Man Overboard!

Industrial Fishing as Driver of Migration out of Africa

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Abstract

Environmental drivers of migration attract more and more attention. This article focuses on the effect of fish stock depletion on human migration in Africa. We leverage a novel dataset on fishing intensity (Kroodsma et al., 2018) to build a panel of the 37 African countries with access to the sea over the period 2012-2018, and we show that within-country variation in fishing intensity increases migration of foreign population flows to OECD countries. We find strong evidence that the competition created by industrial fishing vessels overfishing African seas and depleting fish stocks, increases the flow of foreign population to OECD countries. A 10% increase in the previous year's fishing effort along an African country's coast increases the number of migrants towards the OECD by 0.37%. We do not find such effects on refugees, which comforts the story of economic migration only. We then show that macro-level findings are consistent, in terms of mechanisms, with micro-level estimates using household-level demographic data.

Keywords: Industrial fishing; Migration; Africa.

JEL codes: Q22; Q56; F22; O12; O13; O15.

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1 Introduction

Industrial fishing takes place in more than half of the world's ocean area, about four times the area of land-based agriculture (Kroodsma et al., 2018) and is responsible for more than 75% of catches (Pauly and Zeller, 2016). On the other side, most of the fleet and the employment, especially in developing countries and even more in Africa, is tied to small-scale fisheries (de Graaf and Garibaldi, 2014). In a context of dwindling marine resources where the proportion of fish stocks within biologically sustainable levels decreased from 90 % in 1974 to 65.8 % in 2017 (FAO, 2020), the intensification of fishing activities, mostly by industrial vessels, reduces relative catches by unit of effort (Anticamara et al., 2011; Watson et al., 2013). At the world level, the latest data estimate that more than 90% of fish stocks are fished at or above their biologically sustainable levels (FAO, 2020). This can only increase the pressure on small-scale fisheries.

Whether headlines mention that "Europe takes Africa's fish, and boatloads of migrants follow" (Franière, 2008) or "China's appetite pushes fisheries to the brink" (Jacobs, 2017), newspapers often report a negative link between industrial fishing activities and detrimental consequences for coastal populations in Africa. There are also scattered pieces of evidence about such links in the qualitative scientific literature (Binet et al., 2012; Jonsson, 2019; Jonsson and Kamali, 2012).

Our findings relate industrial fishing off the African coastline and migration at three levels of analysis: immigration to OECD countries, emigration from coastal areas, and rural exodus. At the macro level, we first show that higher industrial fishing efforts along the coast of a given African country in a given year increases registered population movements from this country to European or OECD countries the year after. This echoes the result of Missirian and Schlenker (2017) who were looking at the consequences of negative weather shocks in Sub-Saharan Africa on migration to the European Union. We then show that our macro results are consistent with micro-level findings. Larger fishing efforts of industrial boats near coastal rural villages systematically reduce the size of households living in exposed coastal areas, compared to coastal households in unexposed areas and households inland. This reduction is mostly driven by the absence of young men.[1] We then provide suggestive evidence that industrial fishing effort has detrimental effects on the diet of children.[2] Last, we emphasize the plausible link between urbanization in coastal African countries and variations in industrial fishing over time and space. This provides additional support to our story, in the vein of Beine and Parsons (2015) that uses urbanisation as a proxy of within-country migration and connects, to some extend, the micro and macro findings.

[1]This approach is similar to Libois (2016) and makes sense if the number of households is not affected by the main explanatory variable, a point we discuss at length.

[2]This is the only consumption data we can leverage in the Demographic and Health

Our contribution is twofold. On one side, we quantify the migratory response induced by industrial fishing: a 10% increase in industrial fishing within 36 NM of the coast yields a 0.37% increase in the bilateral flow of foreign population from African coastal countries to OECD countries but not of refugees, who were granted asylum. By measuring one externality associated with industrial fishing we feed the public debate, for instance, when arguing about the removal of subsidies supporting industrial fleets, around 20 billion USD annually, allowing them to evict small-scale fishermen from local resources and markets (UNCTAD, 2016).[3] Our study stresses that regulating access to marine resources in developing countries is not only a matter of fish and local interests: if migration is a common strategy to cope with these environmental pressures, then, foreign fishing activities would have to bear the responsibilities of some national and international population displacements. Regulating the competition led by industrial fishing is essential for both preserving the Oceans (Goal 14 of the 2030 Sustainable Development Goals) and the livelihoods of households relying on small-scale fisheries (Goals 1, 2, and 12 of the 2030 Sustainable Development Goals).

The second contribution stems from the extensive combination of the new dataset released by Kroodsma et al. (2018) with environmental controls and socio-economic data - namely Demographic and Health Surveys. To our knowledge, this is one of the first extensive use of Kroodsma et al. (2018) that precisely investigates the consequences of industrial fishing on local livelihoods. Given the paucity of data about the precise location of fishing efforts, especially in developing countries, and the difficulty to collect information about small-scale fishermen, our reduced form approach provides a first quantitative step in the understanding of the consequences of industrial fishing on human livelihoods. It also paves the way for a large array of research questions on natural resource constraint-based labour mobility, migrations, or political unrest.

Our focus on Africa roots its choice in the importance of small-scale fisheries for the continent. In 2016, there were 5.4 million fishermen in Africa (FAO, 2016). Through self-constructed estimates, Belhabib et al. (2016) found that 18% of the West African coastal population was dependent on small-scale fisheries in 2010. Even if their estimates are to be taken with caution, it is hard to ignore that millions of households' subsistence rely on small-scale fisheries whether it is for their income or their animal protein supply (FAO, 2020). Small-scale fisheries are labour intensive, geographically scattered, mostly unlicensed, and rather difficult to monitor. They generally operate close to the shore, and rely on a multiplicity of species fisheries but remain highly selective. Finally, small-scale fisheries are either full-time or part-time and are minimally managed. Both men and women are involved in the sector, men being mostly responsible for catching fish and women

[3]See also their press release UNCTAD/PRESS/PR/2016/067.

for processing and selling it (Belhabib et al., 2015; Teh et al., 2013). Despite the importance of artisanal fisheries in the region, dwindling fish stocks, partially related to the expansion of the industrial fishing sector, challenge small-scale fisheries. Overexploitation expands the fishing range over time and space (Belhabib et al., 2016), which contributes to increasing fishing costs and risks. In addition to the spatial overlap between small-scale and industrial fisheries that results from an increased fishing range of the artisanal sector and incursions by the industrial sector into artisanal fishing areas, similar species are targeted by the two sectors, especially when industrial vessels target fish meal production. Last but not least, direct tensions exist through collisions between canoes and industrial fishing vessels and the destruction of artisanal fishing gear and canoes (Belhabib et al.).

The remainder of the paper is organized as follows. Section 2 presents the context in light of the literature. Section 3 describes the data. Section 4 details the methodology at both the macro and the micro levels. Section 5 introduces the macro-level results, while section 6 focuses on the micro-level analysis. Section 7 provides extensive discussion and finally, section 8 concludes.

2 Literature review and context

This section describes the strands of the literature to which this paper is related and brings the theoretical mechanisms that will be tested empirically in our work.

2.1 Environmental drivers of migration

The literature on environmental drivers of migration is currently booming with a strong focus on the effects of climate change and meteorological anomalies on the movements of human populations. Closely related to our approach, Missirian and Schlenker (2017) shows that local deviations in temperature in Africa induce an increase in asylum applications in Europe. This is especially true if shocks occur during the growing season in the sending countries. This relationship has also been observed in Indonesia for climatic variations but not for disasters (Bohra-Mishra et al., 2014) or in West Africa when focusing on the intention to migrate (Bertoli et al., 2020).

The mechanisms linking climatic shocks and stress to migration often go through a reduction in income that induces voluntary or forced displacement of population (Beine and Parsons, 2015; Cattaneo et al., 2019; Millock, 2015). This is especially true for countries that are highly dependent on agricultural production (Cai et al., 2016; Chort and de la Rupelle, 2019) even if a growing body of literature underlines the broad implication of global warming on economic performance in the industry (Somanathan et al.) and on the strength of institutions (Burke et al., 2015). We might therefore expect other channels than agricultural income to link a degradation of environmental conditions to the triggers of migration.

Our paper focuses on fishing in the open sea, an activity that shares similar analytical features with greenhouse gas emissions as both of them impact a large-scale common-pool resource and, among many other consequences, both do affect human livelihoods even if in different ways. In the long-run, Dalgaard et al. (2015) argues that the bounty of the sea induces long-term development as richer marine resources stimulated pre-industrial development. When it comes to the short-run, there is a large literature that discusses the link between fishing conditions and fishermen's income. Still, there are very few contributions that systematically investigate the link between access to dwindling fish stocks and international migration or, even more broadly, discuss the effect of renewable natural resources degradation on migration. One exception, for instance, is Shah (2010) which analyses the impact of degradation of private and common pool land resources in Gujarat, India, and finds that it influenced short-term but not long-term migration. This paper belongs to the literature on so-called "environmental migrations" due to short-term direct human activities, rather than to climate variability or to the longer-term process of climate change (Beine and Parsons, 2015).

2.2 Fishing and human activity in Africa

If global warming threatens fish stocks in the medium and long-run (Mendenhall et al., 2020), overfishing is already going on at a very high pace, with more than 90% of fish stocks that are harvested at the maximum biologically sustainable yield or above (FAO, 2020). Half of the oceans that are subject to industrial-scale harvest (Kroodsma et al., 2018) and 75% of fish-catch worldwide that can be attributed to industrial fleets (Pauly and Zeller, 2016). The openness of the world's oceans, where regulation is non-existent on the high seas and monitoring is rather weak, even within the EEZ, further increases the pressure on fish stocks. Cabral et al. (2018) argue that the reduction of illegal, unregulated, and unreported fishing in Indonesia significantly increases fish stocks and national fishermen's income.

Bad fishing conditions have already been shown to reduce fishermen's income and modify their labour supply. In Indonesia, Chaijaroen (2019) shows that coral bleaching reduces fishery household income, decreases their protein intake, and redirects their labour supply towards the industry. It even affects fertility and child development (Chaijaroen, 2021). Hoang et al. (2020) exploits industrial pollution in Vietnam to show that income, as well as employment related to fishing activities, go down and that fishermen change their fishing spots to work more on secondary spots.

A noticeable side occupation for some fishermen is piracy. Several authors highlight mechanisms linking some of the expansion of sea piracy to declining fishing economies (de Sousa and Mercier; Tominaga, 2018). This has been formally tested using a world panel of coastal countries (Flückiger and Ludwig, 2015) or more precisely for Indonesia (Axbard, 2016). The underlying mechanism is that the reduction in income from fishing activities is compensated by diversification in income-generating activities, piracy being one of them. Migration is another alternative, as suggested by Hamilton et al. (2004) in the case of the Faroe Islands in the 1990s.

We do focus on Africa because it is the continent that currently experiences the highest level of overfishing, combined with very high levels of illegal, unreported, or unregulated (IUU) fishing (Cabral et al., 2018). This is especially important because the number of people directly or indirectly dependent on fisheries is large and very much concentrated in the informal economy and in segments of poor populations. FAO (2020) estimates that there are five million fishermen in Africa, while according to Belhabib et al. (2015), there are around 1 million fishermen between Morocco and Namibia, a number that raises to 6.7 million when taking their households into account. According to the authors, 18% of the coastal population in these countries that directly depend on fishing for their daily livelihoods.

Most African fishermen operate very small boats but they face increasing competition from large industrial vessels. In terms of numbers, between 44% and 60% of African fleets do not even have a motor. More than 95% of boats are shorter than 12m, a typical characteristic of the artisanal fleet (Taconet et al., 2019). These small boats enter in competition with large boats. Industrial vessels operating in African waters represent only a small fraction of the fishing fleet and account for less than 5% of total labour (Doumbouya et al., 2017). Despite this very small share of employment, they do have a highly significant effect on fish stocks. Doumbouya et al. (2017) estimate for West Africa that industrial boats catch on average 150 times more fish per unit of labour. The 3,300 industrial boats operating in the region would catch 3.4 million tons of fish per year compared to 2.2 million tons for the 252,000 artisanal boats.

The competition between small-scale fisheries and industrial vessels has large consequences on coastal populations. Based on extensive interviews in Senegalese fishing communities, Jonsson (2019) argues that overfishing increases poverty, unemployment, and social stress in coastal communities. Many people, especially young men, would then decide to migrate, including to European countries. This argument can be extended to other African countries (Jonsson and Kamali, 2012). Migration may occur because fishermen migrate themselves or because they use their boats to carry on migrants over long distances at sea, for instance between Senegal, Mauritania, and the Canary Island (Sall and Morand, 2008). Migration to European countries is of course only the tip of the iceberg and we might as well expect migration within African countries and between them, something harder to measure but that has been consistently reported in the qualitative literature (Binet et al., 2012).

2.3 Mechanisms

In terms of mechanisms, we can describe the situation as a tragedy of the commons over common-pool resources, in the spirit of Hardin (1968). Fish stocks in the open sea, especially in countries with limited regulatory and enforcement capacity, are best described as common-pool resources. Industrial vessels and small-scale fleets compete for an exhaustible renewable resource, with large discrepancies in terms of effort productivity. Industrial vessels are capital-intensive and their catch per unit of human effort outperforms the one of labour-intensive boats. Despite their small number, the former ones have a large impact on the resource while it is the large number of small boats that generate their impact. From a theoretical point of view, this is probably the worst situation for efficient extraction (Dayton-Johnson and Bardhan, 2002) and resource conservation (Libois).

Competition over fish stocks implies that there is a reduction of catches per unit of effort and therefore a reduction of income for fishermen (Baland and Platteau, 1996). This drop in income for traditional users could be compensated if there were given a significant share of the benefits from industrial fishing, through employment or royalties. As employee, their income might even increase in the long run and under a full appropriation by the most productive boats, but only if the fish stocks are preserved (Baland and Bjorvatn, 2013). The African situation is far from this setting. First, industrial fleets do not hire much labour, and even less from local markets. Second, royalties, even under international fishing agreements, remain limited. And last but not least, conservation of fish stocks is far from granted given the strong competition between industrial fleets.[4]

Traditional fishermen, therefore, need to develop new income-earning strategies. Our work focuses directly on international migration and indirectly on domestic migration by looking at urbanisation rates and demographic changes in rural coastal villages. Migration may generate income because migrants change their place of residence and expect to find a new job, whether it is in their country or abroad. Fishermen can also ease up the migration of other migrants given their skills at sea. Of course, as mentioned earlier there exist other strategies such as engaging in piracy, looking for jobs in the industry, investing more time in agriculture, etc. We do not investigate these channels in this paper by the lack of appropriate data and because we think that they deserve a full-fledged analysis on their own. Last but not least, reduced income may also have a negative effect on migration if potential migrants are liquidity or credit constrained and cannot

[4]We provide more details in the discussion section.

finance their migration anymore. We will provide suggestive evidence that the positive channels of migration outweigh the negative ones, especially in African countries with higher incomes.

In this paper, we opt for a reduced form strategy where fishing effort by industrial boats explains migration. Of course, the causal mechanism has to go through a change in income opportunities of small-scale fishermen, something very hard to measure in a consistent way over the African continent because of data scarcity. However, this is both a clear prediction in the theoretical literature and a consistent finding in the empirical literature.

3 Data

This section details the data sources and construction of our outcome and control variables used in our empirical strategy.

3.1 Migration data

To study the relationship between industrial fishing off the African coastline and immigration in OECD countries, we construct a panel of 37 African countries that have access to the sea. The main variable of interest is the total flows of foreign population [5] and asylum applicants in OECD countries by year and by country of destination and origin. We use the International Migration Dataset (IMD) provided by the OECD, knowing that most of the data on asylum applications are provided by the United Nations High Commission for Refugees and are derived from national administrative sources. The data combine initial applications (primary processing stage) from 2012 to 2018. We note an increasing and then decreasing trend of foreign population flows from West and East Africa and relatively stable flows from Southern, North, and Central Africa. Figure 1 displays the temporal evolution of these flows across African sub-regions for foreign population and asylum application flows.

We also include bilateral annual data on migration provided by the European Commission (EUROSTAT) on immigration of foreign population [6] and on first-time asylum applicants for international protection (as defined by Articles 2(h) and 2(i) of Qualification Directive 2011-95-EU) and decisions, between 2012 and 2018. Figure A4 in Appendix displays the yearly evolution across sub-regions and

[5] defined as a change of temporary or permanent residency status of various time-length, see OECD Metadata for destination country-specific definition.

[6] defined as a change of usual residency, see the European Commission's technical guidelines for destination country-specific definitions.

figures **??** and **??** present the bilateral flows of foreign population and asylum application flows towards OECD countries over the 2012-2018 period.

At the micro level and as a proxy of out-migration, we are interested in households' size and composition as measured in the Demographic and Health Survey (DHS). DHS data are a natural candidate for this kind of exercise because they have consistent questionnaires across numerous countries, good quality of enumeration, relatively large geocoded samples, and fairly high frequency in Sub-Saharan Africa[7]. Unfortunately, DHS data do not contain much information about income generating activities and consumption, but we leverage questions about the diet of young children to provide suggestive evidence about the link between industrial fishing and consumption of rural coastal households.

