UNIVERSITÉ PARIS I PANTHÉON-SORBONNE
École doctorale : ED 465 – Économie Panthéon-Sorbonne
UFR02 – Paris Jourdan Sciences Économiques

THÈSE
Pour l'obtention du grade de Docteur en Sciences Économiques
de l'Université Paris 1 Panthéon-Sorbonne

Présentée et soutenue publiquement le 10 mars 2023 par

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Trois essais sur l'exploitation industrielle des ressources naturelles en Afrique

Sous la direction de
Fabrice ÉTILÉ
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UNIVERSITÉ PARIS 1
PANTHÉON SORBONNE

PARIS SCHOOL OF ECONOMICS
ECOLE D'ECONOMIE DE PARIS

UNIVERSITÉ PARIS I PANTHÉON-SORBONNE
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Ph.D. Thesis

Submitted to Université Paris 1 Panthéon-Sorbonne
For the Degree of Doctor of Philosophy in Economics

Prepared and defended on March 10th, 2023

Irène HU

Three Essays on the Industrial Exploitation of Natural Resources in Africa

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Remerciements

Je tiens tout d'abord à remercier mes directeurs de thèse Fabrice Etilé et François Libois pour leur encadrement et leur soutien tout au long de ce travail. Le fruit de ces quatre années vous doit beaucoup. Merci Fabrice d'avoir accepté de superviser mes travaux, d'avoir fourni des relectures attentives et minutieuses, et de m'avoir constamment encouragée à mener à bien cette thèse. Merci surtout d'avoir été présent et infaillible aux moments cruciaux. Merci François pour ton suivi depuis le début de mon mémoire de master en 2016, d'avoir partagé ton enthousiasme pour la gestion des ressources naturelles et les données géolocalisées. Je suis particulièrement reconnaissante pour ta vision d'entreprendre la recherche en économie de manière pluridisciplinaire. Le papier co-écrit sur la pêche industrielle en Afrique restera un souvenir marquant de ma thèse. Je remercie également chaleureusement Thierry Verdier, qui m'a suivie lors de mes comités de thèse, et a su apporter de la hauteur à mes travaux, grâce à ses connaissances bien plus théoriques et structurelles. Merci d'avoir été ce troisième pilier dans ma thèse.

Je tiens à vivement remercier mes rapporteurs, Céline Nauges et Jérémy Laurent-Lucchetti, d'avoir lu et relu mes trois chapitres en détail. Je vous remercie pour vos commentaires lors de la pré-soutenance, et j'espère avoir pu être à la hauteur pour y répondre. Je remercie également chaleureusement Katrin Millock et Raphaël Soubeyran d'avoir accepté d'être membres de mon jury.

Un immense merci à ma binôme et co-auteure Mélanie, qui a su chaque jour me faire venir à PSE avec plaisir pour travailler ensemble. Merci pour ton allégresse, ton élan de vie et ta rigueur scientifique. Cette thèse n'aurait pas vu le bout sans toi, vraiment.

Ma profonde gratitude s'adresse à Toan et Nga. Merci Toan d'avoir été mon mentor depuis 2015, de m'avoir fait découvrir le bonheur de la recherche, pour vos conseils, vos critiques toujours exigeantes mais justes, votre déontologie et votre aide – quand il le fallait. My deepest thanks to Nga for making me discover another part of the analysis of poverty, which scope and pace have provided me with the best training – thank you for your patience, your constant support and your precious advice. I will be forever indebted and grateful to both of you.

Je suis énormément reconnaissante envers David, de toujours prendre de mes nouvelles et de me donner des conseils depuis près de dix ans, de m'avoir ouvert la porte des organisations internationales, et fait découvrir une expérience si riche qui n'a fait que se prolonger jusqu'à présent.

PSE a été un cadre extraordinaire pour faire une thèse. Je tiens à vivement remercier Sylvie Lambert, en tant que professeur de développement, mais aussi pour sa bienveillance, son écoute attentive et sincère, ses conseils et ses encouragements envers tous les doctorants. I am grateful to Sylvie Lambert, Karen Macours, Oliver Vanden Eynde and Liam Wren-Lewis for having fostered a family atmosphere within the development group. Je remercie Jérémie Gignoux, d'avoir encadré mon premier mémoire de statistiques appliquées et d'avoir guidé mes premiers pas en recherche. I would also like to thank Oliver Vanden Eynde for having been of precious advice, at the intersection of Political Economy and Development, for having been in my master's thesis jury and always conducting invaluable guidance. J'aimerais également particulièrement remercier Akiko Suwa-Eisenmann, Katheline Schubert, Hélène Ollivier, Lisa Chauvet, Ekaterina Zhuravskaya, Léa Marchal, Nathalie Ferrière, Anne-Célia Disdier ainsi que Denis Cogneau, Luc Behaghel, David Margolis, Pierre Bachas, Mouez Fodha, Hillel Rapoport, Lionel Fontagné et François Fontaine d'avoir conseillé, suivi, été présents et importants pendant ma thèse. Merci à Catherine Bobtcheff, d'avoir repris le flambeau et la responsabilité de la direction doctorale de PSE et d'avoir rendu possible cette soutenance. Je remercie Stéphane Brice et Radja Aroquiaradja, pour leur aide si précieuse en informatique – merci pour le serveur qui nous a sauvé bien des semaines de travail. Je remercie également Véronique Guillotin, Béatrice Havet, Ania Le Fur, Lucia-Roxana Ban, Monique-Alice Tixeront, Marie Font, Pauline Marmin, Sarah Dafer, Asaria Amador, Julia Piquemal, Matinou Moussa, Marie Philipon, Caroline Bauer, Carla Gomez ainsi que Sylvain Riffé-Stern, Alexandre Dekkil et Samuel Chich d'avoir soutenu si professionnellement la vie des chercheurs, des doctorants, et des étudiants, l'organisation des séminaires, le cycle des projets de recherche, de leur financement à leur mise en valeur. Merci à Valérie Labadie, côté CEPREMAP, de nous avoir dénoué avec une si grande efficacité l'achat des données minières. Je remercie également Christelle Gauvrit, Nathalie Louni et Mathieu Colin de l'ED465 pour leur réactivité et professionnalisme quant à la tenue de cette soutenance.

Le parcours de la thèse aurait été bien triste et solitaire sans les nombreux doctorants qui ont arpenté les murs et égayé les salles de classes, les couloirs et les bureaux. Je te remercie Ismaël – co-bureau attitré depuis Washington – pour ta joie de vivre, ton espérance magnanime, et ta profonde générosité. Merci Matt, mon grand-frère de PSE depuis le master, pour ton calme olympien, ta bonté et tes conseils bienveillants. Merci Normann, pour les découvertes et les aventures dans la recherche depuis Malakoff, pour ton humour grinçant et la révolte de ton esprit. Merci à mes deux compères Alexis et Étienne dont la vivacité, la curiosité, l'engagement et la joie communicative ont rafraîchi ces années studieuses. Merci également à Antonela, pour ton énergie et ton goût pour les spectacles, et à Sonia pour ce début et cette fin de thèse mémorables. Un grand merci à Andréa, Charlotte, Sarah S., Manon, Claire, Julieta, Kelsey, Paola M., Julia H., Anna, Marie, Louise, Lucile, Marion R., Caroline, Julia P., Vivien ainsi que Martin J., Victor, Léo R., Giacomo, Alvaro, Nitin, Zhexun, Sebastian, Christian, Eric, Dave et Casey. Je remercie également mes anciens, Marion et Paul, Maiting et Jonathan, Juni, Sarah D., Justine, Juliette, Martin F-S, Emanuela et Giulio d'avoir montré que l'on pouvait s'en sortir. Merci à mes prédecesseurs Yasmine B., Paul V., Paola V. et Léa R., qui ont su me montrer le chemin après l'ENSAE et partager leurs conseils et expériences. Merci à Emanuela, Antton et Cem de m'avoir aidé dans ma recherche d'emploi.

Je remercie mes anciens professeurs, Messieurs Crépon et d'Haultefœuille, de m'avoir donné les clés en économétrie et de nous avoir très tôt ouverts une fenêtre sur leur recherche passionnante. Je remercie mes anciens professeurs de lycée et de prépa en particulier Mesdames Augé, Lacourcelle et Stoliaroff, ainsi que Messieurs Balaresque et Chevalier.

Enfin, je dois cette thèse essentiellement à ma famille et ce manuscrit leur est dédié.

Résumé

Cette thèse rassemble trois chapitres indépendants qui visent à mettre en lumière les déterminants et les effets de l'exploitation industrielle des ressources naturelles. Chaque chapitre propose une analyse empirique pour décrire la situation contemporaine de la pêche industrielle, de l'industrie minière et des achats de terre à grande échelle en Afrique.

Le **premier chapitre**, intitulé *Man Overboard! Industrial Mining as a Driver of Migration Out of Africa*, et co-écrit avec François Libois, examine l'effet de la pêche industrielle sur la migration. Il combine une base de données géolocalisées sur le nombre d'heures de pêche menées par des navires industriels au large des côtes africaines entre 2012 et 2018 à des flux bilatéraux de migrations des pays Africains vers les pays de l'OCDE. La méthode consiste à estimer des équations de gravité tirées de modèles de maximisation d'utilité aléatoire (RUM). Les résultats montrent que la concurrence créée par les navires de pêche industrielle face à des pêcheurs artisanaux, ainsi que l'épuisement des réserves halieutiques qui en découle, conduit à une augmentation des flux de migrants vers les pays de l'OCDE et d'Europe. Toutefois, nous ne trouvons pas d'effets comparables pour les flux de réfugiés, ce qui conforte l'idée d'une migration économique. Nous obtenons des résultats cohérents au niveau micro-économique en étudiant les données d'enquêtes sur les ménages Demographic Health Survey (DHS). Nous observons une augmentation de la migration des jeunes membres des ménages en réponse à une augmentation de l'effort de pêche industrielle au large de leur village. Le mécanisme mis en avant est celui d'une pression et d'un choc négatif sur les revenus. Nous approximons ce dernier par une baisse de la consommation alimentaire chez les enfants en réponse à une augmentation de l'effort de pêche industrielle au large de leur village.

Le **deuxième chapitre** intitulé, *MiningLeaks: Water Pollution and Child Mortality in Africa*, est un travail co-écrit avec Mélanie Gittard. Nous y étudions les effets de la pollution de l'eau induite par l'exploitation minière industrielle sur la mortalité infantile en Afrique. A l'aide d'un travail personnel intensif où nous avons récupéré

les dates d'ouverture de plus de 1700 sites miniers, nous avons créé un ensemble de données inédit sur la temporalité de l'activité minière industrielle en Afrique, qui vient compléter les informations de localisation initiales. L'estimation combine ces informations minières avec les données d'enquêtes sur les ménages DHS, qui fournissent des informations de santé au niveau individuel de 1986 à 2018 à travers 26 pays Africains. La stratégie de différence de différence appliquée, consiste à exploiter la variation de la date d'ouverture des mines et la position topographique des villages environnants relativement à la mine. La pollution de l'eau induite est analysée indirectement, car nous comparons les effets sur la santé des villages en aval à ceux en amont du site minier, avant et après son ouverture. Les résultats montrent que vivre en aval d'une mine qui a ouvert augmente la probabilité de mourir dans les 24 premiers mois de 25%, en comparaison aux enfants vivant en amont. Nous constatons une augmentation de la mortalité lors des 12 premiers mois uniquement pour les enfants qui n'ont pas été exclusivement allaités et qui avaient consommé de l'eau, ce qui corrobore le mécanisme de la pollution de l'eau. Pour exclure d'autres mécanismes potentiels, nous montrons que l'effet sur cette augmentation de la mortalité n'est lié ni à un changement de fécondité des femmes, ni à l'amélioration d'infrastructures publiques ou privées, et enfin ni à l'afflux de main d'œuvre.

Le **troisième chapitre**, intitulé *Raw Materials Diplomacy, Official Development Finance and the Industrial Exploitation of Natural Resources in Africa*, étudie la relation entre les flux financiers officiels de développement et l'exploitation industrielle des ressources naturelles en Afrique. Ce travail descriptif s'interroge sur l'influence que peuvent avoir l'aide et les prêts que les pays donateurs concèdent à des pays receveurs, sur leur capacité à y extraire des ressources naturelles. Un modèle en parts est appliqué à, d'un côté, des données bilatérales de flux financiers des pays du Comité d'aide au développement (CAD) de l'OCDE, de la Chine et de l'Inde, et, de l'autre côté, à des acquisitions de terres à grande échelle par des investisseurs transnationaux en Afrique. Le chapitre établit la corrélation positive entre l'influence financière acquise par les pays donateurs et la capacité pour leurs investisseurs de mener à bien un achat de terre dans le pays receveur. L'étude expose également un effet de complémentarité entre les flux financiers des Etats-Unis et du Royaume-Uni auprès des investisseurs des pays du CAD, un effet de substitution entre les flux chinois et indiens auprès des investisseurs CAD, et vice-versa. Un exercice de réplication est entrepris pour les cas de l'exploitation industrielle des ressources halieutiques et minières, et une longue discussion est menée pour ouvrir la voie à de futurs travaux.

MOTS-CLEFS : Ressources naturelles ; pêche industrielle ; industrie minière ; achats de terre à grande échelle ; Afrique ; migrations ; pollution de l'eau ; flux financiers officiels de développement.

Summary

This dissertation aims at shedding light on the determinants and the consequences of the industrial exploitation of natural resources in the context of contemporary Africa in three following chapters.

The **first chapter**, *Man Overboard! Industrial Fishing as Driver of Migration out of Africa*, co-authored with François Libois, studies the relationship between overfishing and human migration in Africa. We combine novel geocoded data on industrial fishing which covers the period from 2012 to 2018 to bilateral migration flows towards the OECD countries. Using gravity equations derived from Random Utility Maximisation (RUM) models, we find strong evidence that the competition which is created by industrial fishing vessels that overfish the African seas and deplete fish stocks, increases the flow of foreign population to OECD countries. We do not find similar effects in relation to refugees, which comforts the story of economic migration only. Furthermore, using the household-level Demographic and Health Surveys (DHS) for 13 countries, we show that the macro-level findings are consistent in terms of mechanisms. We find evidence of an out-migration of young individuals from rural and coastal households in response to an increase of industrial fishing close to their homes.

The **second chapter**, *MiningLeaks: Water Pollution and Child Mortality in Africa*, co-authored with Mélanie Gittard, analyses the effects of mining-induced water pollution on child mortality in Africa. Using a unique dataset (retrieved by intensive hand work) on the location and timing of the industrial mining activity in Africa, this paper combines the geo-coded information on 2,016 mines with the DHS micro-data, which contains information about health outcomes for children from 1986 to 2018 across 26 countries. Through a staggered difference-in-difference strategy, we exploit the variation that lies in the mines' opening dates, as well as in the relative topographic position of the surrounding DHS villages. We study water pollution indirectly as we compare the health outcomes of downstream villages downstream

to those that are located upstream of a mining site before and after its opening. Compared to upstream individuals, our analysis finds that being downstream of an open mine increases the 24-month mortality rate by 25%. We find an increase in the 12-month child mortality only for those children that were not exclusively breastfed and consumed plain water, which corroborates the mechanism of water pollution. To exclude other mechanisms, we show that the effect is not driven either by a change in women's fertility, by improved facilities, or by the in-migration of the labor force.

The **third chapter**, *Raw Materials Diplomacy, Official development Finance and the Industrial Exploitation of Natural Resources in Africa*, investigates how aid and credits from traditional and emerging donor countries influence their capacity to exploit natural resources in Africa over the 2000-2014 period. This chapter uses share models to conduct extensive descriptive work that combines panel data on the bilateral development flows from OECD countries, China and India on the one side and novel data on large-scale land acquisitions on the other side. Results suggest that the official development flows from DAC and non-DAC countries are positively correlated with their capacity to conclude large-scale land acquisitions. Furthermore, results show that a donor's official development flows affect the influence of other donors on their capacity to conclude land deals. More precisely, the financial flows from the USA and the UK complement the activity of other DAC land investors, while China's and India's financial flows substitute DAC flows and reduce their investors' capacity to conclude land deals. Additionally, a replication exercise is attempted to compare these findings in the settings of industrial fishing and industrial mining. This chapter concludes with a long discussion that suggests an avenue for future work.

KEYWORDS: Natural Resources; Industrial Fishing; Industrial Mining; Large-Scale Land Acquisitions; Africa; Migration; Water Pollution; Official Development Finance.

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Introduction générale

Ce manuscrit s'articule autour de trois chapitres indépendants, qui ont chacun pour vocation à analyser sous un jour nouveau la "malédiction des ressources naturelles". Les trois chapitres étudient les déterminants et les conséquences de l'exploitation industrielle et à grande échelle des ressources naturelles africaines. Chaque chapitre traite principalement d'un type de ressources naturelles : les ressources halieutiques, les ressources minières et les terres. La pêche et l'exploitation des terres sont d'une importance cruciale pour la subsistance des populations locales, tandis que l'importance des mines ne fera que s'accroître pour répondre à la demande mondiale en minerais dans le contexte de la transition écologique et de la production d'énergie renouvelable (par exemple, panneaux solaires et batteries).

