulations in the industrial fishing sector and establishing exclusive artisanal fishing zones can be vital. While recent studies have highlighted the potential for effective policies (Frank and Oremus 2023; Oremus et al. 2023), challenges remain, especially in countries with weak governance of natural resources. In the absence of effective conservation incentives, further research is necessary to allocate resources efficiently to communities in need of mitigation support. Our results suggest a rationale for investing in targeted nutritional interventions early in life to address the reduced nutrient availability caused by negative shocks to natural resources. Such interventions have proven effective in mitigating both the short- and long-term consequences of malnutrition (see, e.g., Gertler et al. 2014). In addition, in light of the centrality of parental investments for early childhood development (Attanasio et al. 2020), our findings underscore the importance of awareness and education in influencing parental decisions regarding nutrition in low-income settings.

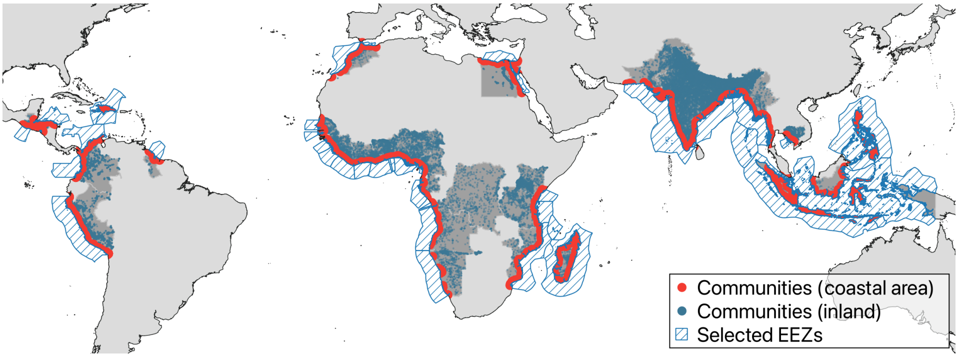


Figure 1. Area covered by the study and geographical distribution of DHS communities. The darker shaded area represents all countries surveyed by the DHS with access to the ocean (the full list is reported in Online Appendix A.1). *Communities (coastal area)* are villages and neighbourhoods within 100 km from the ocean's shore. Most estimates in the paper include only these observations. *Communities (inland)* are villages and neighbourhoods further than 100 km from the ocean's shore. Online Appendix A.2 details the procedure followed to compute the distance from the shore. *Selected EEZs* refer to the Exclusive Economic Zones of all ocean-access countries included in the DHS survey (see Section 3 for the definition). In line with Pauly et al. (2020), we apply current EEZ boundaries (as depicted in the figure) to the whole study period to maintain consistency across years.

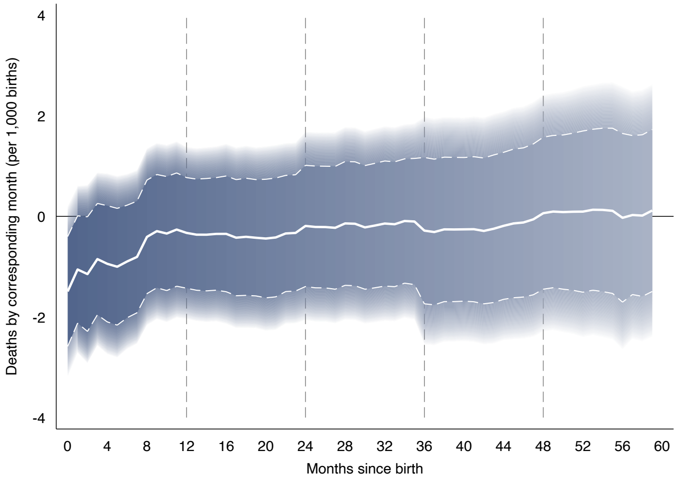


Figure 2. Early-life exposure and mortality. Marginal effect of *in-utero* exposure to ocean pH in the nearest waters on the probability of death at month x (indicated on the horizontal axis). The dependent variable is an indicator variable equal to one if the child is dead at month x from birth, and zero if the child is alive, multiplied by 1,000. Estimates are based on equation (2), including community FEs, birth month by birth year FEs, country by birth year FEs, country by birth month FEs, and control variables (see Section 4). The sample is restricted to communities in the coastal area (see Section 3). 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, colour intensity reflects the relative density of observations across iterations. It is calculated by comparing the density in each iteration to a range between the lower bound (adjusted by 0.7) and the 99th percentile of densities across all iterations. These parameters were chosen to improve visibility. Online Appendix A.1 provides further information on the variables and the list of surveys included in the study.