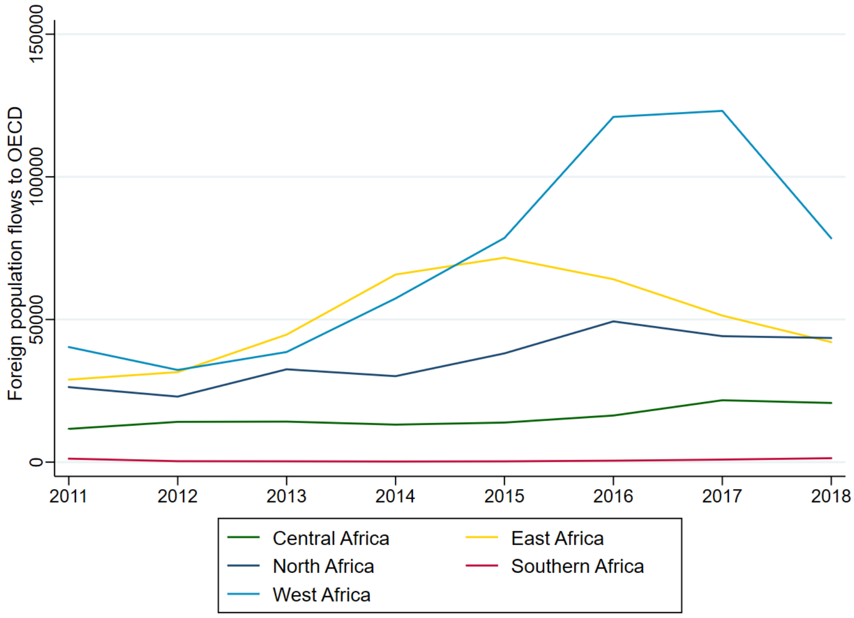
3.2 Industrial fishing data

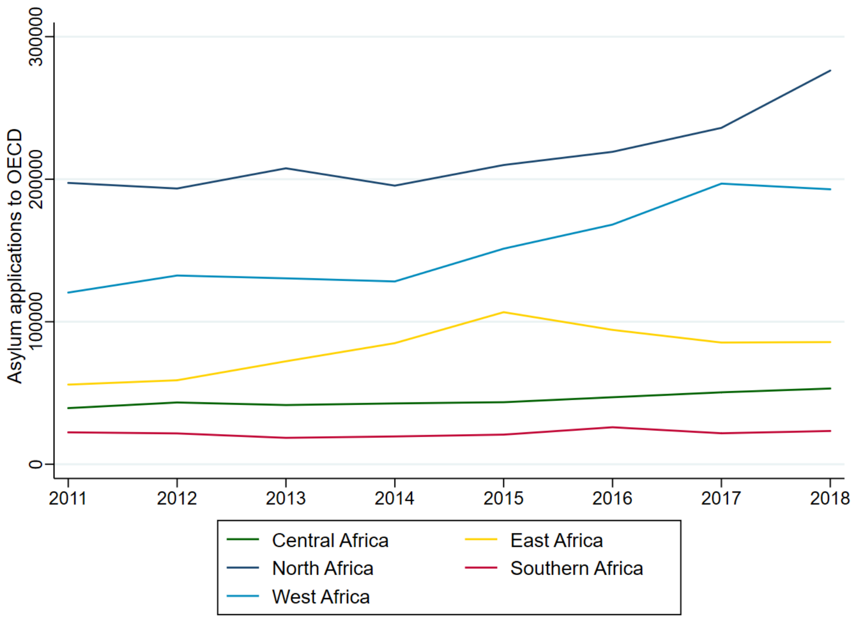
The measure of fishing activity is derived from Kroodsma et al. (2018). It is the most recent and comprehensive dataset to measure fishing activity and contains geocoded information on the daily fishing effort at 0.01-degree resolution. Kroodsma et al. (2018) compute this fishing effort by using the information generated by automatic identification systems of boats (AIS) that are on-board positioning devices necessary for maritime safety to broadcast location, navigate, and avoid collisions. The authors analysed 2 billion global AIS positions from 2012-2016 (20 million messages added per day on average) and used machine learning tools to identify vessel characteristics and to detect AIS positions indicative of fishing activity.[8] Their dataset contains labeled tracks of more than 70,000 identified fishing vessels that are 6 to 146m in length and provides information on the flag under which boats are sailing. Moreover, we added the 2017-2018 provisional data released in 2019 and available on request to their research team. Our final industrial fishing effort variable is the total number of hours that a vessel was detected fishing aggregated by each pixel at the monthly level. Unfortunately, fishing hours are only a best proxy of the intensity of industrial fishing, and no data currently exist on the actual quantity of fish caught at this level of resolution. Figure 2 illustrates the total number of industrial fishing hours that were detected along the African coastline between 2012 and 2018. We see particularly intense activity close to the shore and on the high seas, and spatial heterogeneity between and

[7] Living Standard Measurement Surveys could be the other natural candidate, with much more information on income-generating activities and consumption. Unfortunately, these surveys are less frequent, cover fewer countries, especially over the time span of the fishing effort data, and leave no option to follow households over time. Sample sizes are also much smaller, revealing little information on rural coastal areas

[8] The fishing detection model was trained on AIS data from 503 vessels and identified fishing activity with >90% accuracy.

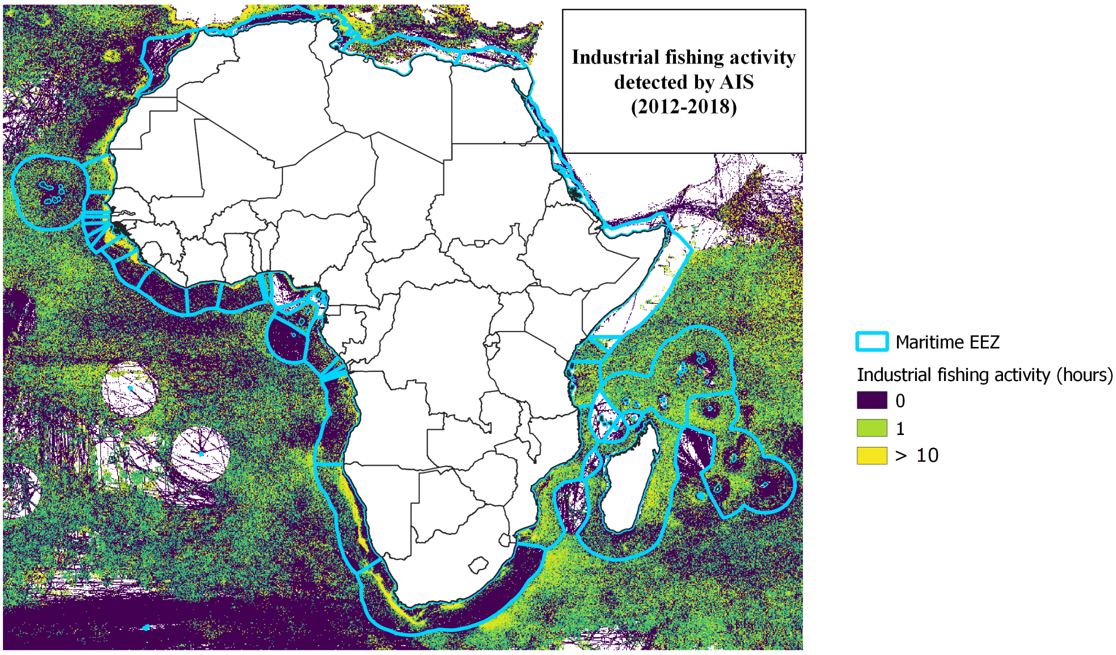
Figure 1: Flows of foreign population and asylum applications towards the OECD countries.





Note: This graph plots the yearly flows of foreign population and asylum applications towards OECD countries.
Source: Authors' elaboration using OECD data.

Figure 2: Map of industrial fishing activity, over 2012-2018

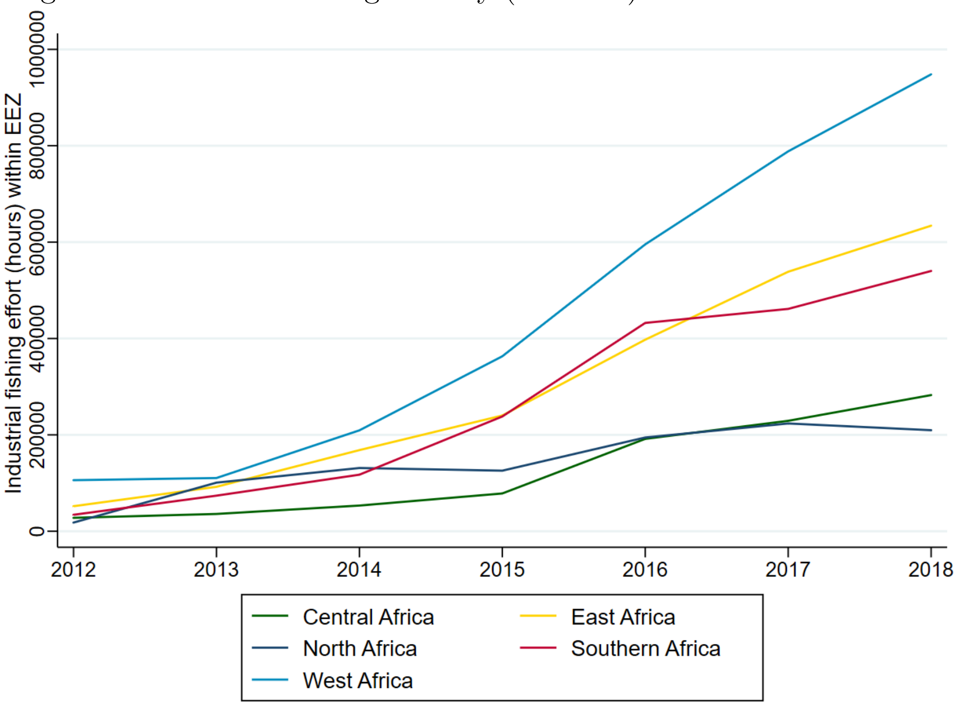


Note: This map represents the total industrial fishing activity (in hours) detected by AIS signals.
Source: Authors' elaboration using Global Fishing Watch data.

within countries' EEZ.

Figures A2 and 3 plot the industrial fishing activity detected within the 36 NM maritime zone and the EEZ, by sub-regions (as defined by the United Nations, see Figure A10 in Appendix. All regions are subject to increasing industrial fishing activity but not at the same intensity. West, East, and Southern Africa are the most exposed regions. Li et al. (2021) argues that AIS based data about industrial fishing effort in Africa is consistent with that derived from Sea Around Us database. They conclude that AIS-derived data is a useful tool to characterize the spatial pattern of industrial fishing in Africa. This however not a perfect source and the African West Coast is one of the world hot spot of unseen fishing vessels (Welch et al., 2022a). The probability that a fishing vessel switches off its AIS system increases in the risk of piracy, fishing productivity and along the limits of EEZ. We further discuss the implications of these measurement issues in the discussion section.

Figure 3: Industrial fishing activity (in hours) detected within EEZ



Note: This graph plots the yearly industrial fishing activity detected along the EEZ of each country, across sub-regions.

Source: Authors' elaboration using Global Fishing Watch data.

3.2.1 Aggregation of fishing efforts

We aggregate fishing efforts along various distances to the coast. At the macro level, we include four different distances (i) territorial waters that are limited to 12 nautical miles (about 22.2 km, shaded in red in figure A3); (ii) a contiguous zone of 24 NM (about 44.4 km); (iii) a zone up to 36 NM (in green, a threshold chosen to match with the average length of the continental shelves where the most important fishing grounds are located (Karleskint et al. (2013)); (iv) the limit of the Exclusive Economic Zone (EEZ), namely 200 nautical miles (about 370 km). Industrial fishing is prohibited in inshore water which exclusion zones vary from 0 to 24 NM from the shore, with the vast majority for African countries being between 0 to 12 NM (Belhabib et al.). The Exclusive Economic Zone (EEZ) is supposed to have regulated access for trespassing and conducting any type of extractive activity. At the micro level, we mainly focus on 24 NM and 36 NM which we consider to be the most relevant areas, as shown in the macro level analysis. It also reduces problems of missing values that we would partially face within the 12 nautical miles limit of each closest access to the sea while the EEZ does not provide much variation between villages of the same country. For fishing conditions, we aggregate relevant variables over the same spatial extent.

3.2.2 Fishing conditions

As in Flückiger and Ludwig (2015) and Axbard (2016) we use ocean satellite images to proxy fishing conditions. Flückiger and Ludwig (2015) use annual phytoplankton absorption coefficient and Axbard (2016) uses monthly Chlorophyll-a concentration. We use the latest generation time series satellite-based ocean-colour data, of higher quality (Couton et al., 2016): Ocean Color CCI from the European Spatial Agency at the monthly level and 4 km per pixel resolution. We combine these data with sea surface temperature (SST) data from NASA's MODIS and VIIRS at the monthly level and 9 km per pixel resolution (see Appendix for more details on the products).

To get at fishing conditions, we borrow from the marine biology literature. This literature first agrees on the complexity of interactions between marine environment properties and the distribution and abundance of fish (Klemas, 2012). Sea surface temperature and chlorophyll concentration are measures commonly used by marine scientists to map potential fishing zones, but they are not the only ones: significant wave height, current velocity, and salinity are also significant features. Yet, out of parsimony, we will restrict ourselves to the two measures most often used (Chassot et al., 2011), as in Axbard (2016), while studying the Indonesian seas knowing that each fish species have different preferences for water temperature and transparency. We are considering a large interval for SST encompassed between 18 and 25 degrees Celsius to encompass a range of fish species preferences (from cool-tempered water tuna to warmer water sailfish), and chlorophyll concentration above 0.2 mg.m-3, considered the minimum threshold for commercially viable fishing (Butler et al., 2003) and below 5 mg.m-3 to control for eventual algae blooms that are improper environments for fish to live in.

Before undertaking the estimations, we verify that our proxy for fishing conditions is valid by regressing industrial fishing efforts at different distances to the shore on the constructed variable of chlorophyll concentration and surface sea temperature. Summary statistics are reported in table A2 and regression results in table A5 of the Appendix.

3.3 Additional controls

We control for weather on land by using Version 4 of time series data from the Climatic Research Unit (CRU) of the University of East Anglia and collected from an extensive network of weather station observations. We extract monthly temperatures (degree Celsius), precipitations (mm), and wet days frequencies at the country level from 2012 to 2018.

We use the Global 10-daily Leaf Area Index (LAI) at the 1 km resolution, provided by the land service of Copernicus, the Earth Observation program of the European Commission to control for the vegetation abundance around DHS clusters and their closest access to the sea.

Additional controls include the number of people affected by natural disasters using the Emergency Events Database collected by the Centre for Research on the Epidemiology of Disasters (CRED) of UCLouvain, which is publicly available[9]. The data comes from the compilation of reports from various sources including national governments, UN agencies, NGOs, insurance companies, research institutions, and press agencies. A disaster is recognized if one of the following criteria is fulfilled: (i) 10 or more people reported killed; (ii) 100 people reported affected; (iii) declaration of a state of emergency; or (iv) call for international assistance. The sample includes data on earthquakes, floods, wind storms, volcanic eruptions, tidal waves, landslides, avalanches, droughts, extreme temperature events, and wildfires.

We control for the number of conflict fatalities based on the PRIO-Uppsala Armed Conflict Location and Event Data (ACLED) which collects reported information on internal political conflict disaggregated by date, location, and actor. Conflict actors include governments, rebel groups, militaries, and organized political groups that are involved in interactions over issues of political authority: battles, riots and protests, strategic development, and violence against civilians.

[9]www.cred.be

Eventually, we use the CEPII Gravity database (Conte et al.) to control for yearly GDP in origin and destination countries, the level of Polity2 index in the origin countries, the distance between the most populated cities of the origin and destination countries, the existence of a formal colonial dependency as well as a common official language.

4 Empirical strategy

We organize the empirical strategy in three major steps: we first test the relationship between industrial fishing and population movements using bilateral migration flows between African coastal countries and OECD countries; we then show that a micro approach yields a consistent story by highlighting the relationship between industrial fishing and rural exodus out of rural villages lying along the coastline. Last, in an attempt to bridge the micro and the micro approach, we provide suggestive evidence linking industrial fishing and urbanisation in African coastal country.