Nous avons choisi de concentrer ce travail sur l'Afrique, en premier lieu en raison de la richesse de ce continent en ressources naturelles. On estime que 65% des terres arables mondiales non cultivées se trouvent en Afrique (AFDB, 2019), ainsi que 30% des réserves minières mondiales, tandis que la pêche réalisée dans les eaux africaines représentait 8,4% des captures en mer mondiales en 2020 [1]. C'est aussi le continent comptant le plus grand nombre d'acquisitions de terres à grande échelle par des acteurs étrangers avec 900 transactions entre 2000 et 2014 (Lay et al., 2021). Enfin le continent a connu un pic minier en lien avec l'augmentation des prix internationaux des matières premières, avec l'ouverture de plus de 871 mines industrielles entre 2000 et 2014, d'après les données SNL Mining and Metals, et le travail à la main entrepris pour les Chapitres 2 et 3.

Les régulations appliquées dépendent du type de ressource naturelle. Les ressources halieutiques sont des ressources communes, libres d'accès dans les eaux internationales,

[1] Estimation réalisée avec l'appication FishstatJ de la FAO, disponible en ligne : `https://www.fao.org/fishery/en/statistics/software/fishstatj/en`. Critère de sélection utilisé : nombre de capture de pêche sauvage dans les eaux territoriales des pays Africains rapporté au nombre de captures mondiales. Cette proportion est très vraisemblablement sous-estimée car le continent est sujet aux plus hauts niveaux mondiaux de pêche illégale, non déclarée ou non régulée (Cabral et al., 2018)

au-delà des zones économiques exclusives (ZEE) et dont l'accès est régulé dans les ZEE conformément à la convention des Nations Unies sur le droit de la mer de 1982. La pêche industrielle est interdite le long des côtes, sur une distance variant de 0 à 24 miles nautiques (NM), cette distance étant de 12 NM pour la grande majorité des pays africains (Belhabib et al., 2020). Les ressources minières sont des ressources non renouvelables qui sont soumises à une régulation plus forte avec la nécessité d'obtenir une concession pour l'exploration et l'exploitation d'un gisement. Cependant tous les acteurs ne respectent pas le cadre légal et l'Initiative pour la Transparence dans les Industries Extractives, signée par 26 des 54 pays africains, vise à améliorer la gouvernance des industries extractives. Enfin les terres sont une ressource renouvelable soumise à différentes régulations dépendant des régimes fonciers. Ces derniers varient de façon importante, de la propriété privée des terres à leur gestion communautaire et à une propriété étatique. Différents acteurs sont donc impliqués dans les processus de décision pour conclure une transaction, des individus privés aux politiciens nationaux, en passant par des chefs communautaires. Les trois chapitres analysent des données empiriques couvrant le début du $21^{ème}$ siècle et ont pour but de contribuer à la réflexion sur l'amélioration de la gestion des ressources naturelles dans un environnement où les capacités de contrôle, l'application des lois et le respect des droits de propriété sont largement imparfaits. L'essence de cette thèse est de mieux comprendre comment une réduction des externalités négatives de l'exploitation des ressources naturelles peut améliorer les conditions de vie des populations locales. Une meilleure gestion de cette exploitation préserverait non seulement l'environnement et la biodiversité, ce qui est déjà un objectif en soi, mais contribuerait également à la protection des populations dont la subsistance dépend directement de ces ressources. Les trois chapitres traitent d'impacts directs de l'activité humaine dont l'amélioration semble plus atteignable à court terme que de régler les problèmes très larges engendrés par le changement climatique.

Cette thèse fournit directement des analyses sur la manière d'atteindre quatre des cibles des Objectifs de Développement Durable de l'Agenda 2030. Le Chapitre 1 concerne (*Objectif 14 sur la conservation et l'usage durable des océans*) la cible 14.4 "*[...] réglementer efficacement la pêche, mettre un terme à la surpêche, à la pêche illicite*" et la cible 14.b "*Garantir aux petits pêcheurs l'accès aux ressources marines et aux marchés*". Le Chapitre 2 est relatif (*Objectif 6 sur l'eau propre et l'assainissement*) à la cible 6.3 : "*améliorer la qualité de l'eau en réduisant la pollution, en éliminant l'immersion de déchets et en réduisant au minimum les émissions de produits chimiques et de matières dangereuses*". Enfin les trois chapitres visent à atteindre (*Objectif 12 sur l'établissement de modes de consommation et* *de production durable*) la cible 12.2 “[...] *parvenir à une gestion durable et à une utilisation rationnelle des ressources naturelles*“.

La “malédiction des ressources naturelles”

La “malédiction des ressources naturelles” a fait l’objet de nombreuses explications théoriques et évaluations empiriques. Jusqu’à aujourd’hui la littérature est concordante sur la complexité de l’interrelation entre la qualité des institutions politiques et l’extraction des ressources naturelles (van der Ploeg, 2011). Au niveau macroéconomique, la “maladie hollandaise” désigne la situation d’un pays qui, découvrant et extrayant des ressources naturelles, pas seulement les trois ressources mentionnées plus haut mais également le pétrole et le gaz, bénéficie d’une augmentation de son revenu accompagnée d’une demande et d’une consommation croissantes. La pression inflationniste mène souvent à une appréciation du taux de change réel qui peut avoir un impact négatif sur les exportations et peut à terme mener à une désindustrialisation (Sachs and Warner, 1997). De plus apparaît souvent une dépendance entre les recettes et dépenses de l’État et les prix des matières premières, caractérisés par une forte volatilité. Plusieurs mécanismes peuvent expliquer les effets pernicieux des flux financiers correspondant à la rente des ressources naturelles. Cela peut d’abord réduire les investissements dans d’autres secteurs d’activité et fausser la vision d’un développement à long terme (Djankov, Montalvo, and Reynal-Querol, 2008). Cela peut éalement être associé à des institutions politiques et économiques affaiblies, dans lesquelles le gouvernement peut éviter de rendre des comptes à ses citoyens et contribuables (Ross, 2001). D’autre part, les leaders politiques peuvent être tentés par des décisions à court terme et adopter des comportement motivés par l’accaparement des rentes et la corruption (Leite and Weidmann, 2002). Enfin le manque d’incitation à développer un système fiscal efficace pour assurer des recettes à l’État peut entraver la croissance économique. Au niveau microéconomique, les populations vivant dans le voisinage d’un site d’exploitation de ressources naturelles peuvent bénéficier du développement industriel local, de l’augmentation de la demande de main d’oeuvre, de l’augmentation de la consommation et de la demande pour les autres secteurs (commerce, agriculture), de l’amélioration de l’accès aux installations et infrastructures publiques comme les hôpitaux, les routes, les connexions au réseau électrique (Kotsadam and Tolonen, 2016; Mamo, Bhattacharyya, and Moradi, 2019). Cependant ces effets d’opportunité peuvent également générer de nombreuses externalités négatives : corruption, violence, voire guerres civiles peuvent surgir pour s’approprier la rente des ressources naturelles (Collier and Hoeffler, 2004;

Berman et al., 2017; Benshaul-Tolonen, 2018; Fourati, Girard, and Laurent-Lucchetti, 2021), l'afflux de main d'oeuvre extérieure peut être associé à de l'insécurité et à la propagation de maladies s'il n'est pas géré de façon adéquate (Corno and Walque, 2012; Atkin, 2016; Aragón and Rud, 2016), et les populations peuvent êtres exposées à une pollution accrue de l'air, de l'eau ou des sols, en fonction du type de ressources naturelles et de la méthode d'exploitation.

Cette thèse s'articule autour de trois chapitres qui ont tous le continent Africain pour cadre. Les Chapitres 1 et 2 étudient les externalités négatives associés à la pêche industrielle et à l'industrie minière. Le Chapitre 1 s'intéresse aux effects de la concurrence créée par les navires de pêche industrielle sur les pêcheurs artisanaux, et s'attache à montrer les conséquences néfastes engendrées sur ces populations locales dont la pêche représente une activité de subsistance. Le Chapitre 2 étudie les effets néfastes de l'extraction industrielle des minerais sur la santé des populations avoisinantes, et en particulier sur la mortalité infantile, et met en exergue le mécanisme de la pollution de l'eau. Enfin, le Chapitre 3 fournit des éléments de preuve de l'existence d'une diplomatie des matières premières, menée par les pays donateurs qui fournissent des financements officiels afin de se garantir un accès à des achats de terres.

Contributions par chapitre

Le premier chapitre, intitulé *Man Overboard! Industrial Fishing as a Driver of Migration out of Africa* et co-écrit avec François Libois, examine l'effet de la pêche industrielle sur la migration. Au niveau macro-économique, les résultats montrent une augmentation des flux de migrants des pays littoraux d'Afrique vers les pays de l'OCDE et d'Europe en réponse à une augmentation de l'effort de pêche industrielle le long de leurs côtes. Aucun effet semblable ne ressort pour les flux de réfugiés, ce qui conforte l'idée d'une migration principalement de nature économique. Au niveau microéconomique, les résultats de notre analyse mettent en évidence une augmentation de la migration des jeunes membres des ménages, en réponse à une augmentation de l'effort de pêche industrielle au large de leur village. Le mécanisme mis en avant est celui d'une pression et d'un choc négatif sur les revenus. Nous approximons ce dernier par une analyse de la baisse de la consommation alimentaire chez les enfants de moins de cinq ans, en réponse à une plus forte activité de pêche industrielle au large de leur village. La première contribution de ce chapitre est tout d'abord de quantifier la réponse migratoire induite par la pêche industrielle : une augmentation de 10 % de la pêche industrielle au large de 36 miles nautiques des côtes d'un pays Africain, conduit à une augmentation de 0.37% des flux de migrants vers les pays de l'OCDE. Notre étude met l'accent sur l'importance de la régulation des ressources marines dans les pays en voie de développement, non pas seulement pour préserver les ressources et protéger les populations locales, mais également en raison de l'impact migratoire vers les pays mêmes qui pêchent dans ces eaux. La seconde contribution de ce chapitre est de constituer une base de données inédite sur l'activité de pêche industrielle pour en évaluer les impacts socio-économiques sur les ménages côtiers.

Le **deuxième chapitre** intitulé, *MiningLeaks: Water Pollution and Child Mortality in Africa*, est un travail co-écrit avec Mélanie Gittard. Il etudie les effets de la pollution de l'eau induite par l'exploitation minière industrielle sur la mortalité infantile en Afrique. Depuis les années 2000, l'augmentation des prix des matières premières a intensifié l'activité minière industrielle, en particulier en Afrique qui fait face à un boom minier attirant de nombreux investisseurs étrangers. Les personnes résidant au voisinage des mines industrielles sont exposées à de fortes concentrations de métaux lourds libérés lors des processus d'extraction du minerai. Séparer les minéraux d'importants volumes de roches génère des déchets oxydés, qui, stockés dans des bassins de rétention, peuvent s'écouler dans l'environnement proche et contaminer les ressources en eau. Cet article utilise un ensemble de données unique sur la localisation et la temporalité de l'activité minière industrielle en Afrique, grâce à un travail à la main intensif destiné à récupérer les dates d'ouverture. Notre estimation combine des informations géocodées sur 2016 mines avec les micro-donnéess d'enquêtes Demographic Health Survey (DHS), qui fournissent des informations de santé au niveau individuel de 1986 à 2018 à travers 26 pays Africains. Utilisant une stratégie de différence de différence, nous exploitons la variation de la date d'ouverture des mines et la position topographique relative des villages DHS environnants. La pollution de l'eau induite est examinée indirectement, car nous comparons les effets sur la santé des villages en aval à ceux en amont du site minier, avant et après son ouverture. Les résultats montrent que vivre en aval d'une mine qui a ouvert augmente la probabilité de mourir dans les 24 premiers mois de 25%, en comparaison aux enfants vivant en amont. Nous constatons une augmentation de la mortalité à 12 mois uniquement pour les enfants non exclusivement allaités et ayant consommé de l'eau, ce qui corrobore le mécanisme de pollution de l'eau. Pour exclure d'autres mécanismes potentiels, nous montrons que l'effet sur cette augmentation de la mortalité n'est lié ni à un changement de fécondité des femmes, ni à l'amélioration d'infrastructures publiques ou privées, et enfin ni à l'afflux de main d'œuvre.

Le **troisième chapitre**, intitulé *aw Materials Diplomacy, Official Development Finance and the Industrial Exploitation of Natural Resources in Africa*, étudie la compétition des pays donateurs pour se garantir l'accès à des ressources naturelles en Afrique. Il s'intéresse en particulier à la relation entre les flux financiers officiels de développement et les acquisitions de terres à grande échelle. Ce travail descriptif s'interroge sur l'influence que peuvent avoir l'aide et les prêts que les pays donateurs concèdent à des pays receveurs, sur leur capacité à y extraire des ressources naturelles. Un modèle en parts est appliqué à d'un côté des données bilatérales en panel de flux financiers des pays du Comité d'aide au développement (CAD) de l'OCDE, de la Chine et de l'Inde, et de l'autre côté à des acquisitions à grande échelle de terres par des investisseurs transnationaux en Afrique. Le chapitre établit la corrélation positive entre l'influence financière acquise par les pays donateurs et la capacité pour leurs investisseurs à mener à bien un achat de terre dans le pays receveur. L'étude expose également un effet de complémentarité entre les flux financiers des Etats-Unis et du Royaume-Uni auprès des investisseurs de pays du CAD, un effet de substitution entre les flux chinois et indiens auprès des investisseurs CAD, et vice-versa. Un exercice de réplication est entrepris pour les cas de l'exploitation industrielle des ressources halieutiques et minières, et une longue discussion est menée pour ouvrir la voie à de futurs travaux.

Bibliography

AFDB (2019). *Feed Africa.* Tech. rep. African Development Bank Group.

Aragón, Fernando M. and Juan Pablo Rud (2016). "Polluting Industries and Agricultural Productivity: Evidence from Mining in Ghana". In: *The Economic Journal* 126.597, pp. 1980–2011.

Atkin, David (2016). "Endogenous Skill Acquisition and Export Manufacturing in Mexico". In: *American Economic Review* 106.8, pp. 2046–85.

Belhabib, Dyhia et al. (2020). "Catching industrial fishing incursions into inshore waters of Africa from space". In: *Fish and Fisheries* 21.2, pp. 379–392.

Benshaul-Tolonen, Anja (2018). "Local Industrial Shocks and Infant Mortality". In: *The Economic Journal* 129.620, pp. 1561–1592.

Berman, Nicolas et al. (2017). "This Mine Is Mine! How Minerals Fuel Conflicts in Africa". In: *American Economic Review* 107.6, pp. 1564–1610.

Cabral, Reniel B et al. (2018). "Rapid and lasting gains from solving illegal fishing". In: *Nature Ecology and Evolution* (2), pp. 650–658.

Collier, Paul and Anke Hoeffler (2004). "Greed and Grievance in Civil War". In: *Oxford Economic Papers* 56.4, pp. 563–595.

Corno, Lucia and Damien de Walque (Feb. 2012). "Mines, migration and HIV/AIDS in southern Africa". In: *Journal of African Economies* 21.

Djankov, Simeon, Jose G. Montalvo, and Marta Reynal-Querol (2008). "The curse of aid". In: *Journal of Economic Growth* 13.3, pp. 169–194.

Fourati, Maleke, Victoire Girard, and Jérémy Laurent-Lucchetti (2021). *Sexual violence as a weapon of war.* Tech. rep. Universidade Nova de Lisboa, Nova School of Business and Economics, NOVAFRICA.

Kotsadam, Andreas and Anja Tolonen (2016). "African Mining, Gender, and Local Employment". In: *World Development* 83.C, pp. 325–339.

Lay, Jann et al. (2021). *Taking stock of the global land rush: Fewdevelopment benefits, many human and environmental risks. Analytical Report III.* Tech. rep. Bern, Montpellier, Hamburg, Pretoria: Centre for Development, Environment,University of Bern; Centre de coopération internationale en recherche agronomiquepour le développement; German Institute for Global, and Area Studies; University of Pretoria; Bern Open Publishing.

Leite, Carlos and Jens Weidmann (2002). "Does mother nature corrupt? : Natural resources, corruption, and economic growth". In: *Governance, corruption, and economic performance. - Washington, DC : International Monetary Fund.*

Mamo, Nemera, Sambit Bhattacharyya, and Alexander Moradi (2019). "Intensive and extensive margins of mining and development: Evidence from Sub-Saharan Africa". In: *Journal of Development Economics* 139, pp. 28–49.

Ross, Michael L. (2001). "Does Oil Hinder Democracy?" In: *World Politics* 53.3, pp. 325–361.

Sachs, Jeffrey D and Andrew Warner (1997). "Sources of Slow Growth in African Economies". In: *Journal of African Economies* 6.3, pp. 335–76.

van der Ploeg, Frederick (2011). "Natural Resources: Curse or Blessing?" In: *Journal of Economic Literature* 49.2, pp. 366–420.