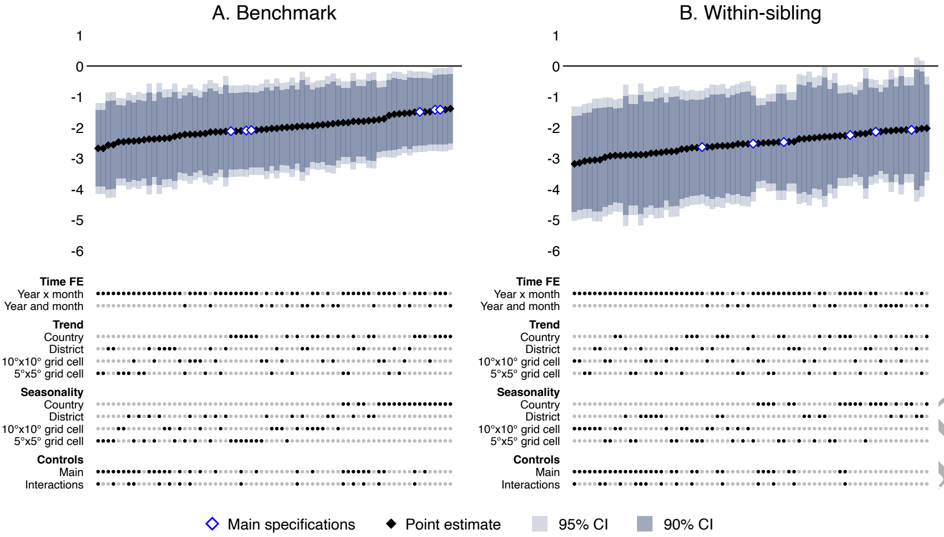
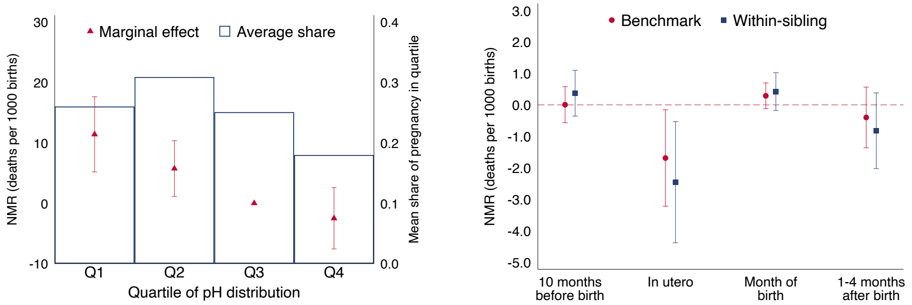


Figure 3. Early-life exposure and neonatal mortality – alternative specifications. Marginal effect of *in-utero* exposure to ocean pH in the nearest waters on NMR under alternative sets of FEs in the benchmark specification (panel A), and in the within-sibling specification (panel B). The dependent variable 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. *pH in the nearest waters (in utero)* is the average pH (multiplied by a factor of 100) in the ocean grid cell closest to the child's community during the 9 months before birth. Marginal effects are estimated using equation (2) with the set of controls reported in the bottom panel. *Main controls* are the weather and demographic controls (see Section 4). *Interactions* are interaction terms between the birth month and indicator variables for different oceans (matched using the shortest straight-line distance from the community). *Main specifications* highlight the estimates presented in Table 3. The sample is restricted to communities in the coastal area (see Section 3). Standard errors are clustered at the ocean raster data point. Online Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.