4.1 Macro level approach

At the macro level, we estimate gravity equations through random utility maximisation (RUM) models (Beine et al., 2016). Given the high proportion of zero flows, we run Poisson Pseudo Maximum Likelihood (PPML) regressions and estimate the following equation to quantify how bilateral migration flows to OECD countries react to changes in fishing efforts in departure countries:

$$M_{odt} = \alpha \ln \left(F^{z}_{ot} + 1\right) + \mathbf{X}_{ot}\beta + \omega_o + \delta_d + \tau_t + \varepsilon_{odt} \quad (1)$$

where the variable of interest, M_{odt}, measures the migration rate $\frac{Mig_{odt}}{Pop_{ot}}$ from the African country of origin o to the destination country d in year t, with Mig_{odt} the number of migrants and Pop_{ot} the number of people who have chosen to stay in their home country. The vector of parameters ω, δ, and τ respectively capture time-invariant origin-related drivers of migration, time-invariant pull factors in destination countries, and yearly variations that are common to all countries, whether they are correlated with migration flows or with industrial fishing effort. The main explanatory variable, F^{z}_{ot} captures the total number of fishing hours by large boats in the zone z, an aggregate that we build using the data produced by Kroodsma et al. (2018). We do include a broad set of controls in the vector $\mathbf{X}$. ε is a country-year idiosyncratic term. We weigh regressions by the estimated population living in the 25 kilometers along the shoreline in 2000. Our estimates are then more representative of what happens in coastal areas where we might expect a larger migration response since if more people live along the coast there is a potentially larger number of people who rely on small-scale fishing. Given the time frame of our study, the choice of the 2000 measure yields a predetermined variable to the number of inhabitants that potentially rely on the ocean for their productive activities or their regular consumption ten years later. The key parameter to estimate is α that we interpret as the marginal effect of an increase in the fishing pressure in the origin country o on the flow of migrants from this country to the destination countries. We expect α to be positive if higher fishing intensities translate into larger migration flows. Results presented later on use OECD data for the main specification but we also show that findings are consistent when using EUROSTAT data.

Even if the origin and destination country as well as year fixed-effects already partial out the estimated parameters from many potential spurious correlations, they may not be sufficient to claim a causal relationship between industrial fishing and migration. We, therefore, have several strategies to clean the estimated parameters from spurious correlations. First, we rely on an extensive set of controls that vary within and between countries of origin. For instance, we add "bad controls" for natural disasters and conflict because a country facing such events may have a hard time devoting resources to the monitoring of fishing while migration outflows typically increase in these conditions. On the opposite of the spectrum, a country that faces a positive political transition may improve the management of sea resources and at the same time offer nicer prospects for its population. The omission of disasters, conflicts, or political transitions could typically lead to a positive bias of the coefficient that associates large-scale fishing with migration. Second, we play on lags and leads and show that the effect of fishing is the largest on migration in years t and $t+1$ and that there is no statistical relationship between future fishing efforts and contemporary migration.

4.2 Micro level approach

We then switch from international migration to a micro level analysis in departure areas and address the determinants of out-migration within countries and at the household level. We build our estimation strategy most consistently with respect to the previous set of estimates. We, therefore, estimate a micro-level model that we frame using the following equation:

$$Y_{ivct} = \sum_{k=1}^{4} \left(\alpha_k ln(F_{vct-1} + 1) + \beta_k\right) \mathbb{1}_{[k-1;k] \times 50km} + \alpha_5 ln(F_{vct-1} + 1) + \mathbf{X_{vct}}\gamma + \omega_c + \tau_t + \varepsilon_{ivct} \tag{2}$$

where Y stands for the size or composition of household i. The total fishing hours F_{vct-1} is measured by summing up the fishing efforts over year $t-1$ in the

24 or 36 nautical miles buffer around the nearest access point on the shoreline to village v in the country c.[10] There is a set of indicator variables grouping villages by distance bins[11]to the nearest point on the shoreline, measured as the crow flies. The reference category is the group of villages located more than 200km from the coastline (see Figure A8 in the Appendix). We expect fishing efforts to have little impact on households located that far and therefore $\alpha_5 = 0$. Last but not least, we include a set of village-specific control variables $\mathbf{X}$, country, and year fixed effects. ε stands for the idiosyncratic component.

The key parameter of interest is α_1. Given the mechanisms that we describe, we expect it to be negative. It implies that higher fishing intensities translate into smaller household sizes. This effect should fade away as the distance to the coastline increases. Notice that it is important to have distance bins fixed effects, namely β_k parameters, as there might be structural differences in household size and composition between villages lying close to the sea and villages located further inland.

The identification assumptions at the micro level rely on the conditional exogeneity of industrial fishing to household demographics. We extensively discuss the threats against this assumption in section 7. In short, we first use inland villages as counterfactual in a spirit very close to a placebo check. Second, we include a broad set of environmental controls to reduce the scope for omitted variable bias. Third, we discuss the plausibility of reverse causality and provide arguments supporting the fact that industrial fleets do not take into account the very local dynamics while deciding on their fishing effort and location and therefore can be considered conditionally exogenous. Last, we provide evidence of the negative effect of industrial fishing efforts on local fish consumption among under five children, and a negative income effect through the decrease in their consumption of other food items. We make sure that there is no substitution effect and no statistically significant increase in the consumption of other food items.

4.3 Urbanization

Optimally, we would like to match the departure data at the village level with arrival in African cities and arrivals in OECD countries. This is however not feasible with our data and unfortunately, we do not know of any source allowing us to track migrants with this level of precision during our period of interest. It is therefore beyond the scope of this paper to match the micro and the macro level whether it would be by aggregating micro estimates to reconstruct macro flows or by tracking households from their village of origin to their destination place.

[10]See figure A7 for an illustration.

[11]Distances bins are chosen to match the macro approach and the coastal population considered : [0;25km], [25km; 100km], [100km; 200km] and further than 200 km.

One imperfect bridge between the micro and the macro approach relates to rural exodus and within country migration. As in Beine and Parsons (2015), we proxy internal migration by urbanisation, and analyse how urbanisation rate varies as a function of industrial fishing effort. We opt for a specification that follows as closely as possible equation 1, namely:

$$\ln\left(U_{ot}\right) = \alpha \ln\left(F^{z}_{ot} + 1\right) + \mathbf{X}_{ot}\beta + \omega_o + \tau_t + \varepsilon_{odt} \tag{3}$$

where U_{ot}, the dependent variable stands for the urbanisation rate $\frac{UrbPop_{ot}}{Pop_{ot}}$ in country o in year t that we define as the ratio of the population living in urban areas $UrbPop_{ot}$ on the overall population Pop_{ot}. This main parameter of interest, α quantifies the change in urbanisation rate as fishing intensity F^{z}_{ot} varies in the zone z. We include a vector of observable controls $\mathbf{X}$ along with fixed-effect capturing country and year unobserved variations. ε is the error term of the model.

Compared to equation 1, this specification has two weaknesses. First, the dependent variable is not precisely measured on a yearly basis. We rely on World Bank data and population trends are often relying on interpolation between a restricted number of population censuses. Second, we are not able to split controls for unobserved heterogeneity between origin (rural) and destination (urban) areas within the same country because there is no consistent measure of population flows within Africa over this period. Still, our focus on variations in urbanisation rate is an important bridge between the macro approach on international migration and the micro approach on departure from coastal rural areas.

5 International migration flows

This section displays the results of the macro level analyses: the impact of industrial fishing on bilateral flows to OECD countries.

5.1 Migration to OECD countries

As a first step in the analysis, we focus on the relation between the previous year's industrial fishing effort and bilateral flows of foreign population towards OECD countries. We estimate equation (1) using Poisson Pseudo Maximum Likelihood estimators.[12] All estimations are weighted by the size of the coastal population.[13]

[12] See Beine et al. (2016) for a practitioners' guide to the use of these estimation techniques in the context of international migrations.

[13] We compute this population size based on the number of people living in the 25km in 2000 along the shoreline using data from WorldPop count data. See Figure A6 in the Appendix for the distribution across countries.

Table 1: Industrial fishing activity and flows of foreign population to OECD countries

	Migration rate of foreign population to $OECD_t$						
PPML	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ln(IndFish)36NM_{t-1}	0.0405**	0.0358**	0.0402***	0.0263*	0.0491***	0.0365***	0.0291***
	[0.0165]	[0.0167]	[0.0156]	[0.0149]	[0.0101]	[0.00950]	[0.0101]
Ln(Distance)			0.665***	0.435*			
			[0.238]	[0.225]			
Colonial tie			-0.189	-0.0264			
			[0.181]	[0.236]			
Common off. language			0.831***	0.815***			
			[0.123]	[0.132]			
Ln(GDP_o)$_{t-1}$				-0.399**			-0.247*
				[0.190]			[0.138]
Polity IV gets worse$_{t-1}$				0.289**			0.343***
				[0.132]			[0.115]
Polity IV gets better$_{t-1}$				-0.0643			-0.106
				[0.172]			[0.113]
Ln(Affected)$_{t-1}$				0.00478			0.00178
				[0.00537]			[0.00380]
Ln(Fatalities)$_{t-1}$				-0.102**			-0.0579*
				[0.0400]			[0.0303]
Constant	-10.19***	-6.020	-9.990	-0.248	-9.877***	2.559	7.166
	[0.117]	[14.45]	[14.80]	[15.14]	[0.0746]	[9.680]	[10.17]
Controls							
Fishing conditions	No	Yes	Yes	Yes	No	Yes	Yes
Weather	No	Yes	Yes	Yes	No	Yes	Yes
Leaf Area Index	No	Yes	Yes	Yes	No	Yes	Yes
Fixed effects							
Origin country	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination country	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination country-year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin-Destination	No	No	No	No	Yes	Yes	Yes
Observations	7,827	7,827	7,827	6,199	5,647	5,647	4,950

Notes: This table gives the results of the Pseudo-Poisson Maxiumum Likelihood (PPML) estimation of equation 1 when using OECD migration data. The industrial fishing effort is aggregated within the 36 NM maritime zone of each African country during the previous year. GDP refers to the economy of each African countries."Affected" refers to the number of people affected by natural disasters and "Fatalities" refers to the number of people victims of conflicts. Standard errors are clustered at the origin country-year level, $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

We report our baseline estimate in column (1) table 1. Controlling for country of origin, destination, year as well as destination-year fixed effects, we find that, on average, a 10% percent increase in the number of fishing hours by industrial boats is correlated with a 0.4% rise in the flow of foreign population between African coastal countries and OECD countries. This effect is statistically different from 0.[14]. Origin and destination country as well as year fixed effects already clean the estimates from factors that could influence both migration and industrial fishing and that are fixed over time for a given country, such as average distance to OECD countries, or that are common to all countries for a given year, such as the economic cycle in OECD countries.

Still, country-specific shocks that affect industrial fishing and migration may bias our estimates. We, therefore, expand the set of controls. In column (2), we include control for meteorological factors that have a direct effect on fishing conditions, such as water temperature and chlorophyll content of seawater, or that could impact income-generating opportunities inland such as rainfall and the leaf area index, a proxy for biomass productivity that captures income generating opportunities in the agricultural and forestry sector. The point estimate of interest goes down by about 12% but remains statistically significant and positive.

We then include in column (3), bilateral controls such as distance between the origin and destination country, the existence of colonial ties between country-pairs, and an indicator variable flagging pair of countries sharing the same language. This does not impact the point estimates of interest nor their statistical significance.

Last, we then add in column (4) a set of socio-economic variables in the countries of origin that may affect both industrial fishing efforts and migration. This set of controls that could be considered as "bad" but allow to discard some potential mediation channels between industrial fishing and migration. It includes the country of origin's GDP, controls for political cycles using PolityIV data, and measures of disasters and conflicts.[15]. This is quite important since GDP usually explains migration and might be correlated with the presence of industrial boats. Industrial fishing may directly affect the GDP for instance if landings of catches in African economies may boost their formal sector. On the opposite, small-scale fishermen experience a reduction in their (mostly informal) income as a consequence of industrial fishing. Disasters and conflicts may induce out-migration while diverting state capacity from monitoring the seas to tackle more urgent needs, a source of positive bias of the coefficient of interest. Political transitions can also lead to an upward bias on the link between industrial fishing and migration: as a political transition may also be a function of the presence of industrial boats if their pres-

[14]We cluster standard errors at the origin country-year level, a rather conservative approach

[15]We lose Eritrea and Somalia by lack of World Bank data and Cape Verde, Comoros, Equatorial Guinea, Mauritius, Sao Tome, and Principe as well Seychelles because there is no PolityIV data for these countries.

ence is a correlate of political support by a foreign country. Moreover, higher state capacity can reduce the scope for illegal, unreported, or unregulated fishing and offer a brighter future for citizens, thereby reducing migration. The stability of point estimates is quite reassuring concerning the extent of this concern.

Finally, we include origin-destination year fixed-effects in the last 3 columns. Again, this has very little impact on point estimates. The most conservative estimation, reported in column (6), yields a 0.37% increase in the bilateral flow of foreign population as a consequence of a 10% increase in industrial fishing. The stability of point estimates provides an omitted variable "ratio" test based on Altonji et al. (2005) which is reassuring for the identification assumption.

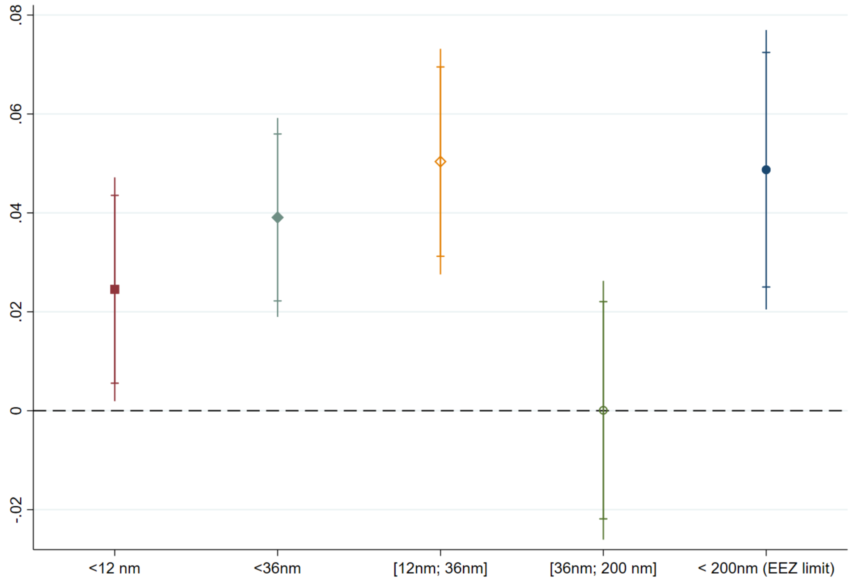
5.2 Heterogeneity and robustness

We then perform several heterogeneity analyses and robustness checks. An important step is to check how the choice of the distance over which we aggregate fishing effort impacts our estimates. Figure 4 reports, in green, the estimated coefficient of interest and its 95% confidence interval for industrial fishing hours aggregated over the 36 NM along the shoreline. It is the coefficient estimated with year, country of origin, and country of destination and origin-destination pair fixed effects as well as the whole set of environmental and socio-economic controls. It corresponds to specification (6) in table 1. We get a slightly smaller point estimate with 12 NM but it remains statistically significant respectively at the 95% and 90% threshold. The highest and most significant effects are to be found between 12 NM and 36 NM, while no significant effect is found between 36 NM and the EEZ. This is all the more consistent with the fact that competition between small-scale boats and industrial vessels is more important in areas that are relatively close to coasts.

A natural counterfactual exercise is to play on the timing of the relationship between industrial fishing and migration. We perform a horse race with the preferred specification (6) in table 1. At $t-2$ and $t-1$, results go through if we restrict the flows to European countries member of the OECD (dark green) but are no longer significantly different from zero when we use EUROSTAT data on foreign population flows (light green). It is only at t that our results hold for all three types of flows. Very reassuringly, none of the three remain significant at $t+1$, meaning that there is no statistical relationship between future fishing efforts and contemporary migration.

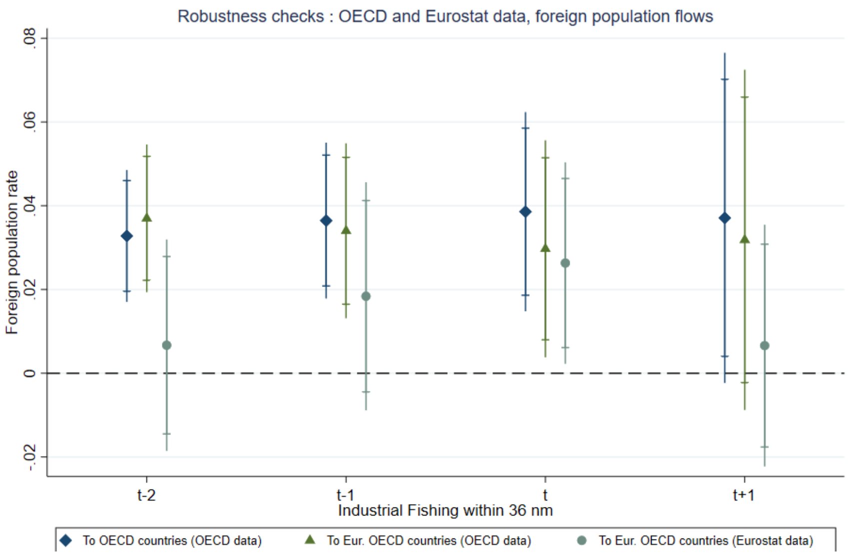
We then look at asylum-seeking applications in Figure 6, in line with the work of Missirian and Schlenker (2017). EUROSTAT data allow us to delve deeper into the migration story by allowing us to check the relation between industrial fishing hours and asylum applications, as well as decisions taken by potential host countries. Results are quite sensitive across the source of data we use. We do not find any effect on asylum-seeking applications as measured by OECD data

Figure 4: Effect of industrial fishing on bilateral foreign population flows to OECD countries, by distance



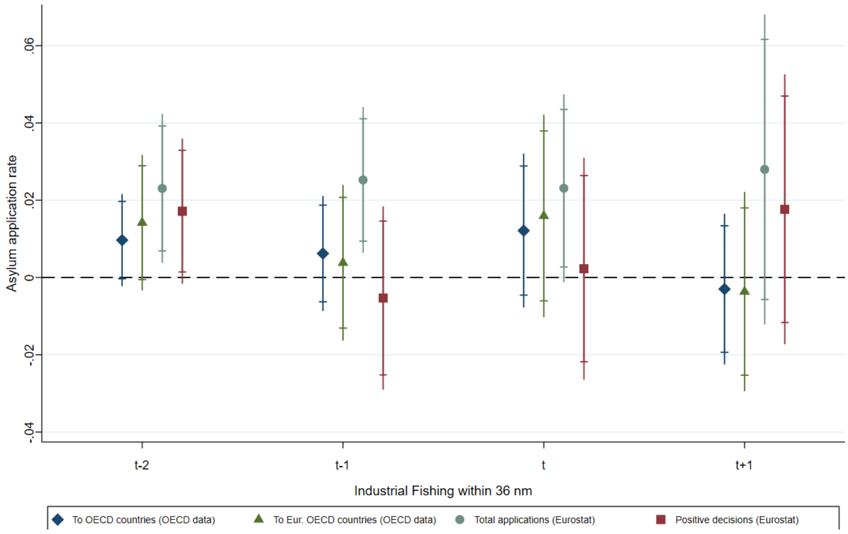
Note: This figure illustrates the coefficients associated with industrial fishing efforts aggregated at different distances from the shore. Each coefficient corresponds to a separate regression. We find that the largest effects are within 12 NM and 36 NM from the shore, which corresponds to the most important fishing grounds and not strictly forbidden industrial fishing (as it is the case within 12 NM).