General introduction

Overview

This dissertation is composed of three independent chapters, that each lay their motivation in shedding some new light on the "natural resource curse". The three chapters study the determinants and consequences of the industrial and large-scale exploitation of natural resources in Africa. Each chapter mainly covers one type of natural resources: fisheries, mines and land. Fisheries and land are key to ensure the local subsistence of livelihoods, and the role of mines will only become more and more significant, to answer the global demand for basic minerals but most of all with the green transition and the thriving demand for minerals to produce the corresponding renewable energy technologies.

Our focus on Africa first roots its choice in the richness of the endowed natural resources. The continent is estimated to hold 65% of the world's uncultivated arable land (AFDB, 2019), 30% of the global mineral reserves (Chuhan-Pole, Dabalen, and Land, 2017), and contributed to 8.4% of the total sea catch worldwide in 2020.[2]. It is also the continent subject to the highest number of transnational large-scale land acquisitions with 900 deals from 2000 to 2014 (Lay et al., 2021). Finally, the continent has been facing a mining boom with the increase of international commodity prices, with more than 871 industrial mines that opened between 2000 and 2014 (SNL Mining and Metals and handwork undertaken for Chapters 2 and 3).

Each type of natural resource is subject to different regulations. Fisheries are common-pool resources, in open access in the high seas, i.e. beyond the Exclusive Economic Zones (EEZ), and where the access is regulated within the EEZ under the 1982 United Nations Convention on the Law of the Sea. Industrial fishing is

[2]Estimation using FAO's application FishstatJ, available at https://www.fao.org/fishery/en/statistics/software/fishstatj/en. Selection criteria used: wild fish catch among the maritime seas of all the African countries, and at the global level. This figure is most likely an underestimation as the continent is subject to the highest levels of Illegal, Unreported, or Unregulated (IUU) fishing on the global scale (Cabral et al., 2018)

prohibited within an inshore distance that varies from the coast to 24 nautical miles (NM) off, with the vast majority of African countries being within 12 NM (Belhabib et al., 2020). Mines are non-renewable resources that are subject to stricter regulation with a need for a license to explore and extract a concession. Yet, the legal framework is not respected by all actors and the Extractive Industries Transparency Initiative signed by 26 out of the 54 countries aims at improving the governance of their extractive activities. At last, land is a renewable resource that can be subject to different regulations according to the Land tenure regime system. The latter varies widely, from private land to community management land, and finally state land. The decision to conclude a deal will therefore involve different stakeholders, from individuals to community leaders and state politicians respectively.

The three chapters analyse empirical data from the 21^{st} century, and have been conducted to bring some hindsight on how to improve the contemporary management of natural resources in a setting where monitoring capacities, law enforcement, and respect of property rights are not perfect. The essence of this thesis is to better understand how local livelihoods can be improved by alleviating the negative externalities associated with the exploitation of natural resources. Better management would not only preserve the environment and biodiversity per se but also contribute to protecting the populations that directly rely on them for subsistence. The three chapters deal with man-made direct activities (fisheries and mining), and their improvement seems more reachable in the short term than tackling wider climate change-related issues.

The current thesis directly provides hindsight on how to reach four targets of the 2030 Sustainable Development Goals. Chapter 1 deals with *(SDG 14 on the conservation and sustainable use of the oceans) Target 14.4. "[...]regulate harvesting, end overfishing, illegal, unreported and unregulated fishing"* and *Target 14. b "[...] provide access for small-scale artisanal fishers to marine resources and markets"*. Chapter 2 deals with *(SDG 6 on Clean water and sanitation) Target 6.3: "improve water quality by reducing pollution, eliminating dumping and minimizing release of hazardous chemicals and materials.* Finally, all three chapters aim at reaching *(SDG 12 on ensuring sustainable consumption and production patterns) Target 12.2 "[...] achieve the sustainable management and efficient use of natural resources.*

The "natural resource curse"

The "natural resources curse" has been subject to many theoretical explanations and empirical tests. The literature has so far agreed on the complexity of the interplay between the quality of political institutions and the extraction of natural resources (van der Ploeg, 2011). At the national level, the "Dutch disease" qualifies the situation when a country discovering and extracting natural resources, not only the aforementioned resources but also oil and gas, encounters a high increase in income, accompanied by growing demand and consumption. The inflationary pressure often leads to an appreciation of the real exchange rate that can negatively impact exportations and can trigger de-industrialisation (Sachs and Warner, 1997). Moreover, government revenues and spending are often becoming dependent on commodity prices, characterized by high volatility. Several mechanisms can explain the detrimental consequences of the inflows of natural resources rent. First, it can reduce the investment in other production sectors and blur the vision of long-term development (Djankov, Montalvo, and Reynal-Querol, 2008). It can be associated with weakened political and economic institutions, as the government can afford not to be accountable to its citizens and taxpayers (Ross, 2001). Second, political leaders can also be tempted by short-term decisions, rent-seeking behaviors, and corruption (Leite and Weidmann, 2002). Third, the lack of incentive to develop an efficient fiscal system to generate government revenues can hamper economic growth. At the micro-level, populations living in the vicinity of an extractive site may benefit from local industrial development, the increased demand for labor, increasing consumption and demand for the non-resource sector (trade, agriculture), improved access to facilities and public infrastructures such as health centers, roads, connection to the electricity grid (Kotsadam and Tolonen, 2016; Mamo, Bhattacharyya, and Moradi, 2019). Yet, many negative externalities can also be generated by these opportunity effects: corruption and violence or civil conflicts may emerge to seek the rents derived from natural resources (Collier and Hoeffler, 2004; Berman et al., 2017; Benshaul-Tolonen, 2018; Fourati, Girard, and Laurent-Lucchetti, 2021), the inflow of labor force from the outside can be associated with insecurity and the spread of diseases if not managed adequately (Corno and Walque, 2012; Atkin, 2016; Aragón and Rud, 2016), and increased exposure to air, water or soil pollution, depending on the type of natural resource and the extraction method.

This dissertation is organized around three chapters that all have Africa as a setting. Chapters 1 and 2 study the negative externalities associated with industrial fishing and industrial mining. In particular, Chapter 1 looks at the effects of industrial fishing that competes with artisanal and small-scale fisheries and negatively affects local livelihoods that are dependent on this activity for its subsistence. Chapter 2 studies the detrimental effects of industrial mining on child mortality in surrounding villages and puts forward the mechanism of water pollution. Finally, Chapter 3 provides suggestive evidence of the existence of Raw materials diplomacy conducted by countries sending official finance flows to secure an access to land.

Contributions by chapter

Chapter 1, *Man Overboard! Industrial Fishing as a Driver of Migration out of Africa* and co-authored with François Libois, studies industrial fishing off the African coastline and migration at two main levels of analysis: international migration flows to OECD countries and emigration from coastal areas. 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 population movements from this country to OECD and European 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 pursue our analysis at the micro level, restricting our analysis to 13 Subsaharan countries. We show that 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 members. We finally provide some consistent evidence of a negative income shock, as we find a reduction in the food consumption of under five children.

Our contribution is twofold. On one side, we quantify the migratory response induced by industrial fishing: a 10% increase in industrial fishing within 36 nautical miles from 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. 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.

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 of collecting information about small-scale fishermen, our reduced form approach provides a first 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 and migrations.

Chapter 2, *MiningLeaks: Water Pollution and Child Mortality in Africa*, co-authored with Mélanie Gittard, looks at the adverse impacts of water pollution on local populations' health. Its main contribution is to nuance the results from the literature, which finds beneficial effects of industrial mining on health, and to give large-scale and indirect evidence of the effects of water pollution. In this paper, by creating a unique dataset and implementing a topographic comparison, we shed light on a natural resource curse. We give insights on the order of magnitude of mining-induced water pollution on child mortality at the scale of the African continent. Since 2000, Africa is facing a mining boom. The health-wealth trade-off of industrial mining activity has been intensively studied in the literature (Mamo, Bhattacharyya, and Moradi, 2019; Aragón and Rud, 2016; Dietler et al., 2021; Berman et al., 2017; Benshaul-Tolonen, 2018). However, few papers focus on the negative externalities that mining activity might create on the environment (Bialetti et al., 2018; Von der Goltz and Barnwal, 2019). In particular, not much has been analyzed and quantified in terms of water pollution, and there is no order of magnitude on the number of individuals it might affect at a continent-level scale. Yet, the ore extraction processes release toxic metals and pollutants prone to contaminate surrounding water sources, including arsenic, cadmium, copper, lead, mercury, and nickel. In this paper, we build a novel database on the location and opening dates of an African industrial mining site from the SNL Mining and Metals database. We retrieved information on the start of production by hand from companies' activity reports and satellite images. We match 2016 industrial mines to the Demographic Health Survey (DHS) over 26 African countries. We conduct a staggered difference-in-difference strategy, comparing the health outcomes of individuals living upstream to those living downstream the mine, before and after its opening. We indirectly isolate the mechanism of water pollution by building the treatment and control groups using an upstream-downstream comparison. Results show that living downstream of a mine that has opened increases the likelihood of dying before 24 months by 25%. The 12-month mortality rate increases only for children non-exclusively breastfed and who consume plain water, which corroborates the fact that the results are driven by water pollution. The adverse effect is particularly severe during mining activity, production peaks, and in the vicinity of mines, as it fades out with distance. Heterogeneity analysis shows that adverse effects are higher for open-pit mines, in line with an intensive extractive process, and foreign-owned only mines. We show that neither changes in women's fertility nor, increased access to better infrastructure nor migration flows drive the results. In this paper, by creating a unique dataset and implementing a topographic comparison, we shed light on a natural resource curse. We give insights on the order of magnitude of mining-induced water pollution on child mortality at the scale of the African continent.

Chapter 3, *Raw Materials Diplomacy, Official Development Finance and the Industrial Exploitation of Natural Resources in Africa* investigates how aid or credits from traditional and emerging donor countries influence their capacity to exploit natural resources in Africa over the 2000-2014 period. The first contribution consists in building a new dataset that combines yearly bilateral official finance flows with three datasets on large-scale land acquisitions, industrial mining, and industrial fishing at the scale of the African continent from 2000 to 2014. This dataset identifies the origin of the companies conducting these natural resources activities and matches them with each OECD-DAC country, China and India.

The second contribution is to provide an in-depth descriptive analysis and comparison of the raw materials diplomacy and competition between DAC and non-DAC donors that has been so far lacking in the economics literature. Using share-model regressions, this paper analyses the association between bilateral official development finance flows of donor countries and their natural extraction activities within a recipient country. In the first step, I find a positive and significant correlation between the share of cumulative official finance flows from donor countries within the recipient country the previous year, and the share of the cumulative number of land deals conducted by an investor from the donor country. An increase of 1 percent of a donor's share of cumulative official financial flows is associated with an increase of 0.067 p.p. [3] of the share of land deals in the recipient country. I find a stronger correlation among OECD-DAC donors, even when introducing donor, recipient, and year-fixed effects, and controlling for many factors among which past colonial or dependency relationships. I find strong heterogeneity among DAC and non-DAC donors across recipient countries' property rights levels. This association is higher among DAC donors in countries with high property rights index and on the contrary, this association is higher among Non-DAC donors in countries with low property

[3] With 95% Confidence interval: [0.017; 0.118]

rights index. In the second st ep, the estimation shows that a donor's official development flows affect the influence of other donors on their capacity to conclude land deals. I find that financial flows from the USA and the UK complement the activity of other DAC land investors, while financial flows from China and India substitute DAC flows, and reduce the capacity for their investors to conclude land deals.

Bibliography

AFDB (2019). *Feed Africa.* Tech. rep. African Development Bank Group.

Aragón, Fernando M. and Juan Pablo Rud (2016). "Polluting Industries and Agricultural Productivity: Evidence from Mining in Ghana". In: *The Economic Journal* 126.597, pp. 1980–2011.

Atkin, David (2016). "Endogenous Skill Acquisition and Export Manufacturing in Mexico". In: *American Economic Review* 106.8, pp. 2046–85.

Belhabib, Dyhia et al. (2020). "Catching industrial fishing incursions into inshore waters of Africa from space". In: *Fish and Fisheries* 21.2, pp. 379–392.

Benshaul-Tolonen, Anja (2018). "Local Industrial Shocks and Infant Mortality". In: *The Economic Journal* 129.620, pp. 1561–1592.

Berman, Nicolas et al. (2017). "This Mine Is Mine! How Minerals Fuel Conflicts in Africa". In: *American Economic Review* 107.6, pp. 1564–1610.

Bialetti, Anca et al. (2018). "Lease Splitting and Dirty Entrants: The Unintended Deforestation Consequences of India's Environmental Clearance Process Reform". In: *PEDL Research Papers.*

Cabral, Reniel B et al. (2018). "Rapid and lasting gains from solving illegal fishing". In: *Nature Ecology and Evolution* (2), pp. 650–658.

Chuhan-Pole, Punam, Andrew L. Dabalen, and Bryan Christopher Land (2017). "Mining in Africa : Are Local Communities Better Off?"

Collier, Paul and Anke Hoeffler (2004). "Greed and Grievance in Civil War". In: *Oxford Economic Papers* 56.4, pp. 563–595.

Corno, Lucia and Damien de Walque (Feb. 2012). "Mines, migration and HIV/AIDS in southern Africa". In: *Journal of African Economies* 21.

Dietler, Dominik et al. (2021). "Impact of mining projects on water and sanitation infrastructures and associated child health outcomes: a multi-country analysis of Demographic and Health Surveys (DHS) in Sub-Saharan Africa". In: *Global Health.*

Djankov, Simeon, Jose G. Montalvo, and Marta Reynal-Querol (2008). "The curse of aid". In: *Journal of Economic Growth* 13.3, pp. 169–194.

Fourati, Maleke, Victoire Girard, and Jérémy Laurent-Lucchetti (2021). *Sexual violence as a weapon of war*. Tech. rep. Universidade Nova de Lisboa, Nova School of Business and Economics, NOVAFRICA.

Kotsadam, Andreas and Anja Tolonen (2016). "African Mining, Gender, and Local Employment". In: *World Development* 83.C, pp. 325–339.

Kroodsma, David et al. (2018). "Tracking the global footprint of fisheries". In: *Science* 359.6378, pp. 904–908.

Lay, Jann et al. (2021). *Taking stock of the global land rush: Fewdevelopment benefits, many human and environmental risks. Analytical Report III.* Tech. rep. Bern, Montpellier, Hamburg, Pretoria: Centre for Development, Environment,University of Bern; Centre de coopération internationale en recherche agronomiquepour le développement; German Institute for Global, and Area Studies; University of Pretoria; Bern Open Publishing.

Leite, Carlos and Jens Weidmann (2002). "Does mother nature corrupt? : Natural resources, corruption, and economic growth". In: *Governance, corruption, and economic performance. - Washington, DC : International Monetary Fund.*

Mamo, Nemera, Sambit Bhattacharyya, and Alexander Moradi (2019). "Intensive and extensive margins of mining and development: Evidence from Sub-Saharan Africa". In: *Journal of Development Economics* 139, pp. 28–49.

Missirian, Anouch and Wolfram Schlenker (2017). "Asylum applications respond to temperature fluctuations". In: *Science* 358.6370, pp. 1610–1614.

Ross, Michael L. (2001). "Does Oil Hinder Democracy?" In: *World Politics* 53.3, pp. 325–361.

Sachs, Jeffrey D and Andrew Warner (1997). "Sources of Slow Growth in African Economies". In: *Journal of African Economies* 6.3, pp. 335–76.

van der Ploeg, Frederick (2011). "Natural Resources: Curse or Blessing?" In: *Journal of Economic Literature* 49.2, pp. 366–420.

Von der Goltz, Jan and Prabhat Barnwal (2019). "Mines: The local wealth and health effects of mineral mining in developing countries". In: *Journal of Development Economics* 139, pp. 1–16.

Chapter 1

Man Overboard! Industrial Mining as a Driver of Migration Out of Africa[1]

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.

[1]Co-authored with François Libois. The authors are grateful to Lisa Chauvet, Denis Cogneau, Golvine de Rochambeau, Quy-Toan Do, Sylvie Lambert, Jérémy Laurent-Lucchetti, Léa Marchal, Céline Nauges, Frederik Noack, Hillel Rapoport, Oliver Vanden Eynde and Xavier Vincent for helpful comments and discussion. They also thank seminar participants at the CISEA, University of British Columbia, Université Laval, Göttingen University, C. Michelsen Institute in Bergen, TSE, the EAERE, and the FAERE annual conference, the CSAE, the AFSE, the Norwegian Conference in Development Economics, the Virtual Migration Seminar, the 14th International Conference on Migration and development, the University of Namur and the Journés Doctoriales du Développement for their feedbacks. Finally, they thank Cheikh Diene, Albin Kasser, and Maxime Pirot for their excellent research assistance. This research received the support of the EUR grant ANR-17-EURE-0001 and the EcoSocio Department of INRAE.