A. Positive vs negative deviations

B. Timing

C. Distance from water bodies

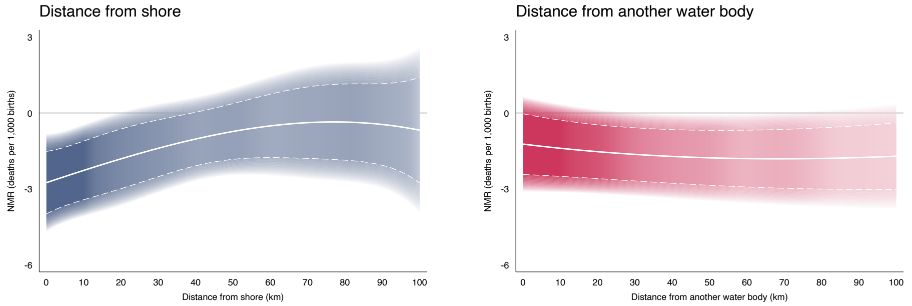


Figure 4. Early-life exposure and neonatal mortality – heterogeneity. Marginal effects of *in-utero* exposure to ocean pH in the nearest waters on NMR, by type of pH deviation (panel A), timing of exposure (panel B), and distance from water bodies (panel C). In panel A, estimates are based on equation (2) where $R_{c,t}$ is substituted by the share of time children were exposed *in utero* to different levels of ocean pH. We classify values in four bins using the quartiles of the 1972–2018 distribution of pH in the 5°×5° grid cell matched to the child's location of birth. The bars (linked to the right vertical axis) presents the average share of time children were exposed *in utero* to levels of ocean pH in the corresponding quartile. The average pH corresponding to each quartile is 8.01, 8.04, 8.06, 8.09, respectively. In panel B, estimates are based on equation (2), in which the *pH in the nearest waters* at different points in time is the pH (multiplied by a factor of 100) in the ocean grid cell closest to the individual's community in the corresponding period relative to birth; when the period refers to multiple months, the value is averaged. In panel C, estimates are based on equation (2) introducing interactions between $R_{c,t}$ and a cubic polynomial in distance. In all panels, estimates are based on the benchmark specification, including community FEs, birth month by birth year FEs, country by birth year FEs, country by birth month FEs, and control variables (see Section 4). In panel C, we further allow FEs to be specific to the areas that are more or less vulnerable, defined by being closer or further away than 40 km from the shore (see Online Appendix B.2). The dependent variable is *NMR*, 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 sample is restricted to communities in the coastal area (see Section 3). In panels A and B, confidence intervals are computed at 90% level. In panel C, the 90% confidence interval is indicated by dotted lines, beyond which the intervals are progressively shaded up to the 99% level. Within confidence bounds, colour intensity shows the relative density of observations by distance from shore. It is calculated by comparing the square root of the density at each point to the square root of the 90th percentile of the overall density. These parameters were chosen to improve visibility. Online Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

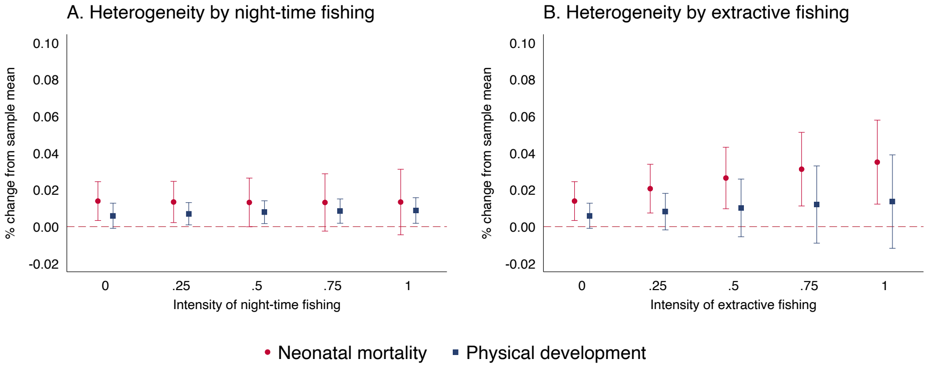


Figure 5. Ocean acidity and resource exploitation. Estimated impacts (and 90% confidence intervals) of a one-standard-deviation increase in water acidity (experienced *in utero*) on neonatal mortality and on physical development as a function of intensity of fishing (0 = no presence / 1 = high intensity). Panel A (B) focuses on night-time (extractive) fishing (see Section 3 for the definitions). Estimates are based on equation (2) introducing interaction terms between pH in the nearest waters (*in utero*) and a quadratic polynomial in the corresponding intensity. *Neonatal mortality* 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. *Physical development* is the average z-score of available anthropometric measures. *pH in the nearest waters (in utero)* is the average pH (multiplied by a factor of 100) in the ocean grid cell closest to the individual's community during the 9 months before birth. The sample is restricted to communities in the coastal area (see Section 3). Standard errors are clustered at the ocean raster data point. 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 4). Online Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures. We exclude surveys for Peru as information for the intensity of night-time fishing is not available.