Figure 5: Effect of industrial fishing when using OECD and Eurostat data, at different timings compared to bilateral foreign population flows.



Note: This figure illustrates the coefficient associated with separate regressions across different timing of industrial fishing, from t-2 to t+1 compared to bilateral foreign population flows. For each timing, we run a regression using different destinations (OECD or European OECD countries) and datasets (OECD and Eurostat).

Figure 6: Effect of industrial fishing when using OECD and Eurostat data, at different timings compared to bilateral asylum application flows.



Note: This figure illustrates the coefficient associated with separate regressions across different timing of industrial fishing, from t-2 to t+1 compared to bilateral asylum application flows. For each timing, we run a regression using (1) application flows to OECD countries from OECD data; (2) application flows to European OECD countries from OECD data; (3) application flows to European OECD countries from Eurostat data, and (4) positive decisions to these applications to European OECD countries from Eurostat data.

while the effect of industrial fishing is positive and significant when relying on EUROSTAT data.[16] We find a positive and significant effect of industrial fishing effort at $t-2$ and $t-1$ on asylum applications when using Eurostat data, but not with OECD data. Again, very reassuringly, we find no statistical effect between future industrial fishing efforts and contemporary asylum applications and positive decisions. An important result is that we find no significant effect on the positive decision rate granted to asylum applications through all the considered timing, showing that the migration flows so far studied do not concern asylum seekers or refugees, but mostly economic migrants.

To shed a more nuanced view on the relationship between industrial fishing and migration, we also test for heterogeneous effects in several important dimensions that we report in Figure 7. First, we split the sample between countries

[16]Strangely enough the correlation between the two data sources is particularly low over the period we consider, despite officially coming from the same sources. Figure A5 displays the absolute difference and the temporal delay across the two sources.

above and below the median GDP or GDP per capita. In both cases, our main finding comes from the richest countries. It is consistent with the literature about migration that consistently finds a positive effect of negative income shocks on migration in contexts where credit constraints are moderate. We then split the sample around the median according to the quality of their institutions, as measured by the PolityIV. There are no significant differences in migration responses to industrial fishing between the two groups. This enables us to partially defuse the potential omitted variable of maritime piracy that could lead to an upward bias of our estimates. Indeed, states with weak institutional levels are facing higher levels of piracy events (de Sousa and Mercier) that could deter industrial vessels to scour the country's maritime zone. Yet, states with weak institutions are also potentially facing more out-migration, and we would wrongly overestimate the effect of industrial fishing. A more descriptive argument is that piracy is not primarily targeting fishing boats, but more freight and cargo vessels as they are more lucrative. de Sousa and Mercier estimated that less than 9 percent of maritime piracy events were affecting non-freight vessels (category to which fishing vessels belong) between 2010 and 2017.

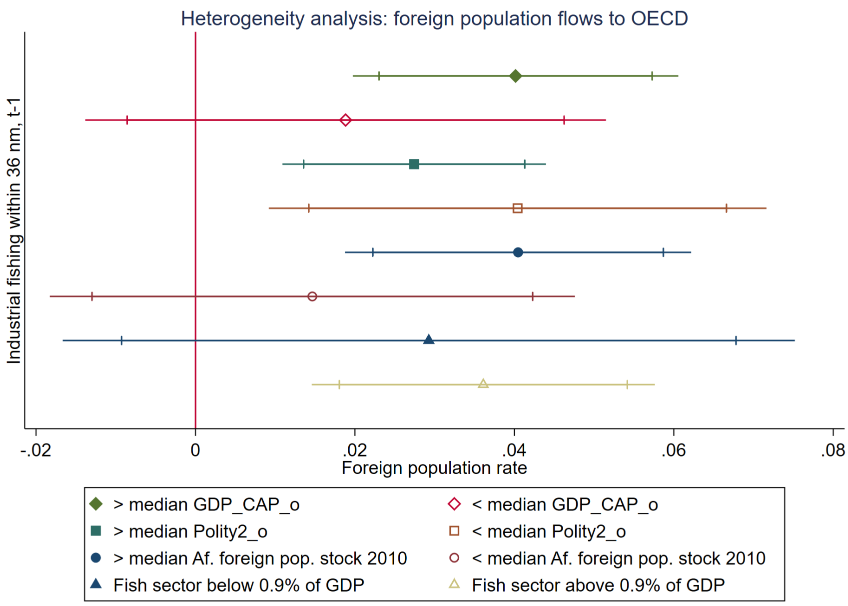
Then, we check whether the stock of former migrants influences current migration responses by dividing our sample between destination countries that have a stock of African migrants coming from coastal areas that are above or below the median stock, and we find a positive effect only among countries with the highest number of African migrants in 2010, in line with results on the importance of networks in destination countries. Finally, we make the distinction across countries with high or low reliance on the fisheries sector in their GDPUsing FAO (2014) data. and coherently find that industrial fishing has significant effects only in economies that are the most dependent on the fisheries sector.

At last, to make sure that the assignment of each industrial fishing effort is indeed what drives our results on migration rates, we run a randomization inference test. We randomly draw 1,000 permutations of the different industrial fishing efforts along countries' 36 NM maritime zone, so that each African country can be attributed to the industrial fishing efforts of another one. The simulations show that the distribution of the effect of industrial fishing is shifted around zero. The red line represents the initial treatment effect using our main specification, which therefore reassures at the 1 percent level that our model is not misspecified.

6 Emigration from coastal areas

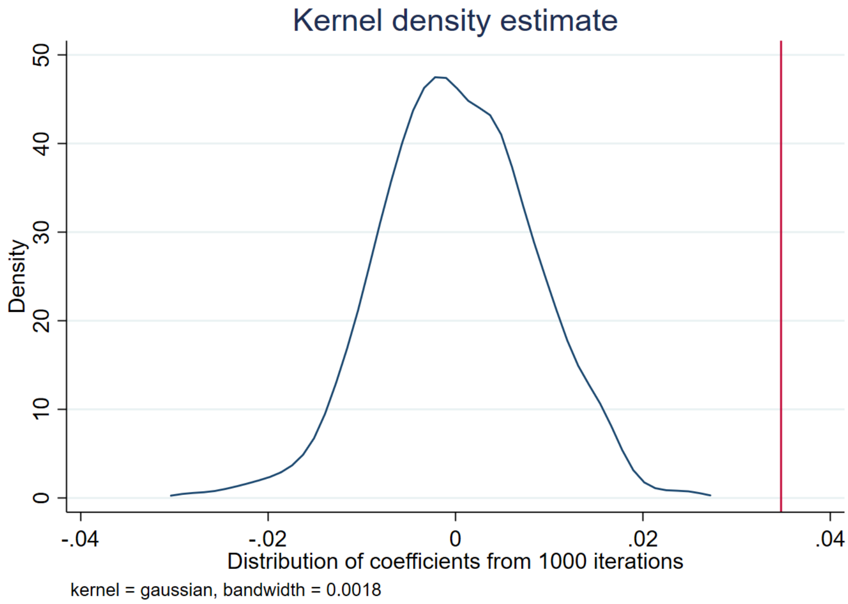
As described in the methodology section, we now show that the macro relationship is consistent with micro-level estimates relying on demographic changes of coastal

Figure 7: Heterogeneity analysis of the effect of industrial fishing on bilateral foreign population flows



Note: This figure illustrates the coefficient associated with the effect of industrial fishing effort on foreign flows to OECD countries when splitting the samples according to each of the criteria: GDP per capita, political index, stock for African population in destination countries in 2010, the weight of fishing sector among the origin countries' GDP.

Figure 8: Randomization of the industrial fishing effort at the country level



Note: This figure displays the distribution of coefficients associated with the industrial fishing effort at $t-1$ within the 36 NM maritime zone when conducting 1,000 permutations of the industrial fishing effort of each country. The red line represents the initial treatment effect using our main specification.

rural households. Following equation (2), we analyse how household size and composition in year t change as a function of industrial fishing effort in year $t-1$.

6.1 Household size and composition as a proxy of migration

We consider household size and composition as an imperfect but relevant proxy for migration in our context. To illustrate this relevance, let us first assume that, before any migration decision, all households have at least two members. If there is always someone who does not migrate and stays behind, and if marriage as well as birth and death rate do not change as a consequence of competition for natural resources, the household size would be a perfect proxy for out-migration. Under these conditions, household size can only change in areas that are more severely affected by industrial fishing if some household members move out of the household and leave the village.

Let us now relax the aforementioned assumptions and discuss changes in household size that would yield a downward biased measure of migration. First, if some households migrate as a whole, something more likely for smaller units, it pushes up the average household size of the remaining households. Second, if the migration of one man leads to a merge of his former household with another unit, or prevents the formation of a new household, it again pushes up the average household size of households enumerated during a survey.[17]

On the other side, we may overestimate out-migration as a consequence of industrial fishing when using household size as a proxy. This is the case if parents postpone birth, for instance following a negative economic shock. Or if the death rate increases in areas that are more severely affected by industrial fishing. One may also witness this if there are fewer marriages and, in the context of patrilocal societies, if spouses, coming from areas that are further away, do not join the household of their husband. Last, household size may also be small if there is an inflow of small households where industrial fishing is higher. This is however rather unlikely because migrants tend to go where economic opportunities are brighter.

To address potential biases, we first try to get the cleanest estimate of the relation between industrial fishing and household size. We then delve into the household composition to discard some additional confounding stories and strengthen our interpretation of the results.

[17] See Bertoli and Murard (2020) for a deeper discussion of the implication of migration on co-residence choice in the context of longitudinal data in Mexico.

6.2 Household size: results

We report estimates of the link between household size and industrial fishing in table 2, following equation 2 while taking into account spatial correlation.[18] Coefficients of interest are related to the interaction terms between the logarithm of fishing efforts and groups of villages. Villages that we group according to their distance to the sea. Villages located more than 200km from the coast play the role of reference category. We compute fishing efforts as the total number of fishing hours over the year before the survey, in a circle of 24 NM (columns 1-4) or 36 NM (columns 5 - 8) around the nearest point of the shoreline to the village. It allows us to impute fishing efforts to all villages, even if they are located far from the sea (see Figure A7). We, therefore, have three sources of variations in fishing efforts. First, within the same wave, we have villages that are along the coastline and that face different levels of industrial fishing efforts. Second, villages that are far from the coast also play a role within wave quasi counterfactual, since we do not expect them to be affected by industrial fishing in the same way as villages lying along the shoreline even if they have the same nearest point on the shoreline. Third, for most countries, we have a tleast two waves of DHS data, allowing us to work with repeated cross-sections and therefore play with variations across time for villages lying in similar locations.

In columns (1) and (5) of table 2, we first look at the effect of industrial fishing on villages while only including year and country fixed effects. This is important since we do not want the relation of interest to be driven by country or year-specific factors such as the geography of culture in a specific country or because in a given year, migration is more attractive in foreign countries. Columns (2) and (6) include country-year fixed effects because different countries may experience year-specific shocks that affect both household size and industrial fishing, for instance, a conflict. We then introduce environmental controls in two steps. In columns (3) and (7), we control for fishing conditions around the nearest point on the shoreline for the relevant distance. Good fishing conditions may both attract industrial fleets and generate income for small-scale fishermen, downward-biasing our estimates. In the last specifications (4) and (8), we bring in location-specific controls that may both affect industrial fishing and household size, namely a built-up index and the leaf area index in the 20km around the village. The built-up index picks up urbanisation, a correlate of smaller household size and eventually different fishing intensity. The leaf area index picks land-based biomass production, a key variable to isolate the effect of fishing conditions from income-earning opportunities in the forestry and agricultural sector. For the sake of completeness and consistency, we also control for Leaf Area Index in the 24 nautical miles or 36 NM (resp. columns

[18]We use the Stata command *acreg* developped by Colella et al. and using a 25 km cut-off.

4 and 8) around the nearest point on the coastline.

Our preferred specification includes all the controls. We find that a 1% increase in industrial fishing in the 24 NM (resp. 36 NM) around the nearest point on the shoreline is associated with a household size reduced by 0.066 members (with 95% CI: [-0.120; -0.012]) (resp. - 0.072 with 95 % CI: [-0.124; -0.021]). At the mean of the logarithm of fishing hours, an increase by one standard deviation of log fishing hours corresponds to a reduction of one member in every 14 households. We interpret this reduction as a piece of evidence showing that locations along the coast become less attractive when industrial fishing increases. Results also show that household size may increase in areas that are further away from the coast when their nearest point on the shoreline experiences more intense industrial fishing. This may suggest a population displacement effect from coastal areas to inland territories, or on the opposite, a reduction of the number of people coming towards the coast from areas that are just a bit further away, something we further discuss in the analysis of changes in household composition.

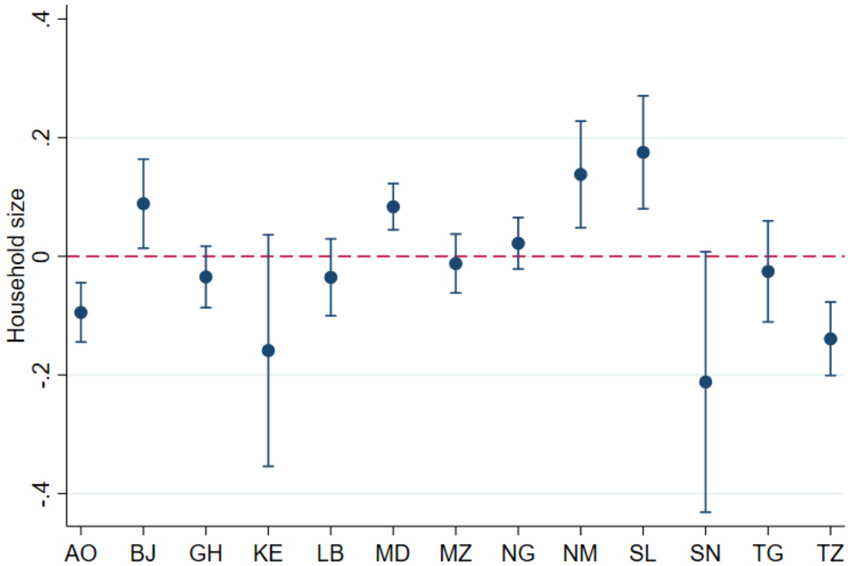
For the sake of completeness, we report the country's average marginal effect of industrial fishing on the size of households living within 25km from the coastline. It follows the estimation of equation 2 where we add triple interactions between fishing effort, distance bins dummies, and country indicators. Figure 9 displays a wide heterogeneity between Sub-Saharan countries. Senegal, Tanzania, and Angola mostly drive the negative relationship between industrial fishing and household size. On the contrary, Benin, Madagascar, Namibia, or Sierra Leone tend to undermine the average negative relationship that we find in the main specification.