1.1 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 (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, Failler, and Agossah, 2012; J. H. Jonsson and Kamali, 2012; J. Jonsson, 2019).

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 increase registered population movements from this country to OECD or European 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 individuals.[1] We then provide suggestive evidence that industrial fishing effort has detrimental effects on the diet

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

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 extent, the micro and macro findings.

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 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, Lam, and W. W. Cheung, 2016 found that 18%

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

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

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 for processing and selling it (L. S. L. Teh, L. C. L. Teh, and Sumaila, 2013; Belhabib, Sumaila, and Pauly, 2015). 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, Lam, and W. W. Cheung, 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, W. Cheung, et al., 2020).

The remainder of the paper is organized as follows. Section 1.2 presents the context in light of the literature. Section 2.3 describes the data. Section 1.4 details the methodology at both the macro and the micro levels. Section 1.5 introduces the macro-level results, while section 1.6 focuses on the micro-level analysis. Section 3.7 provides extensive discussion and finally, section 3.8 concludes.

1.2 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.

1.2.1 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, Oppenheimer, and S. M. Hsiang, 2014) or in West Africa when focusing on the intention to migrate (Bertoli, Docquier, 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; Millock, 2015; Cattaneo et al., 2019). This is especially true for countries that are highly dependent on agricultural production (Cai et al., 2016; Chort and 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., 2021) and the strength of institutions (Burke, S. Hsiang, and Miguel, 2015). We might therefore expect other channels than agricultural income to link worse environmental conditions and the trigger 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 but in different ways. In the long run, Dalgaard, Knudsen, and Selaya, 2015 argues that the bounty of the sea induces long-run development as richer marine resources stimulated pre-industrial development. When it comes to the short run, there is rich 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).

1.2.2 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 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 (Tominaga, 2018; Sousa and Mercier, 2019). This has been formally tested using a world panel of coastal countries (Fluckiger 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 of income-generating activities, piracy being one of them. Migration is another alternative, as suggested by Hamilton, Colocousis, and Johansen, 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 Belhabib, Sumaila, and Pauly, 2015 evaluates 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, this represents 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, Kroodsma, and Fernandes, 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, J. 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 (J. H. 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 also expect migration within African countries and between them, something harder to measure but that has been consistently reported in the qualitative literature (Binet, Failler, and Agossah, 2012).

1.2.3 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 (Francois Libois, 2022).

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 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.

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

1.3 Data

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

1.3.1 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 1.1 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 A.4 in Appendix displays the yearly evolution across sub-regions and figures A.6 and A.7 present the bilateral flows of foreign population and asylum application flows towards OECD countries over the 2012-2018 period.

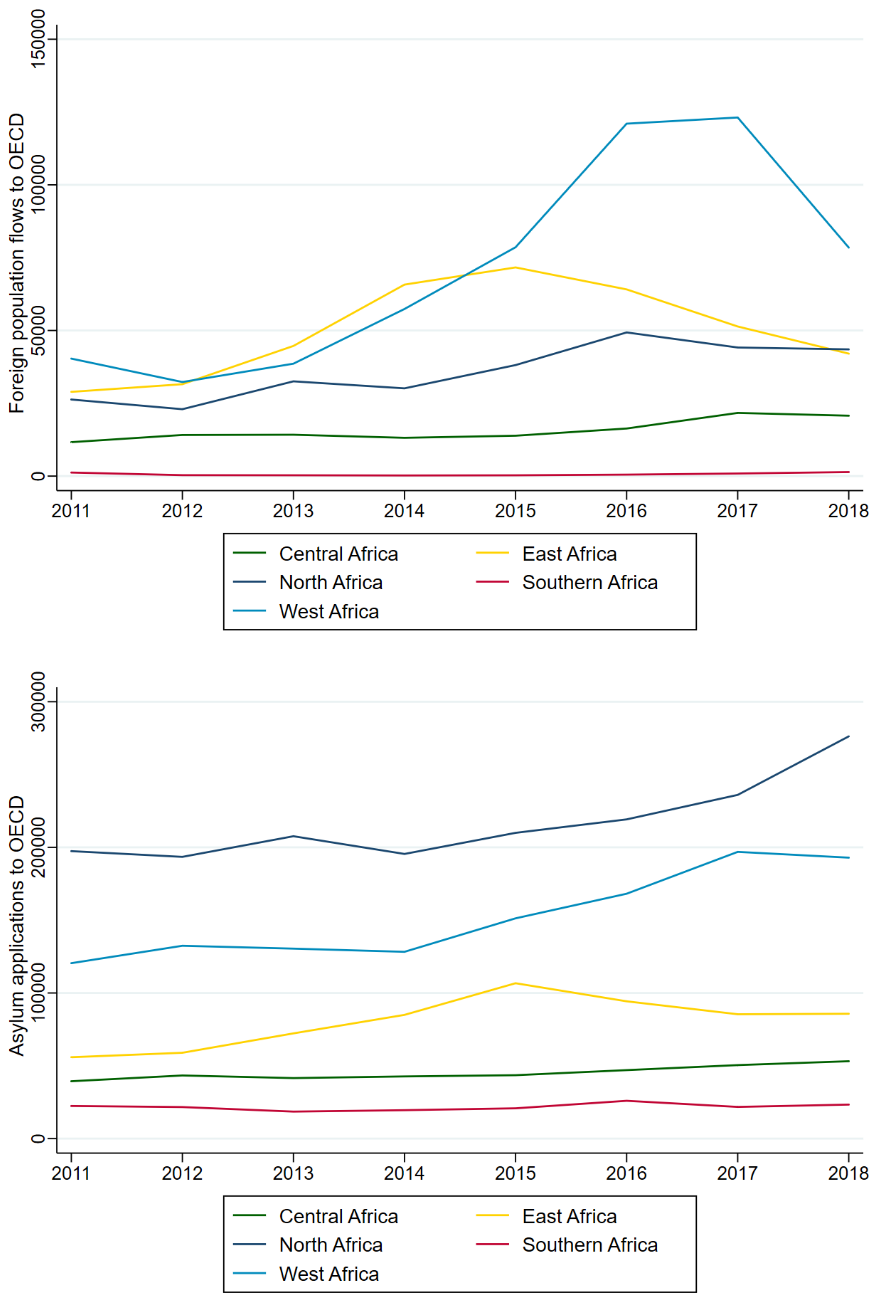
At the micro level and as a proxy of out-migration, we are interested in households' size and composition as measured in the Demographic and Health Survey (DHS). DHS data are a natural candidate for this kind of exercise because they have consistent questionnaires across numerous countries, good quality of enumeration, relatively large geocoded samples, and fairly high frequency in Sub-Saharan Africa[7].

[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.

[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

Figure 1.1: Flows of foreign population and asylum applications towards the OECD countries.



Source: Authors' elaboration using OECD data.

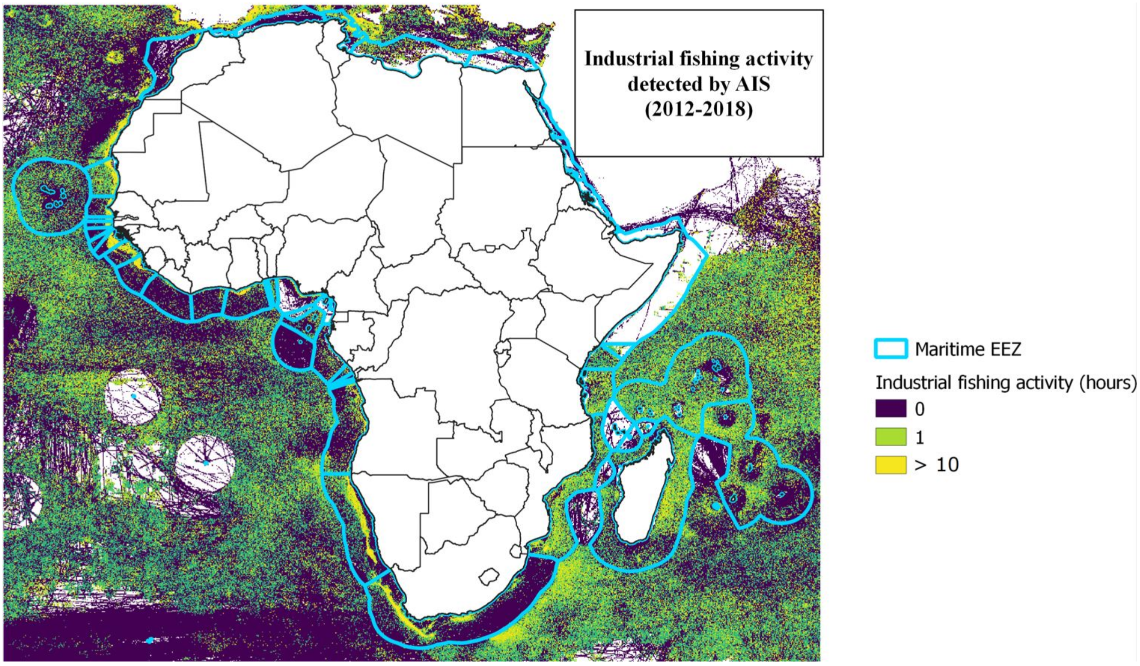
1.3.2 Industrial fishing data

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 1.2 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 within countries' EEZ.

Figures A.2 and 1.3 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 A.12 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 efforts 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 is not a perfect source and the African West Coast is one of the world's hot spots of unseen fishing vessels (**Welch˙al2022**). The probability that a fishing vessel switches off its AIS system increases 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.

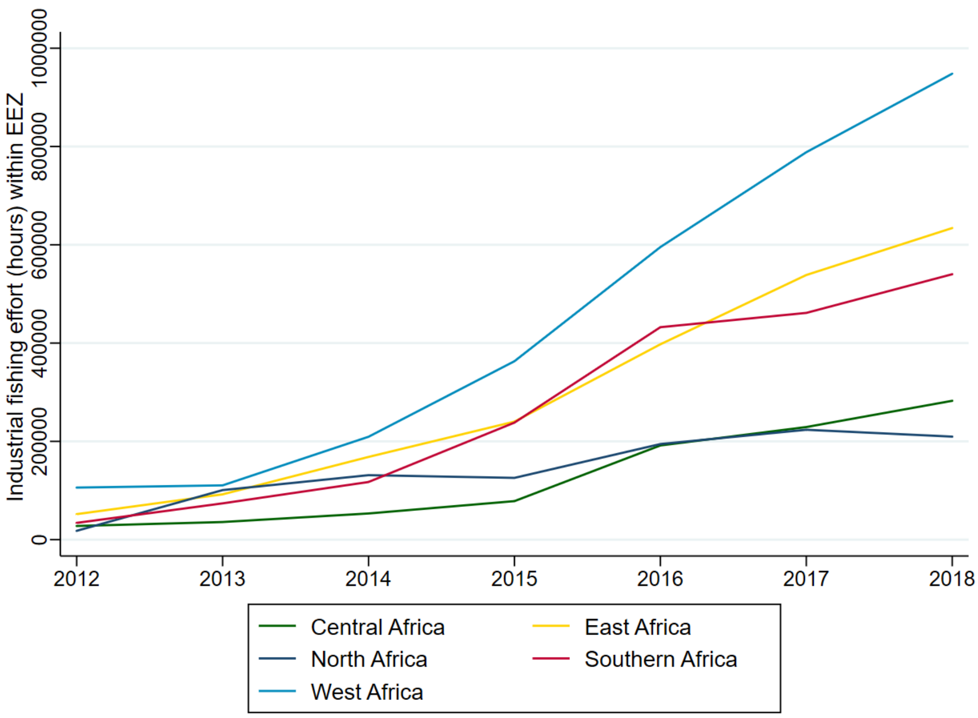
[8]The fishing detection model was trained on AIS data from 503 vessels and identified fishing activity with >90% accuracy.

Figure 1.2: Map of industrial fishing activity, over 2012-2018



Source: Authors' elaboration using Global Fishing Watch data.

Figure 1.3: Industrial fishing activity (in hours) detected within EEZ



Source: Authors' elaboration using Global Fishing Watch data.

1.3.2.1 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 A.3); (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, Turner, and Small, 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, W. Cheung, et al., 2020). 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 12 nautical miles within each closest access to the sea may induce too many missing values and EEZ does not provide enough variation between villages of the same country. For fishing conditions, we aggregate relevant variables over the same spatial extent.

1.3.2.2 Fishing conditions

As in Fluckiger and Ludwig, 2015 and Axbard, 2016 we use ocean satellite images to proxy fishing conditions. Fluckiger 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 A.2 and regression results in table A.5 of the Appendix.

1.3.3 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

[9]www.cred.be

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.

Eventually, we use the CEPII Gravity database (Conte, Cotterlas, and Mayer, 2021) 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.

1.4 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 countries.

1.4.1 Macro level approach

At the macro level, we estimate gravity equations through random utility maximisation (RUM) models (Beine, Bertoli, and Moraga, 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:

$$M_{odt} = \alpha \ln \left(F^{z}_{ot} + 1 \right) + \mathbf{X}_{ot}\beta + \omega_o + \delta_d + \tau_t + \varepsilon_{odt} \tag{1.1}$$

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_{ot}^{z} 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.

1.4.2 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:

$$Y_{ivct} = \sum_{k=1}^{4} \left(\alpha_k ln(F_{vct-1} + 1) + \beta_k\right) \mathbb{1}_{[k-1;k]\times 50km} + \alpha_5 ln(F_{vct-1}+1) + \mathbf{X_{vct}}\gamma + \omega_c + \tau_t + \varepsilon_{ivct} \tag{1.2}$$

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 A.10 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 3.7. 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

[10]See figure A.9 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.

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.

1.4.3 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.

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 1.1, namely:

$$\ln\left(U_{ot}\right) = \alpha \ln\left(F_{ot}^{z} + 1\right) + \mathbf{X}_{ot}\beta + \omega_{o} + \tau_{t} + \varepsilon_{odt} \tag{1.3}$$

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_{ot}^{z} 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 1.1, 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 from the macro approach on international migration to the micro approach on departure from coastal rural areas.

1.5 International migration flows

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

1.5.1 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 (1.1) using Poisson Pseudo Maximum Likelihood estimators.[12] All estimations are weighted by the size of the coastal population.[13]

We report our baseline estimate in column (1) table 1.1. 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.

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

[12]See Beine, Bertoli, and Moraga, 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 A.8 in the Appendix for the distribution across countries.

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

Table 1.1: 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
Origin country-year	Yes	Yes	Yes	Yes	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 1.1 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, $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

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", 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 presence 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.

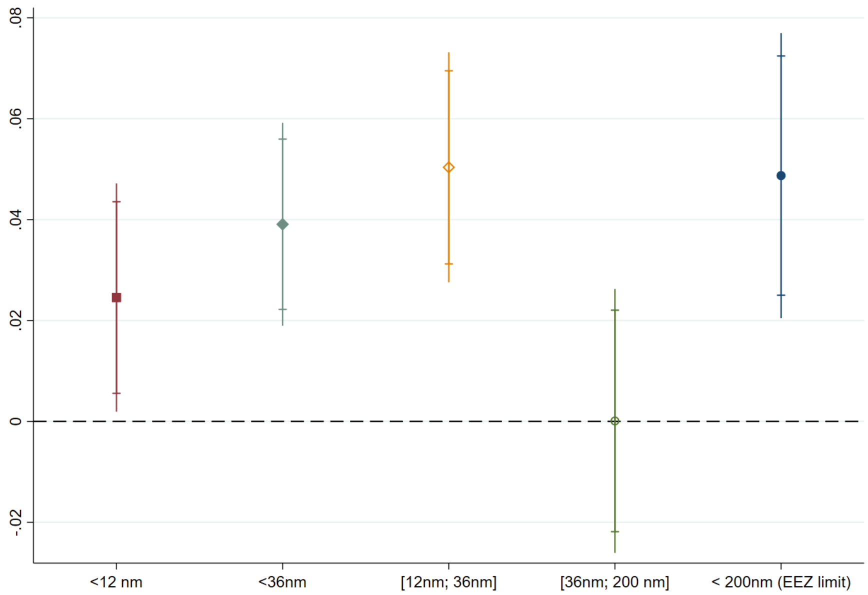
Finally, we include origin-destination year fixed-effects in the last 3 columns. Again, this has very little impact on point estimates. The most conservative estimation, reported in column (6), yields a 0.37% increase in the bilateral flow of foreign population as a consequence of a 10% increase in industrial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

1.5.2 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 1.4 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

[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.