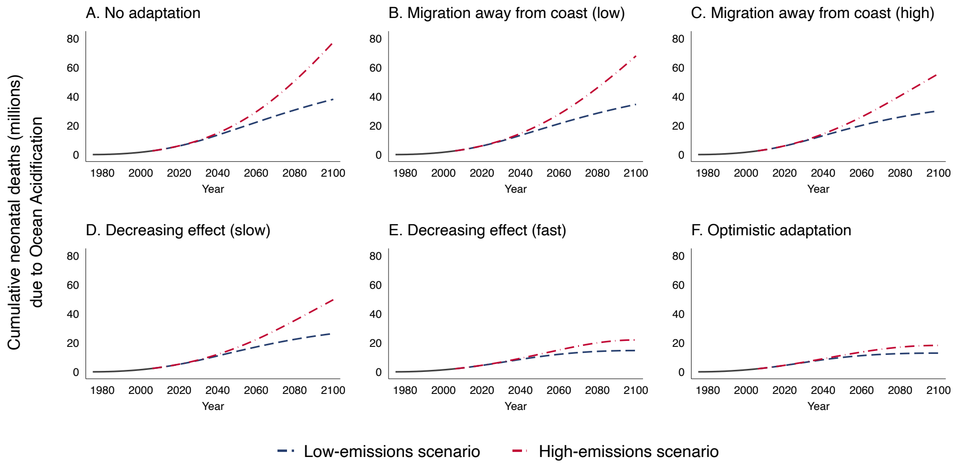


Figure 6. Neonatal deaths attributable to ocean acidification. Cumulative number (in millions) of neonatal deaths attributable to ocean acidification from 1975 to 2100, by year. The *low-emissions scenario* is the RCP2.6 scenario, targeting global warming limits of around 1.5°C–2°C by 2100 through strong mitigation efforts. The *high-emissions scenario* is the RCP8.5 scenario, a worst-case high-emissions scenario with rising emissions potentially increasing temperatures by 4°C–5°C or more by the end of the century. Scenarios are obtained from Tagliabue et al. (2022). Each panel makes alternative assumptions concerning adaptation, detailed in Section 6, ranging from lowest (panel A) to highest (panel F). Online Appendix C details the methodology followed to compute these estimates. Online Appendix Table C1 reports the values in the year 2100, including the confidence intervals accounting for uncertainty in the estimate of the effect of ocean acidity experienced while *in utero* on neonatal mortality.

Table 1. Ocean acidity and marine catches.

Dependent variables:	**Marine catch for human consumption**					**Economic activity**
	Small-scale fishing		Industrial fishing		Median price	Night-time luminosity
	Quantity (1)	Value (2)	Quantity (3)	Value (4)	(5)	(6)
pH in proximity to the coast	0.132 (0.068) [0.061]	0.199 (0.081) [0.019]	0.019 (0.088) [0.829]	0.033 (0.099) [0.742]	-0.091 (0.045) [0.049]	0.006 (0.044) [0.896]
Mean (dep.var.)	1.50	1.51	1.00	1.00	1.00	2.26
Identifying observations	19,129	19,129	19,129	19,129	13,603	777
Singleton observations	0	0	0	0	0	0
Countries	36	36	36	36	36	36
Year range	1972–2018	1972–2018	1972–2018	1972–2018	1972–2018	1992–2012

Notes: Estimates are based on equation (1). Dependent variables in column headers are transformed using an inverse hyperbolic sine transformation to account for zero values (Online Appendix B.4 reports results using alternative transformations). In columns (1)–(5), each observation is the catch or landed value or the median price for a specific seafood group in the corresponding Exclusive Economic Zone (EEZ; see, Section 3 for a definition). In column (5), each observation is a country's yearly average night-time luminosity in its coastal area (see Section 3). *pH in proximity to the coast* is the yearly average pH in the corresponding EEZ (multiplied by a factor of 100). Specifications in columns (1)–(4) include country by seafood group FEs, and fishing area by year FEs. The specification in column (5) includes country FEs, and fishing area by year FEs. All specifications include weather controls (see Section 4). Standard errors clustered at the EEZ level are reported in parentheses, *p*-values are reported in brackets. Online Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

Table 2. Ocean acidity and nutrition among women.