Table 2: Effects of past fishing activity on household size

Outcome	Household size$_t$							
Industrial fishing effort's distance	24 NM				36 NM			
Acreg	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sea[0; 25] × Ln(IndFish)$_{t-1}$	-0.0423	-0.0363	-0.0403	-0.0661**	-0.0567**	-0.0505**	-0.0508**	-0.0722***
	[0.0263]	[0.0263]	[0.0264]	[0.0274]	[0.0258]	[0.0257]	[0.0258]	[0.0263]
Sea[25; 100] × Ln(IndFish)$_{t-1}$	0.00852	0.0147	0.0112	0.00583	0.0289	0.0344	0.0340	0.0306
	[0.0207]	[0.0212]	[0.0213]	[0.0219]	[0.0209]	[0.0213]	[0.0214]	[0.0222]
Sea[100; 200] × Ln(IndFish)$_{t-1}$	0.0406**	0.0445**	0.0427**	0.0274	0.0314*	0.0376**	0.0375**	0.0160
	[0.0198]	[0.0199]	[0.0200]	[0.0204]	[0.0190]	[0.0190]	[0.0190]	[0.0197]
Ln(IndFish)$_{t-1}$	-0.00346	-0.0219	-0.0226	-0.0204	0.0129	-0.000869	-0.00214	-0.00251
	[0.0155]	[0.0157]	[0.0157]	[0.0157]	[0.0153]	[0.0155]	[0.0156]	[0.0158]
Sea[0; 25km]	-0.810***	-0.825***	-0.819***	-0.687***	-0.747***	-0.765***	-0.762***	-0.623***
	[0.130]	[0.129]	[0.129]	[0.136]	[0.136]	[0.135]	[0.135]	[0.140]
Sea[25km; 100km]	-0.886***	-0.913***	-0.906***	-0.756***	-0.955***	-0.983***	-0.979***	-0.823***
	[0.0923]	[0.0919]	[0.0928]	[0.0979]	[0.0946]	[0.0946]	[0.0951]	[0.100]
Sea[100km; 200km]	-0.941***	-0.958***	-0.958***	-0.851***	-0.937***	-0.964***	-0.964***	-0.821***
	[0.0832]	[0.0834]	[0.0847]	[0.0880]	[0.0857]	[0.0859]	[0.0864]	[0.0909]
Year FE	Yes	No	No	No	Yes	No	No	No
Country FE	Yes	No	No	No	Yes	No	No	No
Country-Year FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Fishing conditions	No	No	Yes	Yes	No	No	Yes	Yes
Built-up index	No	No	No	Yes	No	No	No	Yes
LAI controls	No	No	No	Yes	No	No	No	Yes
N	152,830	152,830	152,830	143,998	152,830	152,830	152,830	143,998

Notes: This table gives the results of estimation of equation 2 when using DHS household data. The industrial fishing effort is aggregated within the 24 NM (columns 1-4) and 36 NM maritime zone (columns 5-8) of each closest access to the sea during the previous year. Standard errors are clustered using a 25 km threshold, $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

Figure 9: Average marginal effects of industrial fishing effort (within 36 NM) on household sizes, by country



Note: This graph plots the average marginal effects of past industrial fishing effort within 36 NM of each of the 13 countries included in the micro study (with their 95 percent confidence interval): Angola, Benin, Ghana, Kenya, Liberia, Madagascar, Mozambique, Nigeria, Namibia, Sierra Leone, Senegal, Togo, and Tanzania.

6.3 Household composition: results

We finally leverage household composition to suggest mechanisms that may explain the previous findings. Tables 3 and 4 show that the absence of young people drives the reduction of household size in villages that are close to the sea, as a correlate of industrial fishing. We find negative and significant coefficients for boys and girls aged 0-13 and 14-17 as well as for women and men aged 18-34. Further away from the coast, in villages located between 100 km and 200 km from the sea, industrial fishing is positively associated with the number of young people and the number of female teenagers aged 0-17, but not for males. There is virtually no action for older members. One possible explanation behind this finding is that reduced economic opportunities in coastal areas, coming up as a consequence of industrial fishing, lead to the out-migration of males under 34 years old.[19] The departure of young males can typically decrease the number of marriages in coastal areas and lessen the inflows of brides coming from nearby inland regions, something that directly triggers a reduction of birth in coastal areas.

[19]Young male out-migration may be the result of their individual decision to migrate but also a household-level decision as they often have higher earnings and remittance potential than older members. Chort and Senne (2018) extensively discuss the implication of household-based migration decisions on the selection of migrants in Senegal, using matched data between migrants and their household of origin.

Table 3: Effects of past fishing activity (24 NM) on household composition

Number of	0-13 years old		14-17 years old		18- 34 years old		35 -64 years old		65+ years old	
Gender	M	F	M	F	M	F	M	F	M	F
Acreg	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Sea[0; 25] × Ln(IndFish)24NM$_{t-1}$	-0.0207**	-0.0167*	-0.00415*	-0.00188	-0.00806*	-0.00644*	0.000120	-0.000924	-0.00243*	0.000104
	[0.00853]	[0.00863]	[0.00214]	[0.00215]	[0.00429]	[0.00369]	[0.00230]	[0.00328]	[0.00143]	[0.00168]
Sea[25; 100] × Ln(IndFish)24NM$_{t-1}$	0.00492	0.00553	0.000120	0.00256	-0.00698**	-0.000522	0.00249	0.00120	-0.00109	-0.00120
	[0.00713]	[0.00709]	[0.00183]	[0.00164]	[0.00345]	[0.00321]	[0.00217]	[0.00269]	[0.00107]	[0.00145]
Sea[100; 200] × Ln(IndFish)24NM$_{t-1}$	0.0157**	0.0122*	-0.000353	0.00442**	0.0000233	-0.000822	0.00221	0.00173	-0.00232*	-0.00334**
	[0.00691]	[0.00661]	[0.00190]	[0.00179]	[0.00343]	[0.00316]	[0.00232]	[0.00295]	[0.00131]	[0.00169]
Ln(IndFish)24NM$_{t-1}$	-0.00686	-0.00652	-0.00112	-0.00252**	0.00307	0.000291	0.00146	-0.00364**	-0.00120	-0.00403***
	[0.00515]	[0.00516]	[0.00137]	[0.00123]	[0.00244]	[0.00230]	[0.00158]	[0.00182]	[0.000856]	[0.00103]
i Sea[0; 25]	-0.232***	-0.259***	-0.00628	-0.0142	-0.0377**	-0.0604***	-0.0424***	-0.0295**	-0.0136**	0.00385
	[0.0426]	[0.0417]	[0.00951]	[0.00938]	[0.0176]	[0.0171]	[0.00986]	[0.0136]	[0.00654]	[0.00717]
Sea[25; 100]	-0.251***	-0.250***	-0.0272***	-0.0434***	-0.0748***	-0.0833***	-0.0458***	-0.00447	-0.00865*	0.0215***
	[0.0330]	[0.0317]	[0.00791]	[0.00800]	[0.0147]	[0.0137]	[0.00894]	[0.0120]	[0.00502]	[0.00670]
Sea[100; 200]	-0.308***	-0.283***	-0.0375***	-0.0418***	-0.0735***	-0.0666***	-0.0275***	-0.0149	-0.00409	0.0203**
	[0.0317]	[0.0315]	[0.00821]	[0.00773]	[0.0151]	[0.0130]	[0.00964]	[0.0119]	[0.00593]	[0.00805]
Constant	7.57e-18	-6.92e-18	-1.13e-18	-3.24e-18	8.39e-18	6.27e-18	4.09e-18	1.12e-17	-2.72e-18	4.30e-19
	[0.00809]	[0.00773]	[0.00201]	[0.00195]	[0.00345]	[0.00332]	[0.00227]	[0.00276]	[0.00124]	[0.00159]
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fishing conditions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LAI controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Built-up index	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	143,998	143,998	143,998	143,998	143,998	143,998	143,998	143,998	143,998	143,998

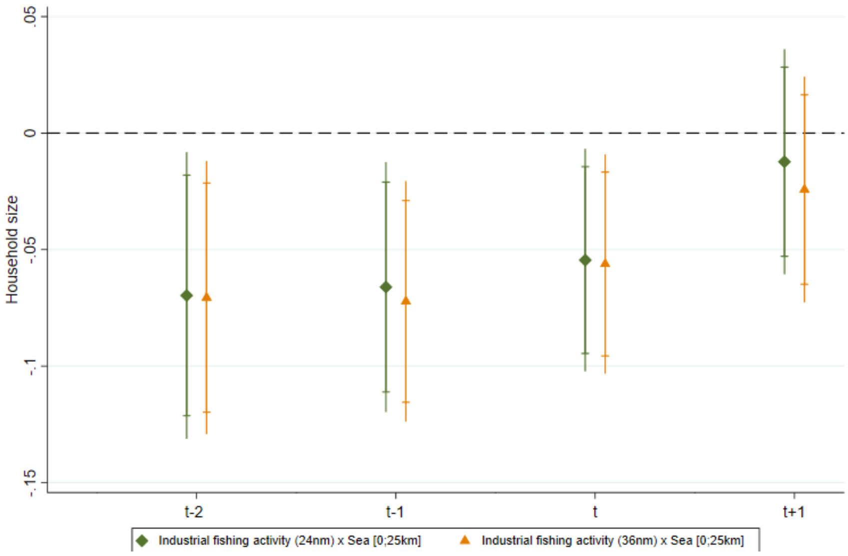
Notes: This table gives the results of estimation of equation 2 when using DHS household data. Standard errors clustered with a 25km threshold. $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$. Reference is households located further than 200 km from the sea.

Table 4: Effects of past fishing activity (36 NM) on household composition

Number of	0-13 years old		14-17 years old		18- 34 years old		35 -64 years old		65+ years old	
Gender	M	F	M	F	M	F	M	F	M	F
Acreg	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Sea[0; 25 km] × Ln(IndFish)36NM$_{t-1}$	-0.0200**	-0.0189**	-0.00502**	-0.00388*	-0.00707*	-0.00679*	0.00126	-0.00147	-0.00193	-0.00157
	[0.00825]	[0.00826]	[0.00210]	[0.00205]	[0.00408]	[0.00352]	[0.00221]	[0.00312]	[0.00140]	[0.00160]
Sea[25 km; 100 km] × Ln(IndFish)36NM$_{t-1}$	0.0139*	0.0138*	0.000868	0.00277	-0.00663*	0.00263	0.00395*	0.00194	-0.000467	-0.00165
	[0.00715]	[0.00707]	[0.00181]	[0.00169]	[0.00339]	[0.00328]	[0.00215]	[0.00271]	[0.00107]	[0.00142]
Sea[100 km; 200 km] × Ln(IndFish)36NM$_{t-1}$	0.0116*	0.00858	-0.00303	0.00310*	-0.000976	0.00161	0.00279	0.00218	-0.00243*	-0.00474***
	[0.00661]	[0.00639]	[0.00195]	[0.00175]	[0.00342]	[0.00358]	[0.00242]	[0.00292]	[0.00129]	[0.00162]
Ln(IndFish)36NM$_{t-1}$	-0.00324	-0.00539	0.00149	0.000608	0.000866	0.000592	-0.000439	0.00114	-0.0000212	0.000209
	[0.00522]	[0.00519]	[0.00140]	[0.00130]	[0.00240]	[0.00225]	[0.00160]	[0.00192]	[0.000861]	[0.00108]
Sea[0; 25 km]	-0.219***	-0.236***	0.000127	-0.00608	-0.0385**	-0.0559***	-0.0457***	-0.0276**	-0.0152**	0.00702
	[0.0440]	[0.0427]	[0.00962]	[0.00949]	[0.0180]	[0.0176]	[0.0103]	[0.0139]	[0.00682]	[0.00753]
Sea[25 km; 100 km]	-0.276***	-0.271***	-0.0275***	-0.0440***	-0.0739***	-0.0930***	-0.0516***	-0.00799	-0.0112**	0.0217***
	[0.0338]	[0.0326]	[0.00818]	[0.00818]	[0.0152]	[0.0140]	[0.00939]	[0.0122]	[0.00522]	[0.00696]
Sea[100 km; 200 km]	-0.300***	-0.272***	-0.0279***	-0.0396***	-0.0715***	-0.0739***	-0.0301***	-0.0177	-0.00330	0.0250***
	[0.0321]	[0.0322]	[0.00821]	[0.00799]	[0.0155]	[0.0132]	[0.0101]	[0.0123]	[0.00611]	[0.00843]
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fishing conditions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LAI controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Built-up index	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	143,998	143,998	143,998	143,998	143,998	143,998	143,998	143,998	143,998	143,998

Notes: This table gives the results of estimation of equation 2 when using DHS household data. Standard errors clustered with a 25 km threshold. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. Reference is households located further than 200 km from the sea.

Figure 10: "Horse-race" at the micro-level



Note: This figure illustrates the main interaction effect of industrial fishing activity off the shore at a different point in time and living on the coast (within 25 km) on household size. We note no effect of future fishing activity.

6.4 Robustness

In the same spirit as the robustness checks conducted in the macro analysis, we display in Figure 10 a "horse-race" graph of the coefficient associated with the interaction of industrial fishing effort and living in a village within 25 km from the ocean. The corresponding table A6 can be found in the appendix. We find a decrease in household size only for past and contemporary fishing efforts ($t-2$ to t) and reassuringly, no effect of future industrial fishing, hinting towards the absence of anticipation. We also conduct a placebo test by randomly drawing 1,000 permutations of the industrial fishing effort around each nearest point on the coastline. Each point can therefore be attributed to the industrial fishing effort of any other point. Figure 11 shows that at both 24 NM and 36 NM, the distributions of the coefficients are shifted towards zero, and significantly different from our initial result at the 1 percent level.

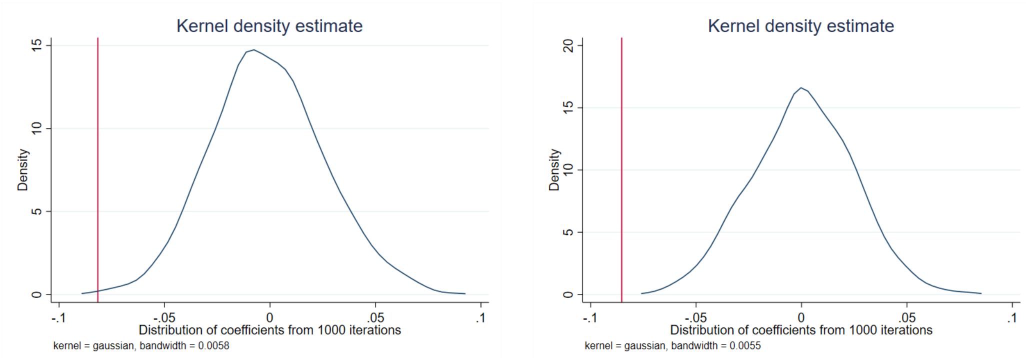


Figure 11: Randomization of the industrial fishing effort within 24 NM (left) and 36 NM (right) at the nearest point to the coastline level

Note: This figure displays the distribution of coefficients associated with the industrial fishing effort at $t-1$ within the 36 NM maritime zone when conducting 1,000 permutations of the industrial fishing effort of each country. The red line represents the initial treatment effect using our main specification.

6.5 Decrease of fish and food consumption

The implicit channel linking industrial fishing to migration goes through a negative income and consumption of small-scale fishermen. While impossible to test directly, Demographic and Health Surveys data do contain some - limited - information about consumption patterns. More precisely, in 15 out of our 26 surveys[20], enumerators asked mothers if their children aged between 0 and 5 and living in their household did consume specific food items over the past 24 hours. These items include fish consumption. As shown in tables 6 and 7, we find that among households living within 25 km from the coast, past industrial fishing effort around 24 NM is associated with a decrease in children's consumption of fish or shellfish. Yet, the result are fragile and are no longer statistically significant when looking at the fishing effort around 36 NM. In terms of magnitude, the largest effects relate to the consumption of tubers and eggs, which could at least provide suggestive evidence of a negative income effect due to increased industrial fishing.

6.6 Urbanisation in African coastal countries

If international migration receives a lot of attention, we may expect that most of the migration responses happen within countries. To get around data constraints, we analyse the response of African coastal countries' urbanisation rate to variations in industrial fishing along their shoreline. We assume that urbanisation partially reflects rural exodus and not just endogenous growth that would be driven by a higher fertility rate in urban areas compared to rural areas. Figure A6 in the Appendix displays the relatively stable but increasing urban population rate across African sub-regions. We, therefore, estimate equation 3 at the African country level using a standard country and year fixed effects specification. Consistently with the analysis of international migration, we start with a pure fixed effects specification. We then include meteorological controls and finally add socio-economic controls. As reported in column (3) of table 5, we find that a 10% increase in industrial fishing in year $t-1$ increases urbanisation rate by 0.02% in year t, a point estimate that is small in magnitude but that statistically differs from 0.