Figure 1.4: Effect of industrial fishing on bilateral foreign population flows to OECD countries, by distance



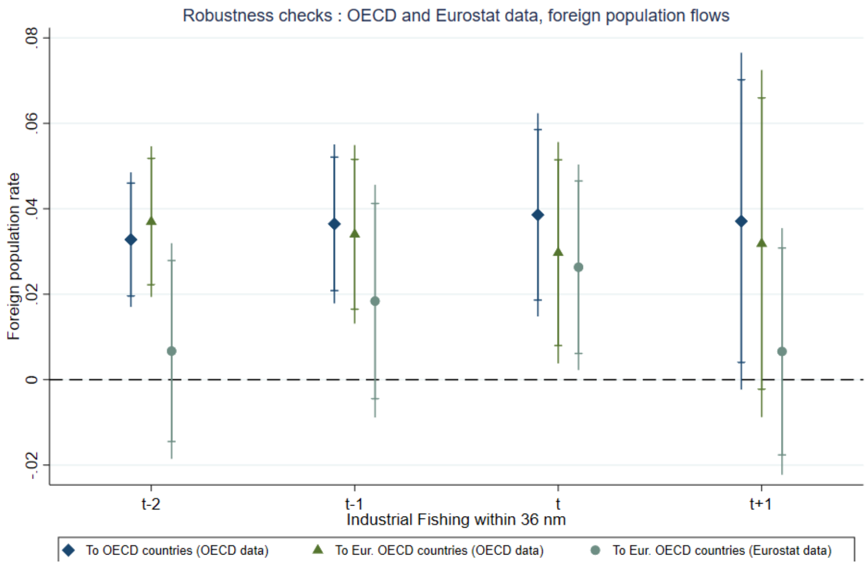
Note: This figure illustrates the coefficients associated with industrial fishing efforts aggregated at different distances from the shore. Each coefficient corresponds to a separate regression. We find that the largest effects are within 12 NM and 36 NM from the shore, which corresponds to the most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

as the whole set of environmental and socio-economic controls. It corresponds to specification (6) in table 1.1. 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 1.1. 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 1.6, in line with the work

Figure 1.5: Effect of industrial fishing when using OECD and Eurostat data, at different timings compared to bilateral foreign population flows.



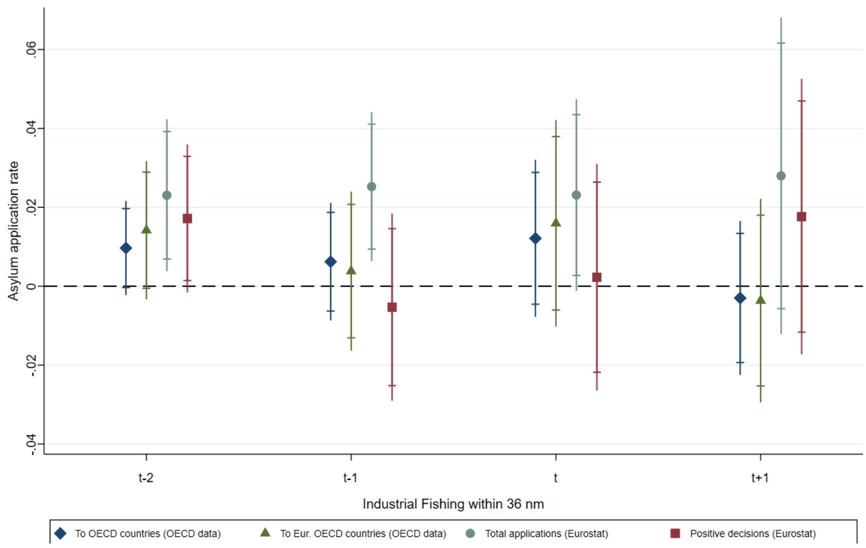
Note: This figure illustrates the coefficient associated with separate regressions across different timing of industrial fishing, from t-2 to t+1 compared to bilateral foreign population flows. For each timing, we run a regression using different destinations (OECD or European OECD countries) and datasets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

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 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

[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 A.5 displays the absolute difference and the temporal delay across the two sources.

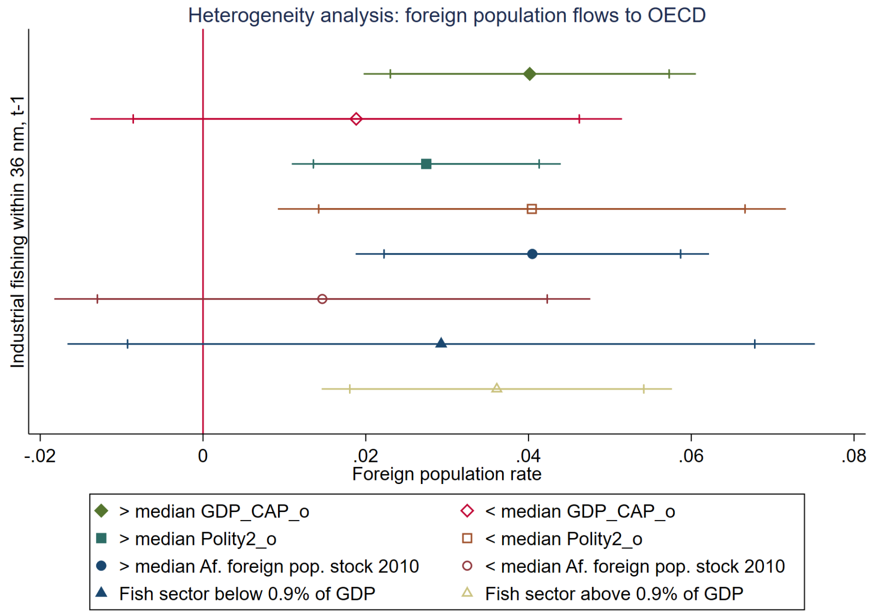
Figure 1.6: Effect of industrial fishing when using OECD and Eurostat data, at different timings compared to bilateral asylum application flows.



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.

that we report in Figure 1.7. First, we split the sample between countries 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 (Sousa and Mercier, 2019) 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. Sousa and Mercier, 2019 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.

Figure 1.7: Heterogeneity analysis of the effect of industrial fishing on bilateral foreign population flows

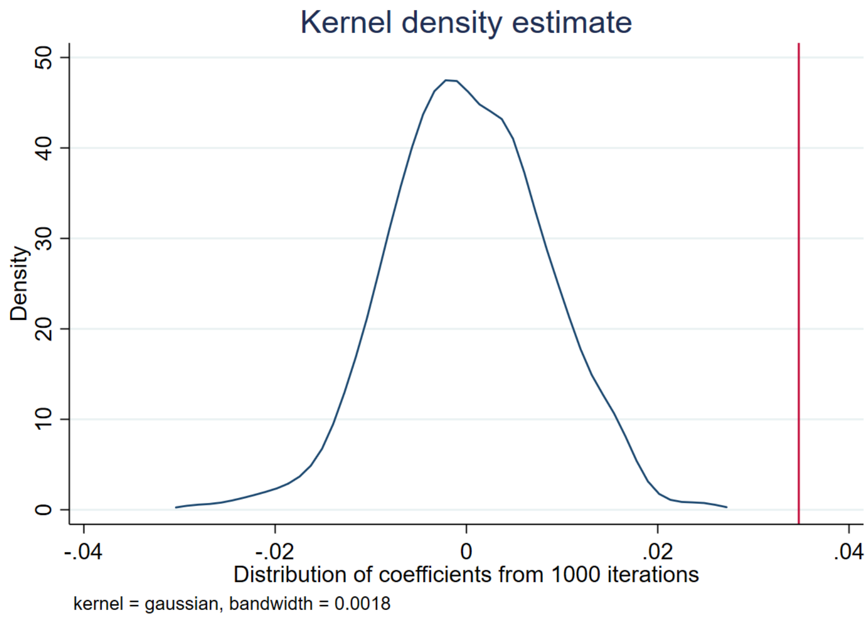


Note: This figure illustrates the coefficient associated with the effect of industrial fishing effort on foreign flows to OECD countries when splitting the samples according to each of the criteria: GDP per capita, political index, stock for African population in destination countries in 2010, the weight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

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

Figure 1.8: 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.

reassures at the 1 percent level that our model is not misspecified.

1.6 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 rural households. Following equation (1.2), we analyse how household size and composition in year t change as a function of industrial fishing effort in year $t-1$.

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.

1.6.2 Household size: results

We report estimates of the link between household size and industrial fishing in table 1.2, following equation 1.2 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 A.9). We, therefore, have three sources of variations in fishing efforts. First, within the same wave, we

[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.

[18]We use the Stata command *acreg* developped by Colella et al., 2020 and using a 25 km cut-off.

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 1.2, 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 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.

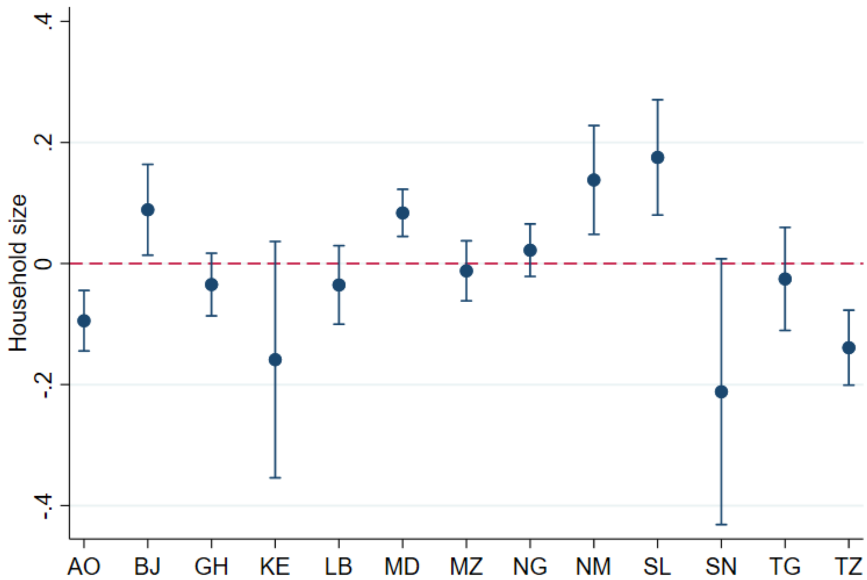
For the sake of completeness, we report the country's average marginal effect of industrial fishing on the size of households living within 25km from the coastline. It follows the estimation of equation 1.2 where we add triple interactions between fishing effort, distance bins dummies, and country indicators. Figure 1.9 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 1.2: 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 1.2 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 1.9: 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.

1.6.3 Household composition: results

We finally leverage household composition to suggest mechanisms that may explain the previous findings. Tables 1.3 and 1.4 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 1.3: 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

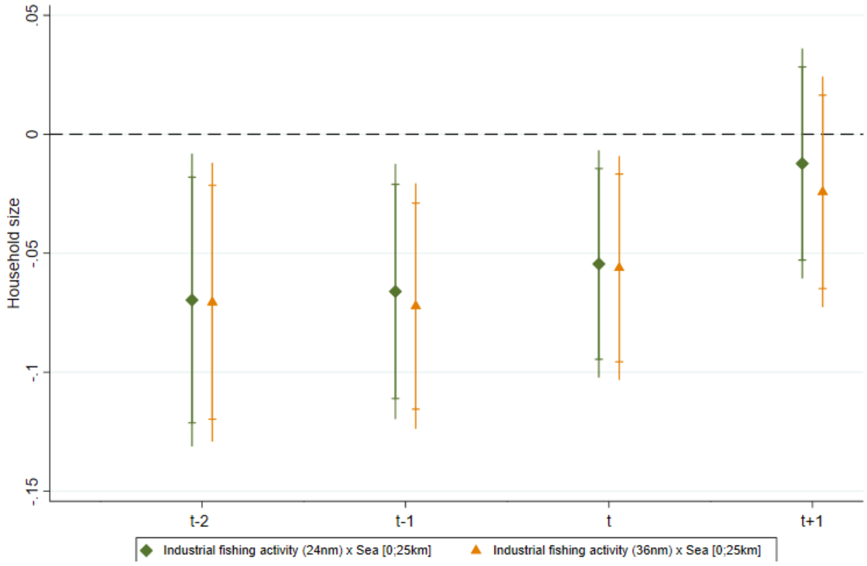
Notes: This table gives the results of estimation of equation 1.2 when using DHS household data. Standard errors clustered with a 25km threshold. $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$. Reference is households located further than 200 km from the sea.

Table 1.4: 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 1.2 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 1.10: "Horse-race" at the micro-level

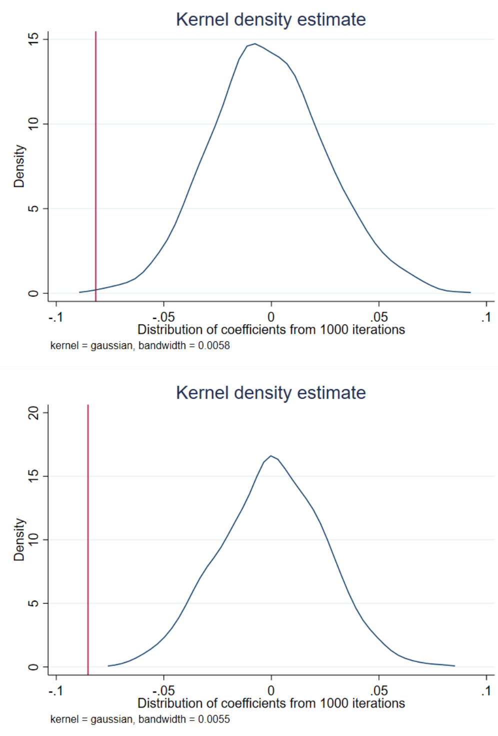


Note: This figure illustrates the main interaction effect of industrial fishing activity off the shore at a different point in time and living on the coast (within 25 km) on household size. We note no effect of future fishing activity.

1.6.4 Robustness

In the same spirit as the robustness checks conducted in the macro analysis, we display in Figure 1.10 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 A.6 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 1.11 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 1.11: 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.

1.6.5 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 1.5 and 1.6, 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.

[20]It covers some surveys in Angola, Benin, Ghana, Kenya, Liberia, Namibia, Nigeria, Senegal, Sierra Leone, Tanzania, and Togo (see exact list in Table A.4 in the Appendix)

Table 1.5: 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] $\times$ Ln(IndFish)24NM$_{t-1}$	-0.0415*	-0.00967	-0.0656*	-0.0883***	-0.0252	-0.00967	0.0133	0.0312
	[0.0243]	[0.0211]	[0.0364]	[0.0267]	[0.0280]	[0.0211]	[0.0289]	[0.0359]
Sea[25; 100] $\times$ Ln(IndFish)24NM$_{t-1}$	-0.0119	-0.0481**	-0.0448	-0.0543**	-0.0272	-0.0481**	0.0386	0.0369
	[0.0259]	[0.0197]	[0.0346]	[0.0222]	[0.0236]	[0.0197]	[0.0257]	[0.0348]
Sea[100; 200] $\times$ Ln(IndFish)24NM$_{t-1}$	-0.0420	-0.0318	-0.0581	-0.0303	-0.000615	-0.0318	-0.00586	-0.00764
	[0.0277]	[0.0215]	[0.0382]	[0.0270]	[0.0272]	[0.0215]	[0.0333]	[0.0341]
Ln(IndFish)24NM$_{t-1}$	0.00592	0.0349**	0.0952***	0.0440**	0.0241	0.0349**	-0.0133	0.00276
	[0.0186]	[0.0151]	[0.0330]	[0.0194]	[0.0184]	[0.0151]	[0.0206]	[0.0252]
Sea[0; 25]	0.627***	-0.0385	0.156	0.0653	-0.414***	-0.0385	-0.143	-0.360**
	[0.104]	[0.0729]	[0.150]	[0.0975]	[0.0966]	[0.0729]	[0.122]	[0.141]
Sea[25; 100]	0.282***	0.142*	0.103	-0.187*	-0.114	0.142*	-0.448***	-0.389***
	[0.0975]	[0.0734]	[0.141]	[0.0977]	[0.0923]	[0.0734]	[0.116]	[0.133]
Sea[100; 200]	0.166	0.0764	0.0350	-0.242**	-0.262**	0.0764	-0.297**	0.0173
	[0.102]	[0.0744]	[0.142]	[0.102]	[0.103]	[0.0744]	[0.127]	[0.116]
Child's age	0.148***	0.173***	0.110***	0.135***	0.166***	0.173***	0.124***	0.134***
	[0.00529]	[0.00671]	[0.00657]	[0.00548]	[0.00571]	[0.00671]	[0.00498]	[0.00554]
Birth order number	-0.0347***	-0.0427***	-0.0718***	-0.0464***	0.00796	-0.0427***	-0.0270*	-0.00408
	[0.0132]	[0.00997]	[0.0222]	[0.0132]	[0.0125]	[0.00997]	[0.0147]	[0.0169]
Mother's age	0.0194***	0.0228***	0.0204***	0.0230***	0.00927**	0.0228***	0.0126**	0.00942*
	[0.00423]	[0.00348]	[0.00640]	[0.00434]	[0.00415]	[0.00348]	[0.00513]	[0.00557]
Mother's education	0.0421***	0.0115**	0.0835***	0.0321***	0.0168***	0.0115**	0.0280***	0.0306***
	[0.00627]	[0.00477]	[0.00823]	[0.00578]	[0.00594]	[0.00477]	[0.00649]	[0.00726]
Constant	-3.220***	-2.617***	-4.576***	-3.939***	-3.018***	-2.617***	-3.853***	-3.666***
	[0.231]	[0.213]	[0.430]	[0.230]	[0.214]	[0.213]	[0.260]	[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 1.2 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 1.6: 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] $\times$ 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] $\times$ 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] $\times$ 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 1.2 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.