Dependent variable:	**Nutrition**		**Prevalence of anæmia**	
	Consumed seafood (1)	Underweight (2)	Overall (3)	In pregnancy (4)
pH in the nearest waters	0.025 (0.012) [0.029]	-0.004 (0.002) [0.073]	0.001 (0.005) [0.841]	-0.017 (0.007) [0.013]
Mean (dep.var.)	0.296	0.120	0.427	0.454
Identifying observations	49,045	407,699	272,688	14,672
Singleton observations	2	3	2	36
Communities	5,952	24,301	17,371	8,993
Countries	14	32	26	26
Interview year range	2005–2016	1992–2018	2000–2018	2000–2018

Notes: Estimates are based on equation (2). Dependent variables are reported in column headers: *consumed seafood* is an indicator variable equal to 1 if the respondent consumed seafood in the 24 hours previous to the interview, and 0 otherwise (information is available for mothers in the sample and for a selected number of countries; see Online Appendix A.1); *underweight* is an indicator variable equal to 1 if the respondent has a BMI below 18.5, and 0 otherwise (information is available for all women with anthropometric measurement); *prevalence of anæmia* is an indicator variable equal to 1 if the respondent has hæmoglobin levels below 110 g/L, and 0 otherwise (information is available for all women with blood samples). *pH in the nearest waters* is the average pH (multiplied by a factor of 100) in the ocean grid cell closest to the female respondent's community in the month of the interview. The sample is restricted to communities in the coastal area (see Section 3). All specifications include location FEs using grid cells at the 1°×1° resolution, interview month FEs, interview year FEs, country by interview month FEs, country by interview year FEs, and control variables (see Section 4; weather controls correspond to the year of interview). Standard errors clustered at the ocean raster data point are reported in parentheses, *p*-values are reported in brackets. Online Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

Table 3. Early-life exposure to ocean acidity and neonatal mortality.

Dependent variable:	**Neonatal mortality rate (deaths per 1,000 births)**					
	(1)	(2)	(3)	(4)	(5)	(6)
A. Benchmark specification						
pH in the nearest waters (*in utero*)	-1.421 (0.691) [0.040]	-1.423 (0.682) [0.038]	-1.493 (0.663) [0.025]	-2.120 (0.755) [0.005]	-2.100 (0.762) [0.006]	-2.086 (0.739) [0.005]
Mean (dep.var.)	30.473	30.473	30.474	30.474	30.474	30.475
Identifying observations	1,583,706	1,583,706	1,581,815	1,583,703	1,583,703	1,581,812
Singleton observations	25	25	25	28	28	28
Communities	31,380	31,380	31,380	31,380	31,380	31,380
Countries	36	36	36	36	36	36
Birth year range	1972–2018	1972–2018	1972–2018	1972–2018	1972–2018	1972–2018
B. Within-sibling specification						
pH in the nearest waters (*in utero*)	-2.077 (0.873) [0.018]	-2.139 (0.854) [0.013]	-2.246 (0.837) [0.008]	-2.476 (0.954) [0.010]	-2.526 (0.953) [0.008]	-2.638 (0.936) [0.005]
Mean (dep.var.)	31.476	31.476	31.476	31.476	31.476	31.476
Identifying observations	1,474,945	1,474,945	1,474,945	1,474,941	1,474,941	1,474,941
Singleton observations	108,786	108,786	108,786	108,790	108,790	108,790
Communities	31,356	31,356	31,356	31,356	31,356	31,356
Countries	36	36	36	36	36	36
Birth year range	1972–2018	1972–2018	1972–2018	1972–2018	1972–2018	1972–2018
Weather controls	-	Yes	Yes	-	Yes	Yes
Demographic controls	-	-	Yes	-	-	Yes
Seasonality	Country	Country	Country	Cell	Cell	Cell

Notes: Estimates are based on equation (2). 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. *pH in the nearest waters (in utero)* is the average pH (multiplied by a factor of 100) in the ocean grid cell closest to the child's community during the 9 months before birth. The sample is restricted to communities in the coastal area (see Section 3). All specifications include community FEs, birth year by birth month FEs, country by birth year FEs. Seasonality is captured by either country by birth month FEs or 5°×5° cell by birth month FEs. In panel B, community FEs are replaced by mother FEs. The full list of controls is presented in Section 4. Standard errors clustered at the ocean raster data point are reported in parentheses, *p*-values are reported in brackets. Online Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

Table 4. Early-life exposure to ocean acidity and health investments.