[20]It covers some surveys in Angola, Benin, Ghana, Kenya, Liberia, Namibia, Nigeria, Senegal, Sierra Leone, Tanzania, and Togo (see exact list in Table A4 in the Appendix)

Table 5: Industrial fishing activity and urbanisation rate along African coastal countries

	Ln(Urban pop. rate)$_t$		
	(1)	(2)	(3)
Ln(IndFish)36NM$_{t-1}$	0.00223*	0.00176	0.00198**
	[0.00126]	[0.00108]	[0.000939]
Ln(GDP$_o$)$_{t-1}$			0.00361
			[0.0103]
Polity IV gets worse$_{t-1}$			0.0192***
			[0.00437]
Polity IV gets better$_{t-1}$			0.00657
			[0.00432]
Ln(Affected)$_{t-1}$			-0.000384
			[0.000279]
Ln(Fatalities)$_{t-1}$			-0.00273
			[0.00167]
Constant	-0.705***	-1.775**	-1.637**
	[0.00706]	[0.840]	[0.712]
Fishing conditions control	No	Yes	Yes
Weather controls	No	Yes	Yes
Leaf Area Index controls	No	Yes	Yes
Country and Year FEs	Yes	Yes	Yes
Observations	7,776	7,776	6,192

Notes: This table gives the results of the estimation of equation 3 when using World Bank urban population data. The industrial fishing effort is aggregated within the 36 NM maritime zone of each African country during the previous year. GDP refers to the economy of each African countries."Affected" refers to the number of people affected by natural disasters and "Fatalities" refers to the number of people victims of conflicts. Standard errors are clustered at the origin country-year level, $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

Table 6: Effects of past fishing activity (24NM) on child food consumption

Consumption in the past 24 hours Logit	Fish (1)	Meat (2)	Eggs (3)	Tubers (4)	Vegetables (5)	Bread (6)	Beans (7)	Fruits (8)
Sea[0; 25] × Ln(IndFish)24NM$_{t-1}$	-0.0415* [0.0243]	-0.00967 [0.0211]	-0.0656* [0.0364]	-0.0883*** [0.0267]	-0.0252 [0.0280]	-0.00967 [0.0211]	0.0133 [0.0289]	0.0312 [0.0359]
Sea[25; 100] × Ln(IndFish)24NM$_{t-1}$	-0.0119 [0.0259]	-0.0481** [0.0197]	-0.0448 [0.0346]	-0.0543** [0.0222]	-0.0272 [0.0236]	-0.0481** [0.0197]	0.0386 [0.0257]	0.0369 [0.0348]
Sea[100; 200] × Ln(IndFish)24NM$_{t-1}$	-0.0420 [0.0277]	-0.0318 [0.0215]	-0.0581 [0.0382]	-0.0303 [0.0270]	-0.000615 [0.0272]	-0.0318 [0.0215]	-0.00586 [0.0333]	-0.00764 [0.0341]
Ln(IndFish)24NM$_{t-1}$	0.00592 [0.0186]	0.0349** [0.0151]	0.0952*** [0.0330]	0.0440** [0.0194]	0.0241 [0.0184]	0.0349** [0.0151]	-0.0133 [0.0206]	0.00276 [0.0252]
Sea[0; 25]	0.627*** [0.104]	-0.0385 [0.0729]	0.156 [0.150]	0.0653 [0.0975]	-0.414*** [0.0966]	-0.0385 [0.0729]	-0.143 [0.122]	-0.360** [0.141]
Sea[25; 100]	0.282*** [0.0975]	0.142* [0.0734]	0.103 [0.141]	-0.187* [0.0977]	-0.114 [0.0923]	0.142* [0.0734]	-0.448*** [0.116]	-0.389*** [0.133]
Sea[100; 200]	0.166 [0.102]	0.0764 [0.0744]	0.0350 [0.142]	-0.242** [0.102]	-0.262** [0.103]	0.0764 [0.0744]	-0.297** [0.127]	0.0173 [0.116]
Child's age	0.148*** [0.00529]	0.173*** [0.00671]	0.110*** [0.00657]	0.135*** [0.00548]	0.166*** [0.00571]	0.173*** [0.00671]	0.124*** [0.00498]	0.134*** [0.00554]
Birth order number	-0.0347*** [0.0132]	-0.0427*** [0.00997]	-0.0718*** [0.0222]	-0.0464*** [0.0132]	0.00796 [0.0125]	-0.0427*** [0.00997]	-0.0270* [0.0147]	-0.00408 [0.0169]
Mother's age	0.0194*** [0.00423]	0.0228*** [0.00348]	0.0204*** [0.00640]	0.0230*** [0.00434]	0.00927** [0.00415]	0.0228*** [0.00348]	0.0126** [0.00513]	0.00942* [0.00557]
Mother's education	0.0421*** [0.00627]	0.0115** [0.00477]	0.0835*** [0.00823]	0.0321*** [0.00578]	0.0168*** [0.00594]	0.0115** [0.00477]	0.0280*** [0.00649]	0.0306*** [0.00726]
Constant	-3.220*** [0.231]	-2.617*** [0.213]	-4.576*** [0.430]	-3.939*** [0.230]	-3.018*** [0.214]	-2.617*** [0.213]	-3.853*** [0.260]	-3.666*** [0.322]
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fishing conditions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Built-up index	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LAI controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	28,127	28,141	28,129	28,135	28,130	28,141	28,130	28,135

Notes: This table gives the results of equation 2 when using DHS children's consumption data. Standard errors clustered at the DHS village level, $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Reference is households located further than 200 km from the sea.

Table 7: Effects of past fishing activity (36NM) on child food consumption

Consumption in the past 24 hours Logit	Fish (1)	Meat (2)	Eggs (3)	Tubers (4)	Vegetables (5)	Bread (6)	Beans (7)	Fruits (8)
Sea[0; 25] × Ln(IndFish)36NM$_{t-1}$	-0.0307	-0.00357	-0.0319	-0.0633**	-0.00417	-0.00357	0.0295	0.0293
	[0.0231]	[0.0187]	[0.0358]	[0.0253]	[0.0267]	[0.0187]	[0.0283]	[0.0347]
Sea[25; 100] × Ln(IndFish)36NM$_{t-1}$	-0.00938	-0.0390**	-0.0215	-0.0326	-0.0218	-0.0390**	0.0611**	0.0419
	[0.0241]	[0.0177]	[0.0339]	[0.0216]	[0.0225]	[0.0177]	[0.0254]	[0.0324]
Sea[100; 200] × Ln(IndFish)36NM$_{t-1}$	-0.0143	-0.0316*	-0.0220	0.00150	-0.00198	-0.0316*	0.0165	-0.00155
	[0.0247]	[0.0186]	[0.0360]	[0.0244]	[0.0252]	[0.0186]	[0.0305]	[0.0309]
Ln(IndFish)36NM$_{t-1}$	0.00991	0.0362**	0.0850**	0.0303	0.0205	0.0362**	-0.0366*	-0.00222
	[0.0197]	[0.0153]	[0.0344]	[0.0199]	[0.0187]	[0.0153]	[0.0221]	[0.0278]
Sea[0; 25]	0.605***	-0.0530	0.0541	0.0160	-0.453***	-0.0530	-0.186	-0.354**
	[0.108]	[0.0757]	[0.153]	[0.0996]	[0.0969]	[0.0757]	[0.127]	[0.147]
Sea[25; 100]	0.286***	0.140*	0.00708	-0.240**	-0.119	0.140*	-0.533***	-0.410***
	[0.103]	[0.0772]	[0.145]	[0.103]	[0.0956]	[0.0772]	[0.124]	[0.138]
Sea[100; 200]	0.123	0.0890	-0.0910	-0.329***	-0.255**	0.0890	-0.348***	0.0225
	[0.108]	[0.0784]	[0.146]	[0.108]	[0.106]	[0.0784]	[0.135]	[0.121]
Child's age	0.148***	0.173***	0.110***	0.135***	0.166***	0.173***	0.123***	0.134***
	[0.00528]	[0.00672]	[0.00655]	[0.00546]	[0.00569]	[0.00672]	[0.00498]	[0.00556]
Birth order number	-0.0334**	-0.0417***	-0.0688***	-0.0442***	0.00921	-0.0417***	-0.0252*	-0.00522
	[0.0131]	[0.00997]	[0.0223]	[0.0133]	[0.0125]	[0.00997]	[0.0148]	[0.0169]
Mother's age	0.0190***	0.0225***	0.0193***	0.0223***	0.00906**	0.0225***	0.0121**	0.0101*
	[0.00421]	[0.00348]	[0.00644]	[0.00435]	[0.00415]	[0.00348]	[0.00515]	[0.00558]
Mother's education	0.0425***	0.0111**	0.0824***	0.0323***	0.0172***	0.0111**	0.0290***	0.0326***
	[0.00626]	[0.00478]	[0.00823]	[0.00579]	[0.00592]	[0.00478]	[0.00648]	[0.00726]
Constant	-3.038***	-2.554***	-4.357***	-3.763***	-2.858***	-2.554***	-3.537***	-3.740***
	[0.255]	[0.225]	[0.456]	[0.245]	[0.225]	[0.225]	[0.275]	[0.366]
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fishing conditions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Built-up index	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LAI controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	28,127	28,141	28,129	28,135	28,130	28,141	28,130	28,135

Notes: This table gives the results of equation 2 when using DHS children's consumption data. Standard errors clustered at the DHS village level, $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$. Reference is households located further than 200 km from the sea.

7 Discussion

This paper demonstrates the direct short-term consequences of industrial fishing off the African coastline on population movements, from African coastal countries to wealthier countries and within African coastal countries to their urban centres, possibly originating from coastal areas that are the most severely affected by industrial fishing. Crossing innovative remote sensing datasets of industrial fishing efforts (2012-2018), we find that at the average, a 10% percent increase in the number of fishing hours by industrial boats is correlated with a 0.037% rise in the number of foreign population and a small but significant increase in urban population rate by 0.002%. We also estimate that at the average, an increase of one standard deviation of log industrial fishing hours at 36 NM (225 hours or 9.4 days) induces a decrease in household size in coastal areas by 0.07, i.e 1 person for every 14 households.

Data limitations

Our results suffer from some limitations that further studies could overcome. First, industrial fishing effort is imperfectly measured and is a lower bound of actual industrial fishing effort. Some boats can switch off their Automatic Identification System (AIS), even if they increase the probability of damage to their vessel. It is more plausible when operating in dangerous water - because of piracy - or at the frontier of legality, especially in countries where there is some capacity to enforce fishing regulations. Vessels switching off their AIS in countries experiencing more piracy would typically downward bias our estimates as we would have lower fishing effort in areas that get more insecure, a driver of out-migration. Larger under-reporting as vessels enter into EEZ is more of an issue but only if it is positively correlated with better management of fisheries and institutional improvements in origin countries as we would then measure both less fishing effort and less out-migration. This is not the most plausible as the use of AIS devices has increased over time and especially in countries trying to improve the management of their marine resources (Cabral et al., 2018). For our study, we use year dummies to capture the effect of the overall increase in reporting at the world level. The country-specific increase related to the expansion of AIS use is a bigger issue since we would attribute higher fishing pressure to areas that are better managed. This would typically downward bias our estimates at the macro level but have no effect on the results at the micro level since they rely on within-country variation in exposure to industrial fishing. Our results are therefore an underestimation of the actual effects of industrial fishing. Future projects may overcome this source of bias by relying on data using Vessel Monitoring Systems and nightlight data, something already existing for Indonesia and Peru but not for African waters. Further work could also introduce the very scarce data that currently exist on illegal, unreported and unregulated fishing (IUU) among which suspicions of AIS disabling (Welch et al., 2022b) that could give at least a proxy of the magnitude of illegal fishing along the African coastline. An additional - less data-intensive - refinement would be to include the length of the distance of the prohibition zone from the shore that varies across countries (Belhabib et al.) and see if it influences the effects found on industrial fishing on migration. This would control for a potential upward bias, as countries with small prohibition zones would be less subject to illegal fishing and more subject to legal fishing and thus more efforts are detected. Yet, the same countries would also be more likely to be less stringently regulated, with weaker political institutions and potentially with higher out-migration flows.

Another limitation is the lack of information on catches by both industrial fleets and small-scale fishermen. Ideally, we would like to show how the competition between fleets reduces fishermen's income and leads to different coping strategies by fishermen and more generally households, directly and indirectly, relying on fishing activities for their livelihoods. This would typically require specific surveys collecting information on catches by small fishermen, prices on local markets, and even consumption and other income-generating activities in coastal areas. This is unfortunately not feasible with our data. Instead, we rely on a reduced form approach where population movements appear as a direct function of industrial fishing, even if, implicitly, we suggest that the income channel should play a role. To argue in this sense, we provide evidence on the decrease of children's food consumption especially fish and make sure that there is no positive effect on other food items. Our reduced form approach would also gain if it could rely on surveys tracking potential migrants from origin to destination, whether they stay in areas affected by industrial fishing, whether they leave for urban areas in their own countries, or whether they migrate outside of Africa. To the best of our knowledge, such systematic data on fishermen's communities do not exist. We, therefore, set side by side three layers of analysis in the most consistent way to stress that people leave areas that industrial fishing affects the most, eventually going to urban areas in their country or to wealthier countries.

To our knowledge, no data on fish stocks are available at the country or FAO fishing area level in Africa for our relatively short and recent period of interest (2012-2018), which would enable us to capture spatial and/or temporal spillovers of industrial fishing activity on local fish stocks. Yet, it is a hint for future research, when industrial fishing data will be available for a longer period or if fish stocks data are refined and improved.

Threats to internal validity

Within our analytical frame, we want to stress three main threats to the internal validity of our results and discuss their implications. First, we always estimate the effect of industrial fishing in one year on demographic outcomes in the subsequent year. In practice additional catch in a given year reduces fish stocks for more than one year, suggesting persistent negative effects currently captured by fixed effects. On top of that, migration may occur with some delay concerning its major determinant. It implies that our estimates probably give a lower bound value of the migration response to industrial fishing. Longer time series on fishing efforts will allow for testing these hypotheses.

Second, reverse causality may threaten the internal validity of our approach. It would be the case if the industrial fleet would systematically catch fish in areas neglected by small-scale fishermen, especially if small-scale fishermen are absent because of past migration or selective mortality.[21] This is however not the most plausible story. Anecdotal evidence tends to suggest that industrial fleets do not care much about what happens in coastal areas. To be a serious threat, these channels should also be true within a country and within a year to permeate the results despite country and year fixed effects.

A more genuine threat comes from omitted variable bias. Fishing agreements could bring more foreign boats to some countries while increasing job opportunities. If job opportunities are concentrated in areas directly affected by industrial fishing, this can only downward bias our estimates. If job opportunities expand in urban areas, it can act as a pull factor for internal migration, overstating our estimates at the micro level if these new opportunities disproportionately attract people living near the sea and who are exposed to industrial fishing. It would also inflate the effect on urbanisation rate. It could even magnify estimated parameters of the effect on foreign population flows to European or OECD countries if easing up population flows is part of the deal. While we can't rule out this channel from a statistical point of view, we think that there are not plausible. Fishing agreements typically do not include very large monetary compensation.[22]. The industrial fleet on their side do hire local fishermen but they are capital-intensive and can't offer many well-paid positions in local labour markets. Taking the example of Senegal, the latest EU fishing agreement from 2019 states that owners of Union fishing vessels operating under this Protocol (i.e. 28 freezer tuna seiners, 10 poles, and line vessels, 5 longliners, and 2 trawlers) should employ "at least 25% seamen from Senegal or possibly from another ACP country" for the fleet of tuna seiners or longliners and deep sea demersal trawlers and at least 30% for the fleet of pole

[21] Typically of young boys and girls in the '80s or '90s to match missing young adults in the micro level estimates.

[22] The 2014/0239 (NLE) fishing agreement between Senegal and the European Union includes annual royalties close to 1 million Euro for 14,000 tons of Tuna and 2,000 of black mullet, roughly €0.0625 per kg of fish and €750,000 per year as support to the Senegalese fishing sector.

and line vessels. The Senegalese Statistics agency has recorded "70,041 artisanal fishermen and 11,912 canoes" in 2018. Belhabib et al. (2015) estimate that the fishing sector in Senegal employed around 430,000 people directly and indirectly (selling, processing, etc.) in 2010, which represented around 8% of total national employment.

Omitting relevant meteorological determinants may also bias our results. Rainfall is a determinant of the abundance of phytoplankton, and consequently of fish abundance while it is a well-known determinant of migration. Good fishing conditions are correlated with more fishing hours (see table A5 in appendix) while rain increases terrestrial income-generating opportunities, typically affecting migration. Even if we do include rainfall as a control variable, improperly controlling for rainfall-related mechanisms could therefore lead to an underestimation of the relationship between industrial fishing and migration. It is possible to overestimate the relationship by omitting meteorological determinants that have opposite effects at sea and inland. Heavy winds and storms for instance can worsen fishing conditions, and reduce industrial fishing while improving agricultural yields. To reduce this concern, we control for the leaf area index inland, an indicator of biomass production, and the potential income from agriculture and forestry.

8 Conclusion

This paper provides evidence of the link between industrial fishing and migration at different levels. This relationship echoes well-developed literature dealing with the effect of environmental shocks on migration, although this literature mostly focuses on rainfall and temperature shocks. We, therefore, contribute to the public debate by expanding the set of natural resources considered in this specific literature. Importantly enough, industrial fishing is an economic activity that is heavily supported by a restricted number of governments, whether it is, for instance, through the signature of bilateral fishing agreements or by tax rebates on fuel. Large players on the market can therefore directly influence the industrial fishing efforts of their fleet, even in foreign water.

We are interested in the global magnitude of our effects and find that an increase of one standard deviation of industrial fishing hours among 36 NM (32,891 hours, i.e. nearly doubling the yearly average) would increase the annual number of foreigners arriving in OECD countries and coming from African coastal countries by 14%. [23]. For the European Union, this represents an immediate trade-off between supporting long-distance fishing boats and managing migration flows. Of course, one may argue that a unilateral drop in the fishing effort by one group of

[23]Estimation based on specification (6) in table 1

countries will be compensated by an increase in fishing effort by competing fleets. This is true but given the concentrated nature of the market, one should not expect the increase to be as large. On top of it, having a small number of players potentially eases up cooperation, at least compared to coordination requirements in a problem such as climate change, the driver behind more extreme rainfall and temperature shocks.