1.6.6 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 A.8 in the Appendix displays the relatively stable but increasing urban population rate across African sub-regions. We, therefore, estimate equation 1.3 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 1.7, 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.

Table 1.7: 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 1.3 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, $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

1.7 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., 2022) 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, W. Cheung, et al., 2020) 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

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

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 and line vessels. The Senegalese Statistics agency has recorded "70,041 artisanal fishermen and 11,912 canoes" in 2018. Belhabib, Sumaila, and Pauly, 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 A.5 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.

1.8 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

[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.

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 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.

[23]Estimation based on specification (6) in table 1.1

Bibliography

Altonji, Joseph G., Todd E. Elder, and Christopher R. Taber (2005). "Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools". In: *Journal of Political Economy* 113.1, pp. 151–184.

Anticamara, J.A. et al. (2011). "Global fishing effort (1950-2010): Trends, gaps, and implications". In: *Fisheries Research* 107.1, pp. 131–136.

Axbard, Sebastian (Apr. 2016). "Income Opportunities and Sea Piracy in Indonesia: Evidence from Satellite Data". In: *American Economic Journal: Applied Economics* 8.2, pp. 154–94.

Baland, Jean-Marie and Kjetil Bjorvatn (June 2013). "Conservation and employment creation: Can privatizing natural resources benefit traditional users?" In: *Environment and Development Economics* 18.03, pp. 309–325.

Baland, Jean-Marie and Jean-Philippe Platteau (1996). *Halting degradation of natural resources - Is there a role for rural communites*. Oxford: Oxford University Press.

Beine, Michel, Simone Bertoli, and Jesus Fernández-Huertas Moraga (2016). "A Practitioners' Guide to Gravity Models of International Migration". In: *The World Economy* 39.4, pp. 496–512.

Beine, Michel and Christopher Parsons (2015). "Climatic Factors as Determinants of International Migration". In: *The Scandinavian Journal of Economics* 117.2, pp. 723–767.

Belhabib, Dyhia, William Cheung, et al. (2020). "Catching industrial fishing incursions into inshore waters of Africa from space". In: *Fish and Fisheries* 21.2, pp. 379–392.

Belhabib, Dyhia, Vicky W.Y. Lam, and William W.L. Cheung (2016). "Overview of West African fisheries under climate change: Impacts, vulnerabilities and adaptive responses of the artisanal and industrial sectors". In: *Marine Policy* 71, pp. 15–28.

Belhabib, Dyhia, U. Rashid Sumaila, and Daniel Pauly (2015). "Feeding the poor: Contribution of West African fisheries to employment and food security". In: *Ocean & Coastal Management* 111, pp. 72–81.

Bertoli, Simone, Frédéric Docquier, et al. (2020). *Weather Shocks and Migration Intentions in Western Africa: Insights from a Multilevel Analysis.* CESifo Working Paper Series 8064. CESifo.

Bertoli, Simone and Elie Murard (2020). "Migration and co-residence choices: Evidence from Mexico". In: *Journal of Development Economics* 142.

Binet, Thomas, Pierre Failler, and Mama Agossah (2012). *Migrations contemporaines des pêcheurs artisans en Afrique de l'Ouest, Synthèse et axes de recherche.* Rapport. UICN.

Bohra-Mishra, Pratikshya, Michael Oppenheimer, and Solomon M. Hsiang (2014). "Nonlinear permanent migration response to climatic variations but minimal response to disasters". In: *Proceedings of the National Academy of Sciences* 111.27, pp. 9780–9785.

Burke, Marshall, Solomon Hsiang, and Edward Miguel (2015). "Global non-linear effect of temperature on economic production". In: *Nature* (527), pp. 235–239.

Butler, Ma et al. (2003). *The application fo remote sensing technolgoy to marine fisheries: an introductory manual.* Food and Agricultural Organization Corporate Document Repository.

Cabral, Reniel B et al. (2018). "Rapid and lasting gains from solving illegal fishing". In: *Nature Ecology and Evolution* (2), pp. 650–658.

Cai, Ruohong et al. (2016). "Climate variability and international migration: The importance of the agricultural linkage". In: *Journal of Environmental Economics and Management* 79, pp. 135–151.

Cattaneo, Cristina et al. (June 2019). "Human Migration in the Era of Climate Change". In: *Review of Environmental Economics and Policy* 13.2, pp. 189–206.

Chaijaroen, Pasita (2019). "Long-lasting income shocks and adaptations: Evidence from coral bleaching in Indonesia". In: *Journal of Development Economics* 136.C, pp. 119–136.

– (2021). "Tradeoffs between fertility and child development attributes: evidence from coral bleaching in Indonesia". In: *Environment and Development Economics*, pp. 1–21.

Chassot, Emmanuel et al. (Jan. 2011). "Satellite remote sensing for an ecosystem approach to fisheries management". In: *ICES Journal of Marine Science* 68, pp. 651–666.

Chort, Isabelle and Maelys de la Rupelle (Mar. 2019). *Managing the Impact of Climate on Migration: Evidence from Mexico.* IZA Discussion Papers 12227. Institute of Labor Economics (IZA).

Chort, Isabelle and Jean-Noël Senne (2018). "You'll Be a Migrant, My Son: Accounting for Migrant Selection within the Household". In: *Economic Development and Cultural Change* 66.2, pp. 217–263.

Colella, Fabrizio et al. (Feb. 28, 2020). "Inference with Arbitrary Clustering". In: *IZA Discussion Paper*.

Conte, Madalena, Pierre Cotterlas, and Thiery Mayer (June 28, 2021). *The CEPII Gravity Database*. Tech. rep. CEPII.

Couton, Andre et al. (July 19, 2016). "Inter-Comparison of OC-CCI chlorophyll- a Estimates with Precursor Data Sets". In: 37, pp. 4337–4355.

Dalgaard, Carl-Johan, Anne Sofie B. Knudsen, and Pablo Selaya (2015). *The Bounty of the Sea and Long-Run Development*. CESifo Working Paper Series 5547. CESifo Group Munich.

Dayton-Johnson, Jeff and Pranab Bardhan (July 2002). "Inequality And Conservation On The Local Commons: A Theoretical Exercise". In: *Economic Journal* 112.481, pp. 577–602.

Doumbouya, Alkaly et al. (2017). "Assessing the Effectiveness of Monitoring Control and Surveillance of Illegal Fishing: The Case of West Africa". In: *Frontiers in Marine Science* 4, p. 50.

FAO (2016). *The state of world fisheries and aquaculture 2016*. Tech. rep. FAO.

– (2020). *The state of world fisheries and aquaculture 2020*. Tech. rep. FAO.

Fluckiger, Matthias and Markus Ludwig (2015). "Economic shocks in the fisheries sector and maritime piracy". In: *Journal of Development Economics* 114.C, pp. 107–125.

Franière, Sh La (Jan. 14, 2008). "Europe takes Africa's fish, boatloads of migrants follow". In: *The New York Times*.

Graaf, G. de and L. Garibaldi (2014). "The Value of African Fisheries". In: *Fisheries and Aquaculture Circular*. No. 1093. Ed. by FAO.

Hamilton, Lawrence C., Chris R. Colocousis, and Samal T. F. Johansen (2004). "Migration from Resource Depletion: The Case of the Faroe Islands". In: *Society & Natural Resources* 17.5, pp. 443–453.

Hardin, Garrett (Dec. 1968). "The tragedy of the commons". In: *Science* 162, pp. 1243–1248.

Hoang, Trung Xuan et al. (2020). "Labor market impacts and responses: The economic consequences of a marine environmental disaster". In: 147, p. 102538.

Jacobs, A. (Apr. 30, 2017). "China's appetite pushes fisheries to the Brink". In: *The New York Times*.

Jonsson, Jessica (July 18, 2019). “Overfishing, social problems, and ecosocial sustainability in Senegalese fishing communities”. In: *Journal of Community Practice* 27.3-4, pp. 213–230.

Jonsson, Jessica H. and Masoud Kamali (2012). “Fishing for development: A question for social work”. In: *International Social Work*.

Karleskint, Ga, Ra Turner, and Ja Small (2013). *Introduction to Marine Biology*. Belmont, CA.

Klemas, Victor (Dec. 2012). “Remote sensing of environmental indicators of potential fish aggregation: An overview”. In: *Baltica* 25, pp. 99–112.

Kroodsma, David et al. (2018). “Tracking the global footprint of fisheries”. In: *Science* 359.6378, pp. 904–908.

Li, Mi-Ling et al. (2021). “Tracking industrial fishing activities in African waters from space”. In: *Fish and Fisheries* 22.4, pp. 851–864.

Libois, François (2016). *Households in Times of War: Adaptation Strategies during the Nepal Civil War*. Tech. rep. CRED, University of Namur.

Libois, Francois (2022). “Success and failure of communities managing natural resources static and dynamic inefficiencies”. In: *Journal of Environmental Economics and Management* 114, p. 102671.

Mendenhall, Elizabeth et al. (2020). “Climate change increases the risk of fisheries conflict”. In: *Marine Policy* 117, p. 103954.

Millock, Katrin (2015). “Migration and Environment”. In: *Annual Review of Resource Economics* 7.1, pp. 35–60.

Missirian, Anouch and Wolfram Schlenker (2017). “Asylum applications respond to temperature fluctuations”. In: *Science* 358.6370, pp. 1610–1614.

Pauly, Daniel and Dirk Zeller (2016). “Catch reconstructions reveal that global marine fisheries catches are higher than reported and declining”. In: *Nature Communications* 7.10244 (1).

Sall, Aliou and Pierre Morand (2008). “Small-scale fisheries and seaborne emigration of young Africans”. In: *Politique africaine*.

Shah, Amita (2010). “Land Degradation and Migration in a Dry Land Region in India: Extent, Nature and Determinants”. In: *Environment and Development Economics* 15.2, pp. 173–196.

Somanathan, E et al. (July 21, 2021). “The Impact of Temperature on Productivity and Labor Supply: Evidence from Indian Manufacturing”. In: *Journal of Political Economy* 129.6, pp. 1797–1827.

Sousa, José de and Marion Mercier (2019). “La piraterie maritime faits stylisés et mécanismes économiques”. In: *Revue française d’économie*.

Taconet, Marc, David Kroodsma, and Jose Fernandes (Dec. 2019). *Global Atlas of AIS-based fishing activity - Challenges and opportunities*. FAO.

Teh, Louise S. L., Lydia C. L. Teh, and U. Rashid Sumaila (June 2013). "A Global Estimate of the Number of Coral Reef Fishers". In: *PLOS ONE* 8.6, pp. 1–10.

Tominaga, Yasutaka (2018). "Exploring the economic motivation of maritime piracy". In: *Defence and Peace Economics* 29.4, pp. 383–406.

UNCTAD (2016). *Trade and Environment Review 2016: Fish and Trade*. Tech. rep. United Nations Conference on Trade and Development.

Watson, Reg A et al. (2013). "Global marine yield halved as fishing intensity redoubles". In: *Fish and Fisheries* 14.4, pp. 493–503.

Welch, Heather et al. (2022). "Hot spots of unseen fishing vessels". In: *Science Advances* 8.44, eabq2109.

Chapter 2

MiningLeaks: Water Pollution and Child Mortality in Africa[1]

Abstract

Industrial mining can be a boon or a bane for communities living in the vicinity of production sites. We assess the effects of mining-induced pollution on health outcomes in Sub-Saharan Africa using the DHS micro-data from 1986-2018 in 26 countries matched with geocoded data of industrial mining sites. Through a staggered difference-in-difference strategy, we exploit the variation of the opening of a mine and the relative topographic position of surrounding villages, comparing upstream and downstream villages. Being downstream of an open mine increases by 2.18 percentage points the 24-month mortality rate, corresponding to a 25% increase. This effect is mainly driven by the consumption of plain water, corroborating the mechanism of water pollution. The effect on mortality is not driven by a change in women's fertility, nor by a change in the access to piped water or other facilities, nor by in-migration. The effect is concentrated while the mine is active and when international mineral prices are high, is larger in areas with high mining density and fades out with distance. It is robust to the estimator of de Chaisemartin and D'Haultfœuille, 2020, to a restriction to a balanced sample, to accounting for measurement errors, and to spatial and temporal randomization inference tests.

[1]Co-authored with Mélanie Gittard. The authors are grateful to Denis Cogneau, Philippe Quirion, Liam Wren-Lewis, Thierry Verdier, Oliver Vanden-Eynde, David Margolis, Luc Behaghel, Sylvie Lambert, Victoire Girard, Jérémy Laurent-Lucchetti, Céline Nauges, Karen Macours, Mathieu Couttenier, Dominic Rohner, Francis Cottard, Aurore Stéphant, Jean-Alain Fleurisson, Laurent Polidori, Eléonore Lèbre, Cédric Rebolho for helpful comments and discussion. We are grateful to the participants of the Casual Development Seminar at PSE (CFDS), the *Atelier Theia*, the CSAE Conference, the JMA, the EAERE, the FAERE and the EuHEA. This research received the support of the CEPREMAP, the EHESS, the EUR-PGSE, and the GPET thematic group of PSE. We thank the support of the EUR grant ANR-17-EURE-0001.

2.1 Introduction

The increase in commodity prices since 2000, especially in the extractive sector, has intensified investments in areas with abundant resources, from hydrocarbons to minerals. The African geology, which is richly endowed containing 30% of the world's mineral reserves (Chuhan-Pole, Dabalen, and Land, 2017), remains largely unexplored due to inhospitable terrains and the lack of infrastructure (UN Environment Program, 2022; Africa Bank, 2022) and represents an opportunity for mining investors. Africa is facing a mining boom since the 2000s, attracting foreign investment mainly from China, Canada, Australia, Brazil, and Russia, which raises concerns about environmental degradation (Taylor et al., 2009; Edwards et al., 2013) and health impact on local populations. Human exposure to heavy metals through the consumption of contaminated water is of prior concern in Africa and Sub-Saharan Africa in particular, where only 24% of the population have access to safe drinking water (UNESCO, 2019).

Throughout each stage of a mine's life cycle, its activity can produce and release chemical and mineral pollutants prone to contaminate the surrounding air, water, and soil. Moreover, the ore extraction processes are water-demanding and need access to a water source that very often competes with the local demand, which is all the more alarming in water-stressed areas. Mining activity mostly consists in extracting small concentrations of minerals from huge volumes of rocks and therefore creates a lot of waste, which leaking is hard to avoid. For industrial mines, these wastes are diluted into water and then stored in retention ponds, where they can leak within the local environment and contaminate soil and water bodies. If low concentration levels of heavy metals can be essential for human health, the abnormal quantities found in the environment within the mine's vicinity can cause several health problems. Individuals living nearby industrial mining are exposed to high concentrations of heavy metals through ingestion, dermal contact, and inhalation of soil particles. We mainly focus on the absorption mechanism as we identify the effects of mining activity through water pollution. Exposure to heavy metals plays detrimental effects on human health in general and child health in particular, especially during their first months of development, both in and ex-utero (Coelho and Texeira, 2011). Children are the most sensitive, even at low concentrations, as they are at a stage of rapid biological development (Dike et al., 2020), but also as they are more exposed, through higher blood concentration linked to incidental ingestion of urban soil and unclean water (He et al., 2020).

In this paper, we focus on Africa and investigate the local impacts of industrial mining activity on health through water pollution using geocoded micro-data. We examine the 12-month and 24-month mortality as a primary health outcome, as effects on children are the most dramatic, and to capture the effects of heavy metal absorption on early-age biological development. Child mortality is a short-term measure (Greenstone and Hanna, 2014; Do, Joshi, and Stolper, 2018), and is available over a long-time span of four decades and across the majority of African countries. We also look at the effects on other children's health outcomes such as anthropometric measures and anemia, as well as women's health and fertility outcomes. We match socio-economic and health data from the Demographic Health Surveys (DHS) with state-of-the-art geolocalized data on industrial mineral resource exploitation from the SNL Metals and Mining database, which provides information on opening dates and mineral types. Our study spans 26 out of the 54 African countries, from 1986 to 2018. We conduct a staggered Difference-in-Difference strategy exploiting the variation of the opening of a mine and the relative topographic position of surrounding villages. We indirectly isolate the mechanism of water pollution by building the treatment and control groups using an upstream-downstream comparison, which is used as a proxy for the exposure to water pollution linked to mining activity.