Dependent variables:	**Antenatal**	**Delivery**	**Postnatal**		
			Healthcare	Breastfed	Vaccinated
	(1)	(2)	(3)	(4)	(5)
pH in the nearest waters (*in utero*)	-0.002 (0.007) [0.820]	-0.002 (0.004) [0.727]	0.004 (0.009) [0.629]	0.001 (0.003) [0.699]	-0.002 (0.006) [0.804]
Mean (dep.var.)	1.808	1.359	0.441	0.972	0.435
Identifying observations	155,980	168,460	101,075	206,350	208,765
Singleton observations	217	481	3,078	2,336	2,269
Communities	14,669	18,481	18,445	28,029	27,887
Countries	29	29	34	36	36
Birth year range	1985–2018	1985–2018	2002–2018	1987–2018	1987–2018

Notes: Estimates are based on equation (2). The dependent variables are reported in column headers: *antenatal* and *delivery* aggregate different investment indicators (see Online Appendix B.12), ranging from 0 (no investment) to 2 (larger investment); *healthcare* is an indicator variable equal to 1 if the mother or the child younger than 2 years old received postnatal care within 2 days of birth; *breastfed* is an indicator variable equal to 1 if the mother reports ever breastfeeding the child, and 0 otherwise; *vaccinated* is an indicator variable equal to 1 if the mother reports or the vaccination card shows the completion of the basic cycle of vaccinations according to the World Health Organization (WHO), and 0 otherwise. *pH in the nearest waters (in utero)* is the average pH (multiplied by a factor of 100) in the ocean grid cell closest to the child's community during the 9 months before birth. The sample is restricted to communities in the coastal area (see Section 3). Column (3) excludes the surveys for Indonesia and Morocco because information is not available in the corresponding surveys. For cross-survey comparability, the sample in columns (1)–(3) is restricted to the last birth, independently from the child being alive at the time of the interview, while in columns (4)–(5) is restricted to living children under three years old and can therefore be affected by mortality selection. 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 4). Standard errors clustered at the ocean raster data point are reported in parentheses, *p*-values are reported in brackets. Online Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

Table 5. Early-life exposure to ocean acidity and physical development.

Dependent variables:	*z*-**scores**		**Indicators**	
	Weight-for-height (1)	Height-for-age (2)	Wasted (3)	Stunted (4)
A. Overall effect				
pH in the nearest waters (*in utero*)	-0.021	-0.012	0.006	0.004
	(0.016)	(0.015)	(0.003)	(0.004)
	[0.196]	[0.405]	[0.090]	[0.279]
Mean (dep.var.)	-0.309	-0.984	0.080	0.234
Identifying observations	232,339	232,575	232,339	232,575
Singleton observations	1,106	1,124	1,106	1,124
Communities	24,824	25,110	24,824	25,110
Countries	33	33	33	33
Birth year range	1985–2018	1985–2018	1985–2018	1985–2018
B. Heterogeneity by sex				
pH in the nearest waters (*in utero*)	-0.001	-0.033	0.008	0.011
	(0.017)	(0.020)	(0.006)	(0.007)
	[0.969]	[0.100]	[0.179]	[0.147]
× female	-0.014	0.057	-0.011	-0.023
	(0.020)	(0.028)	(0.010)	(0.010)
	[0.461]	[0.047]	[0.303]	[0.022]
Mean (dep.var.)	-0.312	-0.993	0.080	0.236
Identifying observations	226,567	226,685	226,567	226,685
Singleton observations	6,878	7,014	6,878	7,014
Communities	23,979	24,248	23,979	24,248
Countries	33	33	33	33
Birth year range	1985–2018	1985–2018	1985–2018	1985–2018

Notes: Estimates are based on equation (2). Dependent variables are reported in column headers: *weight-for-height (w/h)* and *height-for-age (h/w)* are *z*-scores from a reference scale; *wasted* and *stunted* are indicator variables equal to 1 for an abnormally low weight-for-height and height-for-age, respectively, and 0 otherwise. *pH in the nearest waters (in utero)* is the average pH (multiplied by a factor of 100) in the ocean grid cell closest to the individual's community during the 9 months before the birth of the child. The sample is restricted to communities in the coastal area (see Section 3). All panels exclude the surveys for Indonesia, Pakistan, and the Philippines because information is not available in the correspondent surveys. 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 B, FEs are sex-specific. Standard errors clustered at the ocean raster data point are reported in parentheses, -values are reported in brackets. Online Appendix A.1 provides detailed information on variables, selected surveys, and weighting procedures.

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