We also contribute to the literature about the effects of industrialization. The productivity of labour on industrial boats far exceeds the one in small-scale fisheries. It transfers some added value from labour to capital. This affects the income of traditional users in terms of composition and possibly in levels (Baland and Bjorvatn, 2013). Our work does emphasize that migration is one channel of labour reallocation following a capital intensification in the food production sector, a phenomenon that has been previously described when analysing drivers of rural exodus.

A Appendix

A.1 Data and Descriptive statistics

Table A1: Descriptive statistics: Migration flows and industrial fishing hours in coastal Africa, over 2012-2018

Variable	Median	Mean	SD	Min.	Max.	Obs.
Origin-Destination-Year level						
Foreign population flows						
To OECD countries : prop. of zeros		0.56				
To OECD countries : if >0	33	308	1,158	1	26,698	4,153
To Eur. OECD (OECD) : prop. of zero		0.50				
To Eur. OECD (OECD) : if >0	33	339	1,261	1	26,698	3,337
To Eur. OECD (Eurostat) : prop. of zero		0.26				
To Eur. OECD (Eurostat) : if >0	18	378	2,056	1	60,935	3,358
Asylum applications flows						
To OECD countries : prop. of zeros		0.36				
To OECD countries : if >0	39	616	2,215	1	60,935	5,997
To Eur. OECD (OECD) : prop. of zeros		0.36				
To Eur. OECD (OECD) : if >0	34	600	2,383	1	60,935	4,319
To Eur. OECD (Eurostat): prop. of zeros		0.49				
To Eur. OECD (Eurostat): if >0	40	356	1,292	5	27,105	3,411
Positive decisions to Eur. OECD (Eurostat): prop. of zeros		0.54				
Positive decisions to Eur. OECD (Eurostat): if >0	30	316	1,215	5	20,835	3,082
Origin-Year level						
Annual industrial fishing hours						
Within 12 nm	155	2,507	6,184	0	58,755	259
Within 24 nm	893	8,381	18,260	0	153,240	259
Within 36 nm	2,646	17,906	32,953	0	176,163	259
Within EEZ	8,552	34,921	57,711	0	385,054	259
Population						
Living within 25km from the coast in 2000 (in thousands)	1,517	2,954	3,522	66	14,563	333
Urban population rate	0.49	0.51	0.15	0.25	0.89	252

Note: This table represents the summary statistics of the main dependent and independent variables used in our empirical strategy. Yearly bilateral flows gather a high proportion of zero and we give the summary statistics of non-zero flows for each type of data source. Our main migration variable comes from the OECD dataset, and we take Eurostat data as a robustness check. We compare the two sources on the same subset of European OECD countries. We also provide the average annual number of industrial fishing hours detected along each of the 37 coastal African countries' different distances to the shore. EEZ = Exclusive Economic Zone.

Table A2: Descriptive statistics: economic, weather and political controls, 2012-2018

Variable	Median	Mean	Std. Dev.	Min.	Max.	N
Fishing conditions						
Sea surface temp. within 12 NM	27.22	25.77	3.18	15.43	29.13	259
Sea surface temp. within 24 NM	27.16	25.73	3.1	15.73	29.08	259
Sea surface temp. within 36 NM	27.24	25.78	3.03	16.36	28.98	259
Chlorophyll (mg.m-3), within 12 NM	.91	1.29	1.18	0	6.93	259
Chlorophyll (mg.m-3, within 24 NM	.65	1.05	1	0	5.53	259
Chlorophyll (mg.m-3, within 36 NM	2.11	2.98	2.76	.05	13.67	259
Yearly share of good fishing conditions (12 NM)	.08	.18	.25	0	1	296
Yearly share of good fishing conditions (24 NM)	.08	.19	.26	0	1	296
Yearly share of good fishing conditions (36 NM)	0	.14	.24	0	1	296
Vegetation						
LAI, max. yearly average (country)	2.28	2.32	1.56	.01	5.17	333
LAI, max. yearly average (25km coast)	2.53	2.29	1.41	.02	5.14	333
Weather						
Annual mean precipitations (CRU)	1,066	1,079	717	25	2,651	296
Annual mean temperatures (CRU)	25.4	25.12	2.71	17.4	29	296
Wet days frequency (CRU)	101.2	98.48	54.7	4.5	256.7	296
Political						
Affected by disasters (CRED-EMDAT) (in thousands)	2	253	892	0	8,150	272
Conflict fatalities (ACLED)	30	686	1,610	0	11,388	255
GDP (World Bank) (billions USD)	37	147	264	0.481	1,222	281
Polity IV gets worse	0	.04	.19	0	1	333
Polity IV gets better	0	.04	.2	0	1	333

Notes: This table details the summary statistics of the macro analysis.

Table A3: Descriptive statistics in our 13 countries over 2012-2018

Variable	Med.	Mean	Std. Dev.	Min	Max	Obs.
Household characteristics						
Household size	4	4.88	3.35	1	66	273,458
Household living in a rural area	1	.59	.49	0	1	273,458
Rural within 25 km from the sea	0	0.41	0.49	0	1	59,139
Rural within 25-100 km from the sea	1	0.69	0.46	0	1	44,535
Rural within 100-200 km from the sea	1	0.63	0.48	0	1	42,357
Rural further than 200km from the sea	1	0.67	0.47	0	1	127,427
Hub coast characteristics						
Presence ind. fishing within 12 NM	1	.54	.5	0	1	21,077
Presence ind. fishing within 24 NM	1	.66	.47	0	1	21,077
Presence ind. fishing within 36 NM	1	.69	.46	0	1	21,077
Ind. fishing within 12 NM (hours/year)	12	635	1,491	0	18,273	19,055
Ind. fishing within 24 NM (hours/year)	82	1,757	3,761	0	41,292	19,055
Ind. fishing within 36 NM (hours/year)	192	2,597	5,659	0	47,954	19,055
Surface sea temperature within 36 NM	27.71	26.78	2.65	13.79	31.16	18,165
Chlorophyll within 36 NM (mg/m3)	.69	1.04	.96	.12	16.55	18,787
Dum Fish. cond. 36 NM	0	.54	.39	0	1	21,077

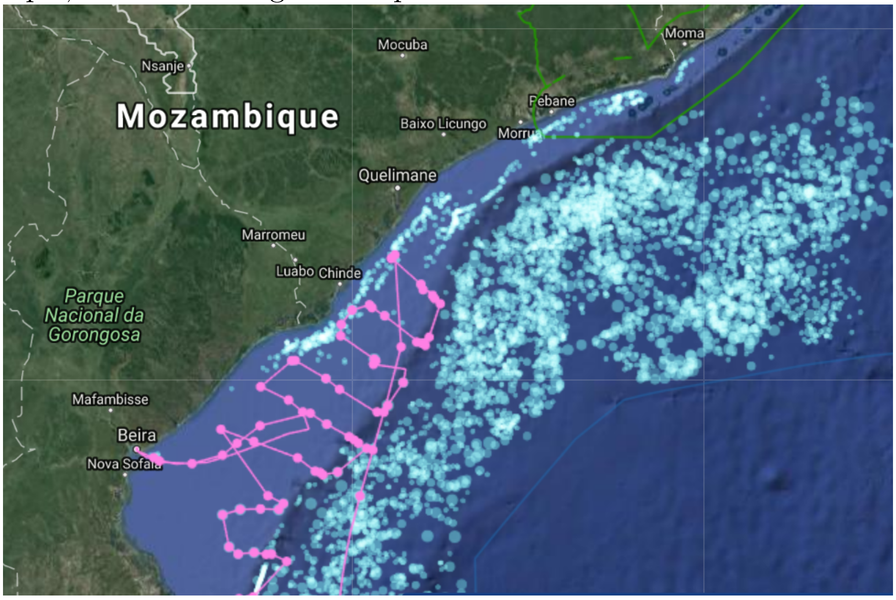
Notes: This table gives the summary statistics of our micro analysis. The hub coast is the closest access to the sea of each DHS cluster. We run buffers of three different distances around each hub and sum up the industrial fishing efforts detected as well as the fishing conditions.

Table A4: DHS surveys from all coastal countries of Africa over 2012-2018

Country	Year	Households	Clusters
Angola	2015-2016*	16, 109	625
Benin	2017-2018*	13, 776	540
Ghana	2014*	11, 716	423
	2016	5, 602	192
Kenya	2014*	36, 224	1, 585
	2015	6, 481	245
Liberia	2013*	9, 333	322
	2016	4, 218	150
Madagascar	2011	16, 097	266
	2016	11, 284	358
Mozambique	2015	7, 170	307
	2018	6, 117	221
Namibia	2013*	9, 849	550
Nigeria	2013*	38, 215	889
	2015	7, 650	322
Senegal	2012-2013*	4, 175	200
	2014*	4, 169	197
	2015*	4, 511	214
	2016*	4, 437	214
Sierra Leone	2013*	12, 629	435
	2016	6, 719	336
Tanzania	2011-2012*	9, 862	573
	2015-2016*	12, 563	608
	2017	9, 202	436
Togo	2013-2014*	9, 549	330
	2017	4, 909	171
Total		273, 458	10, 644

Notes: This table lists all the DHS surveys used in our micro analysis, i.e. 13 countries of Subsaharan Africa. * indicates surveys where child consumption data has been collected.

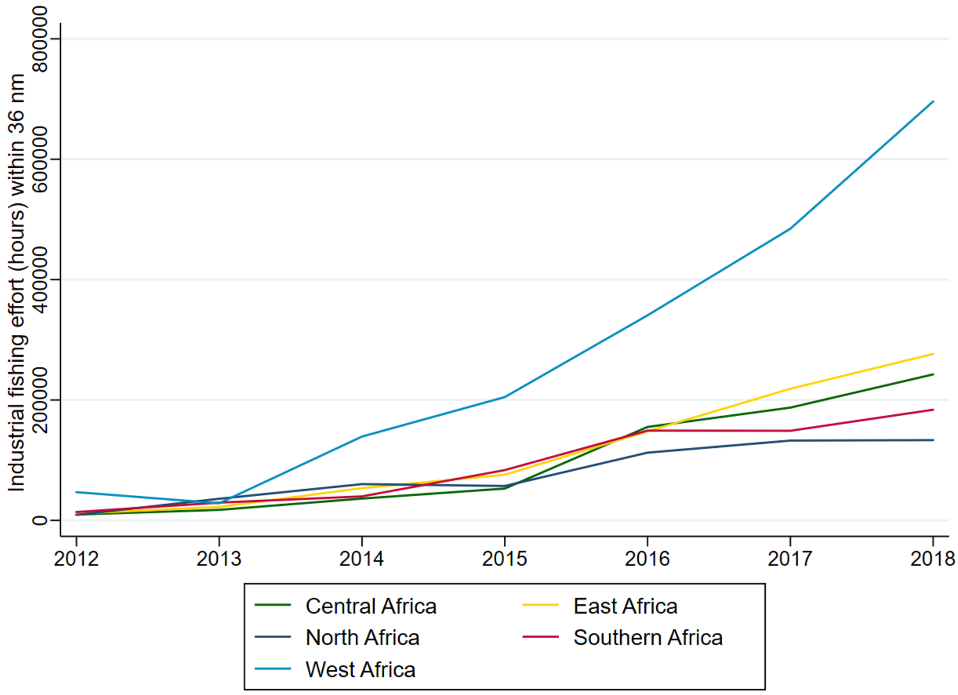
Figure A1: Exemple of vessel tracking in July-December 2014 by the coast of Mozambique, Global Fishing Watch platform



Note: This figure illustrates the industrial fishing activity detected along the coast of Mozambique between July and December 2014. Each light blue dot corresponds to the industrial fishing hours detected. The pink trace represents the itinerary of an industrial fishing vessel, and each dot corresponds to the location of its actual fishing activity.
Source: Global Fishing Watch, accessible at `https://globalfishingwatch.org/map`.

A.2 Industrial fishing data

Figure A2: Industrial fishing activity (in hours) detected within 36 NM



Note: This graph plots the yearly industrial fishing activity detected along 36 NM of each region.
Source: Authors' elaboration using Global Fishing Watch data.

A.3 Fishing conditions

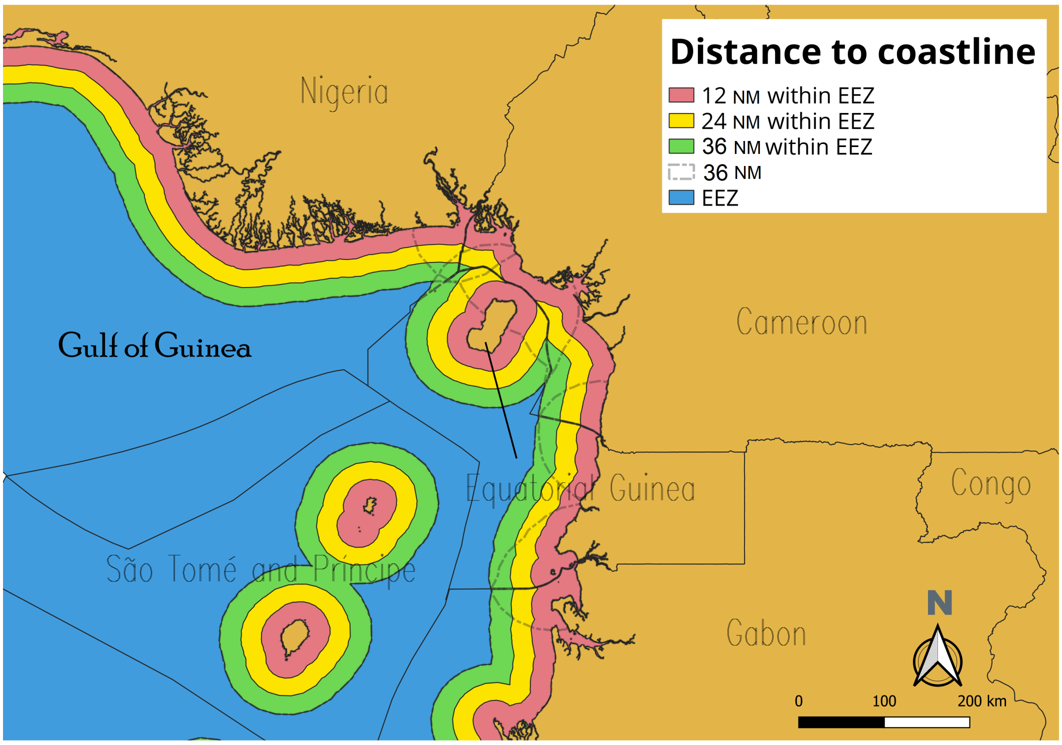
Data on chlorophyll concentration were retrieved from the European Spatial Agency (ESA) Climate Change Initiative (CCI) program, and the product used is entitled Ocean Color CCI[24], which aims at producing the highest quality data adjusted in the light of recalibration or assessment. The dataset is created by band-shifting and bias-correcting Medium Resolution Imaging Spectrometer (MERIS), Moderate Resolution Imaging Spectroradiometer on the Aqua Earth Observing System (MODIS-Aqua), and Visible Infrared Imaging Radiometer Suite (VIIRS) sensor data to match Sea-viewing Wide Field-of-view Sensor (SeaWiFS) data, merging the datasets, and computing per-pixel uncertainty estimates (Sathyendranath et al.). Chlorophyll-a in the OC-CCI products have units of mg/m^3 and are provided as daily products with a horizontal resolution of 4 km/pixel. The chlorophyll-a values are calculated by blending algorithms based on the water type. For v3.1, this involved the blending of the OCI algorithm (as implemented by NASA, itself a combination of CI and OC4), the OC5 algorithm (NASA 2010), and the OC3 algorithm, weighted by the relative levels of membership in specific water classes.

The sea surface temperature (SST) data were accessed through the Giovanni online data platform, at the monthly level and 9 km resolution. SST is measured between 1 millimeter and 20 meters below the surface using spectral bands produced by NASA's MODIS and VIIRS.