Our main result shows that being born in a village located downstream of an open mine increases the mortality rates under 24 months by 2.18 percentage points, which corresponds to an increase by 25% of the mortality rate. We find no significant result for the 12-month mortality rate, which suggests a lag in the effect of water pollution on early-childhood health and in the absorption of toxic elements. Our analysis suggests that this could be explained by the protection provided by breastfeeding (VanDerSlice, Popkin, and Briscoe, 1994; Fängström et al., 2008), as we find a significant increase in the 12-month mortality rate among children who were given plain water, in comparison to those who were not. We find effects neither on other children's health outcomes nor on women's health outcomes and fertility. We exclude many potential mechanisms that could explain our main result on infant mortality and show the robustness to controlling for households' access to water and facilities such as health facilities and electricity as well as in-migration flows. Our main effect is mainly driven by the mortality of boys, and by individuals living downstream of an open-pit mine that has opened. The effect fades out with distance and increases with surrounding mine density and the intensity of production, proxied by yearly international mineral prices. It seems to be mainly occurring during the mining activity status, as it is robust to restricting the analysis to mines for which we have the closure year. Last but not least, we conduct a battery of robustness checks: the de Chaisemartin and D'Haultfœuille, 2020 estimator, using a balanced sub-sample of DHS repeated cross-sections, correcting for DHS random displacement, restricting to the sample of mines for which we have the exact coordinates to account for measurement errors, testing for spatial spillovers, and running spatial and temporal randomization inference tests.

The major contributions of this paper are twofold. First, it lies in the construction of the industrial mines dataset, as we checked over 1,700 mines by hand to complete their opening date [1]. Our second contribution is to introduce the topographic heterogeneity of the effects of mining activity on health and to identify the negative effects induced by water pollution, and how they outweigh the positive effects. It nuances the results from the literature looking at average effects by using geographical distance to a mine as a proxy for exposure to mining activity, which finds a reduction in mortality rates (Benshaul-Tolonen, 2018; Cossa et al., 2022).

The remainder of the paper is organized as follows. Section 2.2 reviews the literature and presents our contribution. Section 2.3 describes the context and the data. Section 2.4 details the methodology and the main empirical strategy. Section 2.5 introduces the main results, while section 2.6 investigates the mechanisms, and section 2.7 the heterogeneity of the results. Section 2.8 looks at the dynamic effects, and section 2.9 at the intensive margins, digging into the heterogeneity of the results according to the distance of the mine, the mining density, and the production intensity. Section 2.10 proposes a list of robustness checks and placebo tests. Section 2.11 discusses the limits of the study and section 2.12 proposes a policy discussion. Eventually, section 2.13 concludes.

2.2 Literature review and contributions

This section first displays the literature on the trade-off of mining activity in developing countries. It then describes the mining-induced pollution literature and the economic literature on the health effects of mines. Thirdly, we discuss the issues emerging from this literature and the solutions we propose to tackle them.

[1] Opening dates indicate when production first began. Data available in the SNL database was gathered by SNL from the mining companies' reports, and the hand-check work we made has completed this database by going deeper into archival mining reports

2.2.0.1 Trade-off of mining activity

Our work is related to the strand of literature analysing the health-wealth trade-off of industrial mining activity in developing countries, which results are still under debate. If mining can improve health and well-being through local industrial development, it can also damage health through negative externalities such as conflicts, massive migration waves, and exposure to harmful pollution. Determining which of these effects is predominant is still debated in the literature studying the relevance of a natural resource curse (Ploeg, 2011; Cust and Poelhekke, 2015; Venables, 2016).

At a broad scale of analysis, Mamo, Bhattacharyya, and Moradi, 2019 look at the effects of the discoveries of industrial mining deposits in Sub-Saharan Africa. They find an increase in district-level night light emissions but no significant effects on household wealth [2].They find temporary positive effects on public service provisions but a degradation of the sewerage system and piped water supply in the medium and long run. Mining creates also negative effects on the environment and agricultural productivity. Aragón and Rud, 2016 find that the expansion of large-scale gold mining in Ghana (1997-2005) is responsible for agricultural total factor productivity decrease in the vicinity of mines. The use of cross-sectional satellite imagery of NO2 concentration suggests that air pollution is the main explaining factor. Dietler et al., 2021 analyse a panel of 52 mines in Sub-Saharan Africa using the same DHS and SNL databases. They find improvements in access to modern water and sanitation infrastructures after a mine opens, when comparing individuals living within 50 kilometers of an isolated mine. Yet, proxying exposure to mining activity with distance and focusing on areas with low mining density raise many identification issues, that will be largely discussed in Section 2.2.3.1. Our paper deals with these issues and encompasses a wider sample of mines. Other negative externalities of mining activity are the increase of rapacity and corruption and the trigger of insecurity, violence and conflicts (Berman et al., 2017; Fourati, Girard, and Laurent-Lucchetti, 2021), migration flows of mine workers fueling the spread of infectious diseases such as HIV (Corno and Walque, 2012), and discouragement of educational attainment among children (Atkin, 2016; Ahlerup, Baskaran, and Bigsten, 2020; Malpede, 2021).

Our paper focuses on industrial mining and does not encompass artisanal and small-scale mining (ASM). Few papers have looked at the effects of artisanal and

[2] Household wealth was measured through the dimensions of access to electricity, wealth index, urbanization, mortality, and education.

small-scale mining (ASM), mainly due to data limitations. Bazillier and Girard, 2020 compare the local spillovers between artisanal and industrial mining sites in Burkina-Faso. They find positive impacts of artisanal mining (labor intensive and managed in common) and an absence of industrial mines' opening (capital intensive and privatized) on household consumption. Our paper focuses on the effects of industrial mining pollution. If ASM has severe effects on miners' health due to hazardous working conditions it is likely to be of smaller magnitude than industrial mining which extracts and treats larger volumes [3]. If ASM is often accused of generating more severe pollution than the industrial sector because of their illegal use of mercury [4], the latter often use cyanide instead. Both chemicals being highly toxic pollutants, focusing on industrial mining only is a lower-bound analysis of the impacts of mining activity on local populations' health.

2.2.1 Mining-induced pollutions

Each stage of industrial mining activity produces chemicals and minerals likely to pollute the surrounding air, water and soil (Coelho and Texeira, 2011). The exploration and prospecting stage can last several years before a mine is considered economically viable and worthwhile to open. Meanwhile, mining companies conduct mapping and sampling, as well as drilling, boreholes, and excavation that require both physical and chemical measurement methods likely to pollute at the surface and underground, depending on the nature of the deposit in the targeted area. If found financially viable, the company launches the discovery phase where the design and planning of the construction are undertaken, and the feasibility study of the project requires further exploration and engineering studies. Subsequently, the development stage takes place and the mine's infrastructures and processing facilities are constructed. It is only after all these stages that production can start. Once the deposit is exhausted comes the closure and reclamation stage, where the company is supposed to clean, stabilize and rehabilitate the land and isolate contaminated material. Yet, it is common that waste, tailings, or retention dams are just left abandoned without care and maintenance, and this constitutes a potential disaster if the hazardous materials are leaked and discharged into the environment. Figure B.9 in the Appendix proposes a scheme to explain the life cycle of a mine. Figure B.8 displays satellite images of the different stages of the Essakane mine, an open-pit gold mine in Burkina-Faso.

[3] Industrial mines are responsible for 80% of the gold production and 75% of the diamond production McQuilken and Perks, 2020.

[4] Mercury has been officially banned in over 140 countries (Minamata Convention on Mercury, adopted in 2013).

Throughout all these stages, different types of pollution can be engendered. Air pollutants can be carried by dust over long distances by ore transportation and the wind, they can damage surrounding soils and crops, and be inhaled mostly by mine workers but also by the local population. The leakage of pollutants in the air can also affect water through acid mine drainage that ends up polluting the surface and then groundwater. During the digging and processing to extract the targeted ore from waste rocks, rocks are crushed and then go through either heap leaching, froth flotation, or smelting. These techniques require the addition of chemicals such as cyanide or acid, that can separate the targeted minerals from waste. Moreover, these processes are water-demanding and need access to a water source in competition with the local demand. Last but not least, even without the use of these chemicals, leaching happens through the contact of water and oxygen with sulfide minerals contained in the extracted rocks , which accelerates the acidification process and modifies the pH levels of water bodies. Pollutants can be released into the environment during the process by spills or after by leaks of humid waste stored in retention dams but also through the erosion and the sedimentation of solid wastes that are piled in the tailings around the mining site and that drain to the soil with rain. The wastes actively pollute during the whole life cycle of the mine, starting from its opening and during production, but also can continue to pollute when a mine closes and is left without maintenance. This is the case when retention ponds are not covered and dry, letting these wastes go directly through the environment.

Few papers have managed to show to what extent industrial mining activity creates negative externalities on the environment. Bialetti et al., 2018 look at the effects of mining industries on deforestation in India, Von der Goltz and Barnwal, 2019 have suggested the mechanism of water pollution but without strong empirical evidence (looking at anemia). Yet, in-situ measurements have shown the contamination of water drinking sources by harmful levels of nitrate, turbidity, iron, cadmium, manganese, and arsenic by industrial mining sites (Cobbina, Kumi, and Myilla, 2013). To our knowledge, we are the first to provide indirect, systematic, and large-scale evidence of the mechanism of water pollution by industrial mining activity.

The main toxic metals released by mining sites are arsenic, cadmium, copper, lead, mercury, and nickel. Depending on their blood level concentration, they can be essential or non-essential for human health (El-Kady and Abdel-Wahhab, 2018). However, heavy metals released by mining activity are non-biodegradable, have long-term impacts on the environment, and are found at abnormally high concentrations in the vicinity of mines, within the soil, water resources, vegetation, and crops (Oje et al., 2010; Dike et al., 2020). People living in that environment are exposed to high quantities of heavy metals through ingestion, dermal contact, and inhalation of soil particles, which can cause several implications for their health. High blood metal concentrations are associated with neurological effects (which induce behavioral problems, learning deficits, and memory losses, especially among children) (Dike et al., 2020), neurodegenerative diseases, cardiovascular effects, gastrointestinal hemorrhages (Obasi et al., 2020), organ dysfunction (kidney, decrease of the production of red and white blood cells, lung irritation) (Briffa, Sinagra, and R, 2020), higher probability of cancer development (Madilonga et al., 2021; Obasi et al., 2020), but also a higher probability of infertility, miscarriages for women, and malformation of newborns (Briffa, Sinagra, and R, 2020). Thus, exposure to heavy metals plays detrimental effects on human health in general and child health in particular, especially during their first months of development, both in and ex-utero (Coelho and Texeira, 2011). Besides, children at an early age are the most sensitive, even at low concentration, as they are at a stage of rapid biological development, but also as they are more exposed, through higher blood concentration linked to incidental ingestion of urban soil and dirty water (less conscious of their environment and danger, playing with polluted soil, eating and drinking without care (He et al., 2020)).

2.2.2 Health effects of mining activity

The empirical economic literature on the local effects of mining on local communities has been growing during the past decade, yet the debate remains on the costs and benefits, and the positive and negative impacts of industrial mining activity in developing countries. Diverse results have been found on the effects on health, and there is still uncertainty on the direction and the magnitude of the impacts of mines on the local population's health. Besides, if geographical proximity to a mining site is usually used as a proxy for pollution exposure, few papers observe the negative externalities on the environment and its consequences on health.

Papers studying the effects of industrial mines on health proxy the exposition to mining activity by the distance to the mine and can be found in the literature different thresholds and mixed results. Using cross-section data in the state of Orissa in India, Saha et al., 2011 uses the distance to the mine as a proxy to measure environmental effects, and finds that individuals living near a mine report higher respiratory illness and more work days lost due to malaria. Cross-sectional data prevent identifying a clear causal relationship and from adjusting to specific time and spatial confounders. Benshaul-Tolonen, 2018 uses a Difference-in-Difference strategy, comparing individuals living within 10 kilometers to those living between 10-100 kilometers of a mine, before and after its opening. The paper finds that large-scale gold mining in nine countries of Sub-Saharan Africa [5] decreases infant mortality within 10 km during the opening and operating phases, with no effect on further communities (10-100km). Cossa et al., 2022 uses a similar methodology studying a broader set of countries and find a decrease in child mortality as well.

Von der Goltz and Barnwal, 2019 assess the effects of industrial mines in 44 developing countries from 1988 to 2012. The paper also relies on a Difference-in-Difference strategy, comparing households living within 0 to 5 km to households living between 5 and 20 km before and after the opening of a mine. They find gains in asset wealth, increased anemia among women, and stunting in young children. As anemia and growth deficits are argued to be mainly the consequences of exposure to lead, the observed effects on health are interpreted to be the results of pollution due to metal contamination and lead toxicity. They find that women in mining communities show depressed blood hemoglobin, recover more slowly from blood loss during pregnancy and delivery and that children in mining communities suffer some important adverse growth outcomes from in-utero exposure (stunting).

2.2.3 Challenges and contributions

The most common way to proxy exposure to mining activity is to rely on the distance to an active or open mine, however, there is no clear consensus on which threshold to use, and the treatment allocation seems arbitrary. The disparities in the results from the literature could be explained by these differences in terms of empirical strategies and distance choices. Beyond this, using the Euclidian distance to a mine as treatment raises endogeneity concerns. This subsection discusses the main issues arising when studying the local impacts of industrial mining activity on health.

2.2.3.1 Endogeneity issues

In this section, two challenges are discussed: the endogeneity issues that arise (i) when using the Euclidian distance as a proxy for exposure to mining activity, and those when using (ii) repeated cross-sectional data such as the DHS.

[5] Burkina Faso, Ivory Coast, the Democratic Republic of the Congo, Ghana, Guinea, Ethiopia, Mali, Senegal, and Tanzania between 1987 and 2012

Using the interaction between being close to a mine and the mine's activity status raises endogeneity concerns. For instance, Von der Goltz and Barnwal, 2019 uses a mine panel and pairs each DHS village to its closest mine. This creates unbalanced treatment and control groups, and such imbalance might be endogenous to socio-economic outcomes or polluting behaviors. As each village is paired to its closest mine, this *de facto* excludes from the control group villages that are in both distance categories (within 5 km of mine A but 5-20 km of mine B). Thus, there is a higher probability to be treated in areas with high mining density, which is not a random allocation. As a mine fixed-effect identification relies on a within-mine buffer-area comparison, the estimator is driven by mines that have been paired to villages both in the treated and control areas, which is correlated to the mining density of the region. The estimation endogenously selects mines from regions of low or middle mining importance, which might be correlated with the intensity or the type of pollution, the socio-characteristics of the neighboring population, and thus the way health is affected by pollution. To reduce endogeneity issues, Von der Goltz and Barnwal, 2019 instrument the mine location with mineral deposit information from S&P, which are *deposits that are being explored or prepared for exploitation*. However, mining exploration is not a random allocation and raises the same concerns as it is directly correlated to mining density. Benshaul-Tolonen, 2018 reduces endogeneity issues linked to the pairing by using an administrative district fixed-effect panel and extending the distances (10-100km), but the same concern remains.

A second concern is linked to the nature of the DHS data, which are repeated cross-section surveys. The literature argues that the conditions for an industrial mine to settle are the presence of mineral deposits, which is considered random. However, the presence of a mine and of a declared mineral deposit is correlated to the population density. As mining exploration is labour intensive, it is more likely to occur in dense areas, where DHS is more likely to have surveyed individuals. A treatment allocation based on geographic proximity to the mine is endogenous: treatment groups close to the mine might not be comparable to control groups located further. As district fixed-effect relies on a within-district comparison, the estimation is driven by districts with both control and treated groups, before and after a mine opening, which is correlated to the probability of being surveyed. As DHS renews the surveyed villages at each wave, and as the probability to be surveyed is determined by the population density, the estimation is driven by specific areas. The regression *de facto* and endogenously selects districts that were already dense before the opening and remained after. This might be areas that are more stable, well-off, and where individuals might be less affected by pollution. This might bias the estimation upward (i.e less mortality linked to mining activity), and explain the positive effect of mines that Benshaul-Tolonen, 2018 find on mortality in Africa.

In Appendix section B.6, we propose a replication analysis of Benshaul-Tolonen, 2018, taking advantage of our handwork which extends the SNL database. We find similar results as Benshaul-Tolonen, 2018 using the same set of countries and our extended sample of mines (only gold mines as in the paper). However, we find no longer significant results when applying to our more comprehensive sample, meaning when including other African countries and industrial mines, which suggests that the effects are context and regional-dependent.

2.2.3.2 Upstream-downstream analyses

Using geographic distance to a mine as treatment allocation raises endogeneity concerns. An upstream-downstream analysis, which relies on a topographic comparison, reduces these concerns as individuals are compared from similar distances.