A.4 Migration and asylum applications data

[24] Ocean Colour Climate Change Initiative dataset, Version 3.1, European Space Agency, available online at http://www.esa-oceancolour-cci.org/

Figure A3: Aggregation at different distances from the shore



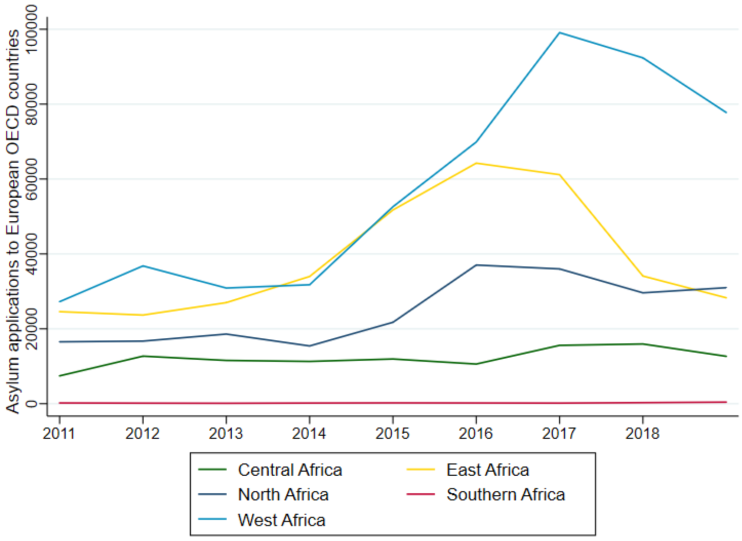
Note: This figure represents the different distances used for the aggregation of industrial fishing efforts and fishing conditions: (i) territorial waters that are limited to 12 nautical miles (about 22 km, shaded in red); (ii) a contiguous zone of 24 NM (about 44 km, in yellow); (iii) a zone up to 36 NM (about 67 km in green, a threshold chosen to match with the average length of the continental shelves where the most important fishing grounds are located (Karleskint et al., 2013); (iv) the limit of the Exclusive Economic Zone (EEZ), namely 200 nautical miles (about 370 km). Industrial fishing is prohibited in inshore water where exclusion zones vary from 0 to 24 NM from the shore, with the vast majority for African countries being between 0 to 12 NM (Belhabib et al.). The Exclusive Economic Zone (EEZ) is supposed to have regulated access for trespassing and conducting any type of extractive activity.
Source: Authors' elaboration.

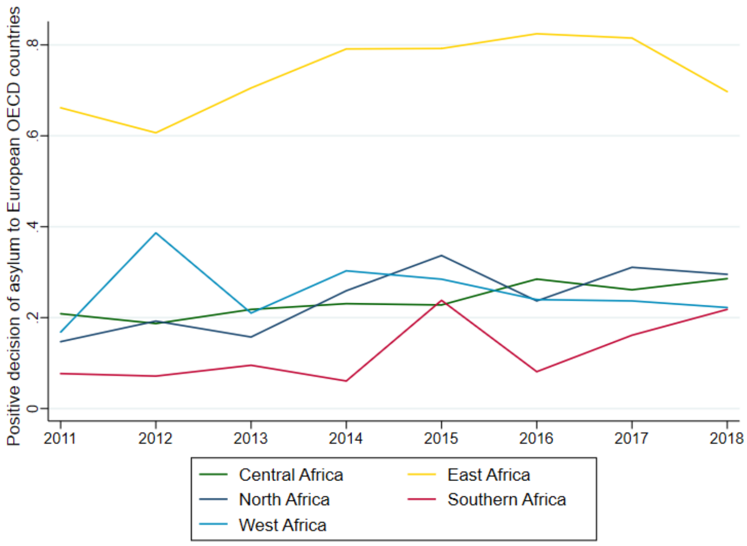
Table A5: Industrial fishing and fishing conditions (chlorophyll concentration and sea surface temperatures)

Outcome	Log(Industrial fishing hours)							
	OLS						Probit	
Off-shore distance	24 NM	36 NM	24 NM	36 NM	24 NM	36 NM	24 NM	36 NM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Chlorophyll)	0.223*** [0.0600]	0.205*** [0.0287]	0.201*** [0.0540]	0.205*** [0.0325]				
Annual SST	-0.0279*** [0.00997]	-0.0610*** [0.0150]	-0.0186*** [0.00716]	-0.0296*** [0.00723]				
Dummy fishing cond.					0.306*** [0.0849]	0.185*** [0.0420]	3.055*** [0.445]	3.353*** [0.374]
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	259	259	259	259	259	259	259	259

Notes: This table tests the construction of our fishing conditions dummy variable at 24 NM and 36 NM distances. Standard errors clustered at the DHS village level, $^{*}p < 0.1$,** $p < 0.05$,*** $p < 0.01$.

Figure A4: Bilateral flows of asylum application and positive decisions rates

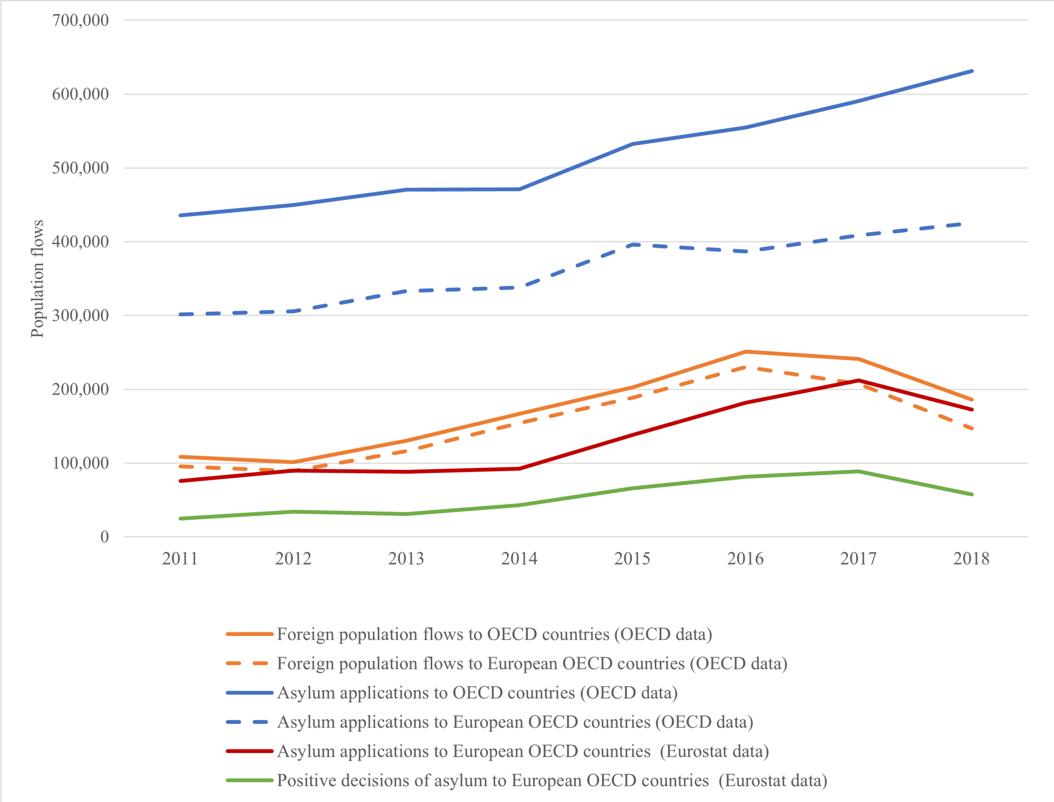




Note: These graphs display the yearly evolution of asylum applications towards European OECD countries and the positive decision rates of these applications, across African sub-regions.

Source: Authors' computation using Eurostat data.

Figure A5: Comparison of population flows between OECD and Eurostat data

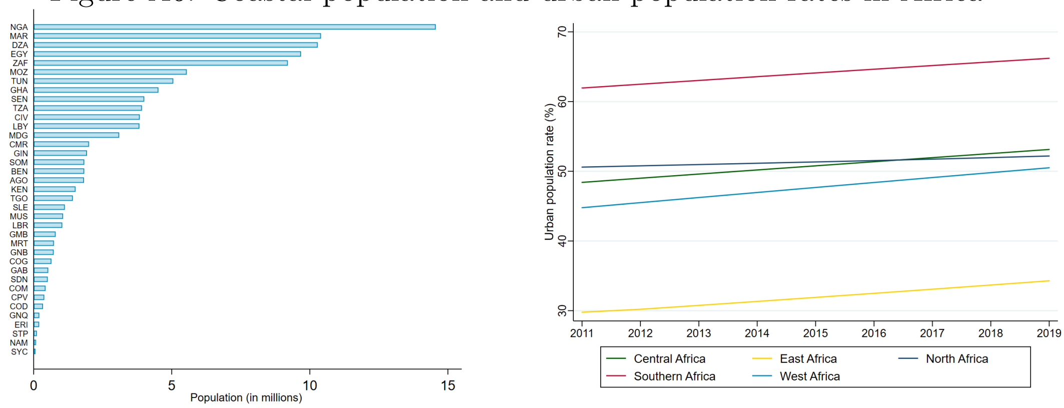


Note: This graph compares the bilateral foreign flows recorded by OECD and Eurostat and aims at highlighting the discrepancy across these sources for the same destination (European-OECD countries).

Source: Authors' computation using OECD and Eurostat data.

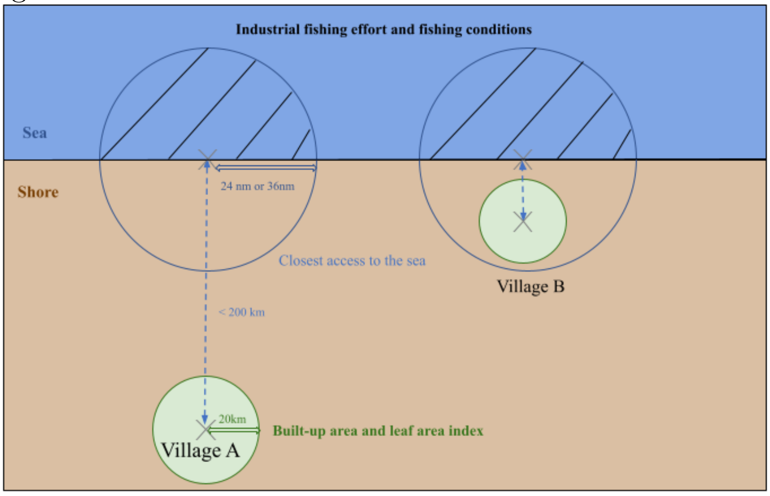
A.5 Population data

Figure A6: Coastal population and urban population rates in Africa



Note: The graph on the left plots the coastal population living within 25 km from the sea, by country, in 2000 used for weighting the regressions included in our analysis. The graph on the right displays the relatively stable but overall increasing urban population rates across African sub-regions.
Source: Authors' elaboration using WorldPop count and World Bank data.

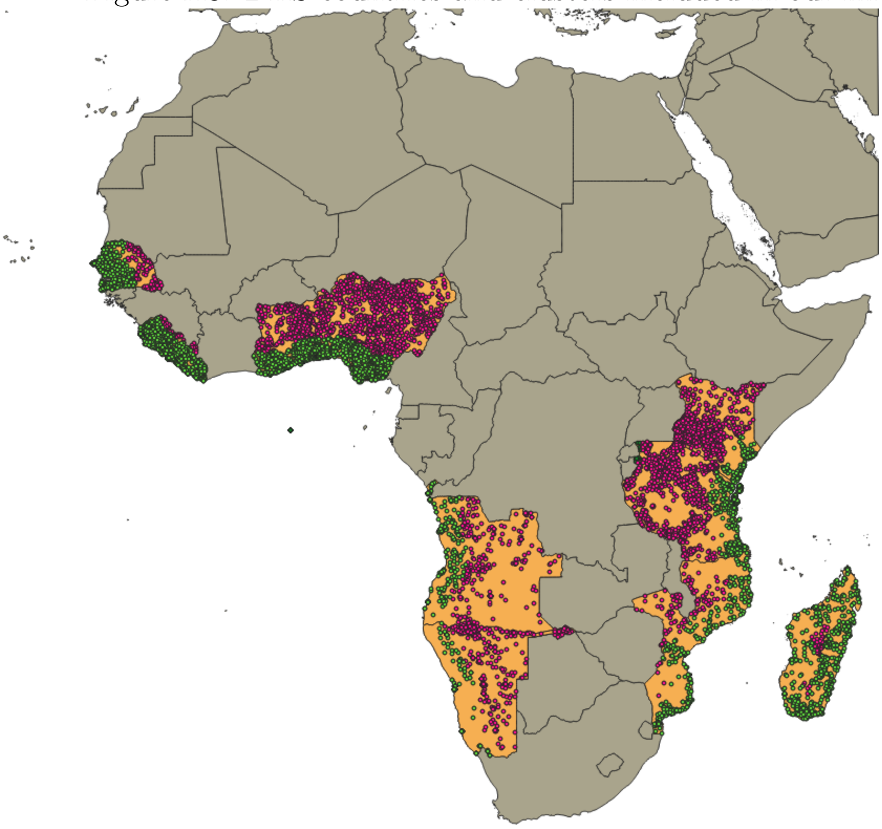
Figure A7: Difference-in-difference for the micro-level analysis



Note: This figure illustrates the difference-in-difference strategy implemented for the micro-level analysis. We calculate the closest access to the sea of each village and draw buffers around them. The industrial fishing efforts and the fishing conditions are aggregated within 24 NM or 36 NM around each village's closest access to the sea. We also control for built-up area and leaf area index around 20 km of each village.
Source: Authors' elaboration.

A.6 Empirical strategy

Figure A8: DHS countries and clusters included in our micro study



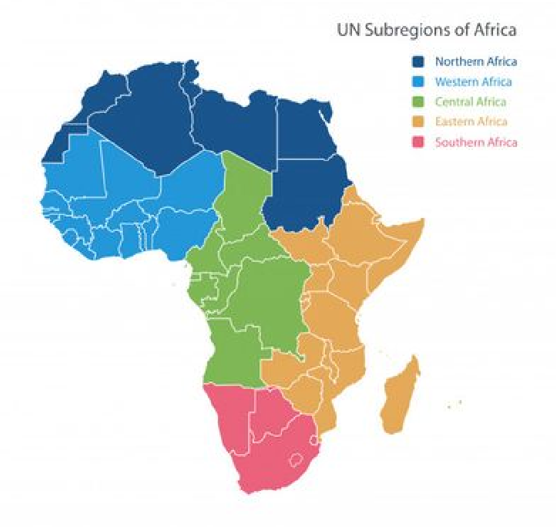
Note: This figure illustrates the DHS clusters included in our micro-analysis. Green dots correspond to coastal clusters located within 200 km of the ocean, and red dots to inland clusters living farther than 200 km from the ocean.
Source: Authors' elaboration using DHS data.

Figure A9: List of countries in OECD and Eurostat Data

OECD	Europe (Eurostat data)	Missing foreign flows from Africa (Eurostat)
Austria	Austria	Cyprus
Belgium	Belgium	France
Czech Republic	Czech Republic	Greece
Denmark	Denmark	Malta
Estonia	Estonia	Portugal
Finland	Finland	
France	France	
Germany	Germany	
Greece	Greece	
Hungary	Hungary	
Iceland	Iceland	
Italy	Italy	
Latvia	Latvia	
Lithuania	Lithuania	
Luxembourg	Luxembourg	
The Netherlands	The Netherlands	
Norway	Norway	
Poland	Poland	
Portugal	Portugal	
Slovak Republic	Slovak Republic	
Slovenia	Slovenia	
Spain	Spain	
Sweden	Sweden	
Switzerland	Switzerland	
United Kingdom	United Kingdom	
Australia	Bulgaria	
Canada	Croatia	
Chile	Cyprus	
Columbia	Liechtenstein	
Israel	Malta	
Japan	Romania	
Mexico	North Macedonia	
New Zealand	Montenegro	
Turkey		
United States		

Note: This table lists the countries belonging to the OECD and surveyed by Eurostat. Countries belonging to both are in light blue. Non-European OECD countries are in yellow, and non-OECD European countries are in dark blue.

Figure A10: African sub-regions as defined by the United Nations



A.7 Results

Table A6: Effects of future, current and past fishing activity on household size

Outcome	Household size			
Time of industrial fishing effort	t+1	t	t-1	t-2
Acreg	(1)	(2)	(3)	(4)
Sea[0; 25] × Ln(Ind.Fish)24 NM	-0.0123	-0.0545***	-0.0661***	-0.0697***
	[0.0204]	[0.0195]	[0.0227]	[0.0265]
Sea[25; 100] × Ln(Ind.Fish)24 NM	0.0597***	0.00131	0.00583	0.0572***
	[0.0158]	[0.0167]	[0.0188]	[0.0221]
Sea[100; 200]× Ln(Ind.Fish)24 NM	0.0321**	0.00275	0.0274	0.0538**
	[0.0144]	[0.0157]	[0.0189]	[0.0219]
Ln(Ind.Fish)24 NM	-0.0226**	-0.0271**	-0.0204	-0.0478**
	[0.00953]	[0.0133]	[0.0139]	[0.0217]
Sea[0; 25]	-0.735***	-0.650***	-0.687***	-0.551***
	[0.120]	[0.101]	[0.100]	[0.104]
Sea[25; 100]	-0.890***	-0.721***	-0.756***	-0.764***
	[0.0950]	[0.0892]	[0.0820]	[0.0962]
Sea[100; 200]	-0.883***	-0.761***	-0.851***	-0.811***
	[0.0784]	[0.0776]	[0.0724]	[0.0869]
Constant	5.536***	5.545***	5.495***	5.471***
	[0.136]	[0.135]	[0.134]	[0.147]
Country-Year FE	Yes	Yes	Yes	Yes
Fishing conditions	Yes	Yes	Yes	Yes
Built-up index	Yes	Yes	Yes	Yes
LAI controls	Yes	Yes	Yes	Yes
N	137,871	144,474	143,998	99,806

Notes: This table gives the results of estimation of equation 2 when using DHS household data and playing with the timing of industrial fishing effort within the 24 nm maritime zone of each nearest access to the sea. Reference is households located further than 200 km from the sea. Standard errors clustered at the DHS village level, $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.