Few papers have dealt with upstream and downstream at the scale of a continent, since it requires much more computational capacity and a complex pairing methodology. Duflo and Pande, 2007 study the productivity and distributional effects of large irrigation dams in India and use river networks and calculate gradients computed from digital elevation maps for India. Do, Joshi, and Stolper, 2018 use river networks and pollution monitoring stations data in India to conduct their upstream-downstream analysis. Unfortunately, it is impossible in our case study due to the absence of water quality data at the scale of Africa. Garg et al., 2018 use river networks in Indonesia and re-calculate the upstream-downstream relationship between village pairs using a 30m resolution Digital Elevation Model. Their very refined level of study is not likely to be undertaken at the scale of the African continent in our case, so we choose secondary data computed by hydrologists (HydroSheds). We use systematic and highly disaggregated data on water sub-basins that enable us to encompass a wider set of countries, overcoming the issue of pairing a mine or a village to the closest river, since there is uncertainty about whether this point is located above or below in altitude compared to the level of the river. E. Strobl and R. O. Strobl, 2011 studied the distributional effects of large dams on agricultural productivity at the scale of the African continent, using Pfafstetter level 6 with an average area of 4200 km^2.

Our study takes into account sub-basins at the Pfafstetter level 12, with an average area of 100 km^2.

2.3 Data and Context

This section describes the data used for our empirical strategy, and some descriptive statistics on the context of industrial mining and child mortality in Africa.

2.3.1 Data

In this paper, we match socio-economic data from the Demographic Health Surveys to an industrial mining database provided by SNL Mining and Metals.

2.3.1.1 Health and socio-economic data

We use all available survey rounds from the Demographic Health Surveys that contain GPS coordinates, from 1986 to 2018, covering 36 out of the 54 African countries. We then select all the countries which have at least two survey waves to be able to implement our Difference-in-Difference strategy with a sufficient time length before and after the opening of a mine and end up with 26 countries[6], 12,442 clusters and 240,431 children under the age of five. We consider that doing a Difference-in-Difference strategy on the sample of countries that have only one round of survey, hence a maximum of five years period, will not enable us to capture the longer-term effects of mining activity[7]. Table B.2 in the Appendix displays the DHS survey years and countries that we use for the analysis.

We construct the variables of child mortality based on the DHS child recode database which has information on the age and death of children under five years old, whose mothers are aged between 15 and 49 years old. Our dependent variable is the probability of 12-month and 24-month mortality for each DHS cluster (i.e. for each child, we build a dummy equal to 1 if she or he is alive and 0 if not, conditional on having reached 12 and 24 months respectively). We also estimate the effects of mining activity on biomarker variables and other indicators of occurrences of illness

[6]The list of countries within our sample are: Benin, Burkina Faso, RDC, Burundi, Cote d'Ivoire, Cameroon, Ethiopia, Ghana, Guinea, Kenya, Liberia, Lesotho, Madagascar, Mali, Malawi, Nigeria, Niger, Namibia, Rwanda, Sierra Leone, Senegal, Togo, Tanzania Zambia, and Zimbabwe

[7]Please note that our final sample does not include Egypt which has 7 DHS waves and is a well-known mining country. This is explained by the fact that the SNL database characterized Egypt within the Middle East rather than in Africa and thus was dropped from our sample.

(diarrhea, fever, and cough) within two weeks preceding the day of the interview among young children. We extend our analysis to women's fertility behavior and health: current pregnancy, total lifetime fertility, miscarriage, and anemia. Finally, as the aim of this article is to isolate the mechanism of water pollution, we use the questions from the DHS on the main source of drinking water, the presence of flushed toilets, electricity, and the access to health facilities to control for households' sanitary and economic environment.

2.3.1.2 Mineral resource exploitation data

The industrial mining variables come from the SNL Metals and Mining database, which is privately owned by *S&PGlobal* and on license [8]. The SNL database is the best existing panel of mine production, providing information on the location, the dates of opening and closure, the commodity type, and the yearly production (for some mines). This is a non-exhaustive panel of industrial mines in Africa, yet to our knowledge, it constitutes the most comprehensive sample of mines giving the timing of the industrial activity. This dataset has been intensively used in the literature and argued to be the best product available (Aragón and Rud, 2016; Berman et al., 2017; Kotsadam and Tolonen, 2016; Benshaul-Tolonen, 2018; Von der Goltz and Barnwal, 2019; Mamo, Bhattacharyya, and Moradi, 2019). We emphasize here that this paper focuses on the effects of industrial mining, and that we do not include artisanal mining (ASM) that are not available in the SNL database.

Overall, the SNL database gathers 3,815 industrial mines in Africa from 1981 to 2021, and 2,016 were located within 100 km of a DHS cluster from a country with at least two surveys. For our difference-in-difference strategy, we need information on the timing of the beginning of the mining production. The SNL database gives this information for 278 mines and we retrieved from a handwork the start-up year for the 1,738 remaining mines. The hand-check was realized using information on the mining history available in the SNL database and mine reports (cross-checked with Google maps and aerial images). We describe this handwork more extensively in the Appendix B.1.2.

We build three main variables from the SNL Mining and Metals database, relying on the geocoded information and the time of opening. According to the estimation

[8]We are grateful to CEPREMAP, PjSE, EHESS, and the GPET thematic group of PSE, for their financial support and their help in purchasing the access to the data.

strategy, we will use a variable of proximity (distance to the closest mine), position (whether individual i is upstream or downstream), and a dummy for being open or not. Opening dates that were available in the SNL database were computed by the SNL team, and indicate the actual start-up year of the mine, i.e when production first began. We used the same criteria for our handwork. Finally, we restrict the main analysis that are associated with heavy metal mines (metals with density higher than $5g/cm3$ (Briffa, Sinagra, and R, 2020), which are the metals listed in Table B.6 in Section B.2.2 of the Appendix. We also include coal mines, as their extraction is associated with mercury and arsenic which are highly toxic heavy metals.

2.3.1.3 Water basins

We consider the topographic relationship of water basins where mines and villages are located. A water basin is an area where all the surface water converges towards the same point. We use the HydroBASINS sub-basins geographic information provided by HydroSHEDS, which delineates water basins consistently and subdivides sub-basins into multiple tributary basins to the network of nested sub-basins at different scales. Following the topological concept of the Pfafstetter coding system, each polygon of the sub-basin has a unique direction flow and provides information on the up-and down-stream connectivity. We take the finest Pfafstetter level (12 out of 12) that breaks down sub-basins at an average area of 100 km^2. See Figure 2.6a for an example. We conduct our analysis taking into consideration the three closest sub-basins to each industrial mine, meaning that we take each mine's sub-basin A and tag the one just downstream that we call B, the one just downstream of B that we call C, and then the one just downstream of C that we call D. Thus, B, C, and D are the three closest sub-basins of A.

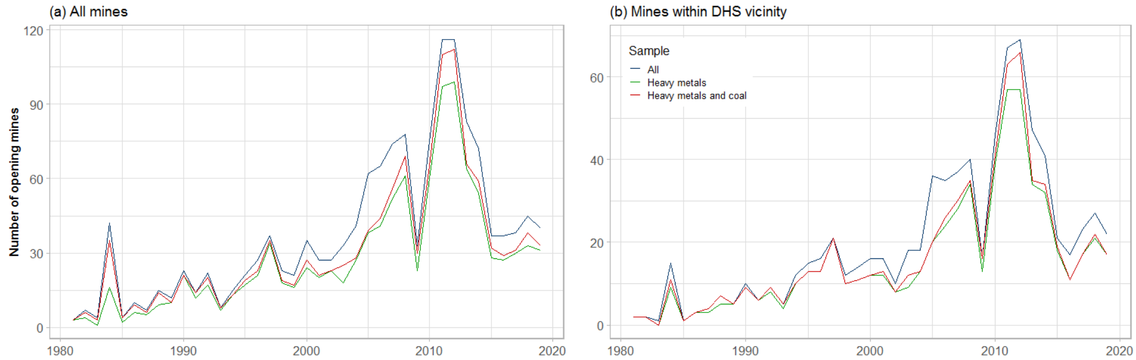
2.3.2 Descriptive statistics

2.3.2.1 Mining in Africa

Temporal and spatial variation

Figure 2.1 shows the evolution of the yearly number of mines that opened in Africa over the 1981-2019 period, Figure 2.1 (a) for the entire mining sample while Figure 2.1 (b) for the mines that are in the sample of the main analysis. The mining boom since 2000 is captured in the Figures, with the first peak in 2007, in line with the peak in exploration activity that occurred in 2003 (Taylor et al., 2009) (as the exploration phase is on average a couple of years before a mine opens), and the second one

Figure 2.1: Temporal evolution of mine opening



Notes: The Figures plot the number of mines opening each year over the 1981-2019 period, for all mines, heavy metal mines including coal (sample of the main analysis), and only heavy metal mines. Figure (a) displays the temporal evolution of the total mine sample, while Figure (b) of mines that are within the sample of the main analysis, meaning mines that have DHS clusters upstream at most at 100km and DHS clusters downstream within the three closest sub-basins.
Sources: Authors' elaboration on DHS and SNL data.

in 2012. For instance, around 120 industrial mines opened in 2012 (based on the non-exhaustive SNL database). The Figures also distinguish the evolution according to the mines' characteristics: it distinguishes the pattern for all mines, heavy metal mines, and heavy metals including coal mines. We observe no differences in timing patterns between Figure 2.1 (a) and (b), neither between mine types.

What is striking in Figure 2.1 is that the evolution of mine openings follows the same pattern as the evolution of industrial metal prices, as plotted in Figure B.10 from Section B.2.2 in the Appendix. The mining boom since 2000 follows the increase in real prices of Copper, Tin, Lead, Aluminum, Zinc, Nickel, and other heavy metals, while the sharp fall around 2008/2009 corresponds to the financial crisis. Again, the local minimum around 2016 corresponds to the drop in commodity prices in June 2014 (Khan, Nguyen, and Ohnsorge, 2016; Glöser et al., 2017). This similar evolution suggests that heavy metal prices are good Instrument Variables for the variable year of mine opening, such as Berman et al., 2017; Bazillier and Girard, 2020 used in their analysis. In Section 2.9.3 we will use it as a proxy for production intensity.

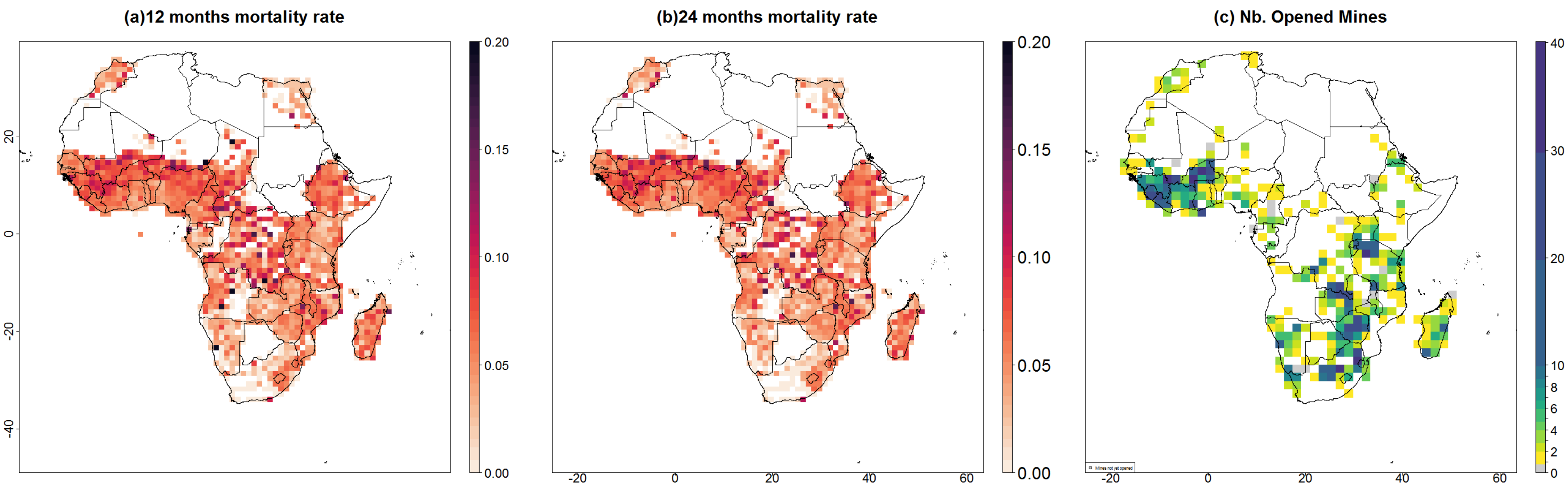
Figure 2.2 (c) shows the map of the number of mines that have opened before 2019, including mines that opened before 1986, averaged at the cell level (160 km cells). Cells in grey represent areas where no mine opened before 2019, but where at least one will open in the future (whether we know from the data that it has opened between 2019-2021, or if the opening is planned further). The main mining countries in the SNL database are Guinea, Sierra Leone, Ivory Coast, Ghana, Niger, Burkina Faso, Zimbabwe, Tanzania, Zambia, and the north of South Africa. Please note that, as we exclude countries with only one DHS wave in our main analysis' sample (cf Tables B.1 and B.2), to avoid comparing areas with too many differences in terms of temporal variations, we did not undertake the hand work for these countries, which explains why South Africa (which is not in the final sample) does not appear as a major mining country in Figure 2.2 (c). Figure 2.3 shows both the temporal and spatial variation of mine opening in Africa (for all the mines sample, and not the restricted one for our main analysis), as it plots the number of mines that opened over different periods of our analysis per grid cell. The cells in red are areas where no mines opened during the period, but where at least one mine has opened before, whereas cells in grey are areas where no mines have ever opened while at least one will open in the future. We observe that the increase in mine opening was higher during the third period 2008-2019 (which is in coherence with Figure 2.1), and was particularly important in West Africa.

2.3.2.2 Health risks

Africa faces high infant mortality rates, as the average 12 months mortality rate is 6.4 % and the average 24 months mortality rate is 8.3% according to DHS data (cf Table B.3). Figures 2.2 (a) and (b) plot the average mortality rates for all DHS from 1986-2019 averaged at the grid level, and show the spatial variation of mortality rates [9]. Figures 2.4 and 2.5 map both spatial and temporal variation of mortality rates as it shows the average mortality rates for the three main periods of our DHS sample. We can observe the global reduction of mortality over the period and also the DHS cluster distribution. Figures B.12, B.13 and B.14 plot the same maps for the sample restricted to the one used in the main regression.

[9]Please note that the higher the DHS cluster density, the more accurate the average. The spatial variation is endogeneous to the DHS sample.

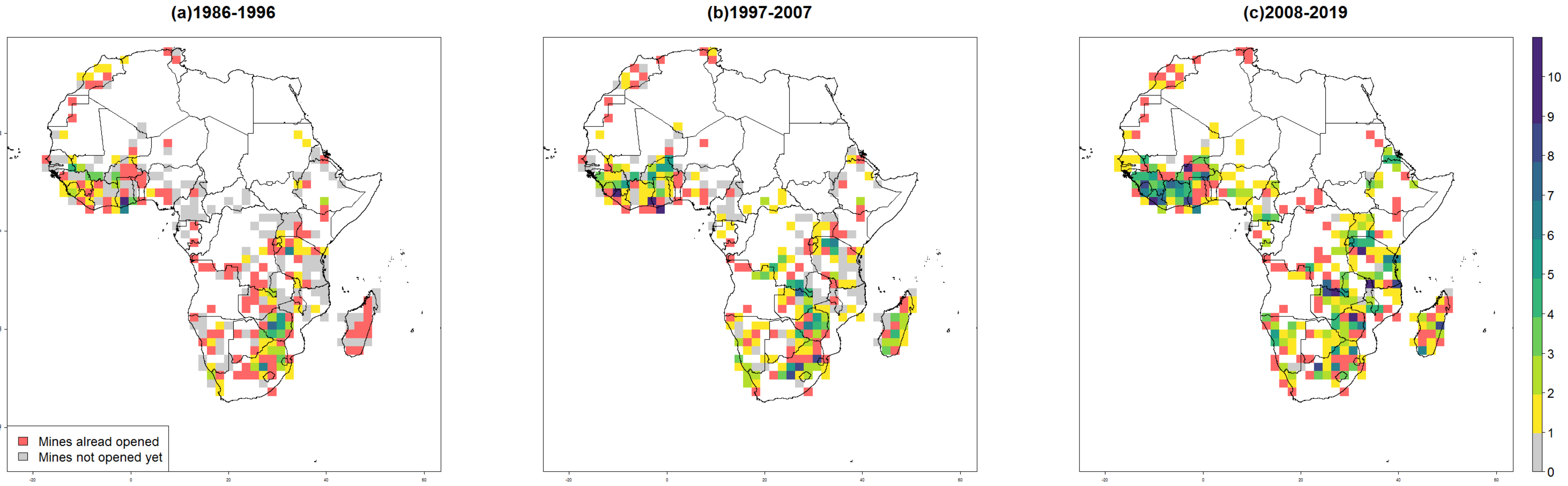
Figure 2.2: Outcomes spatial distribution



Notes: Figures (a) and (b) represent the means of 12- and 24-month mortality rates for each DHS wave available (listed in table B.2), from 1986 to 2019. Means are computed at the grid level (100km mean size). The mortality rates are estimated without the children that did not reach 12/24 months at the time of the survey. Figure (c) displays the stock of mines that opened before 2019 (including mines that opened before 1986). Means are computed at the grid level (100km mean size).

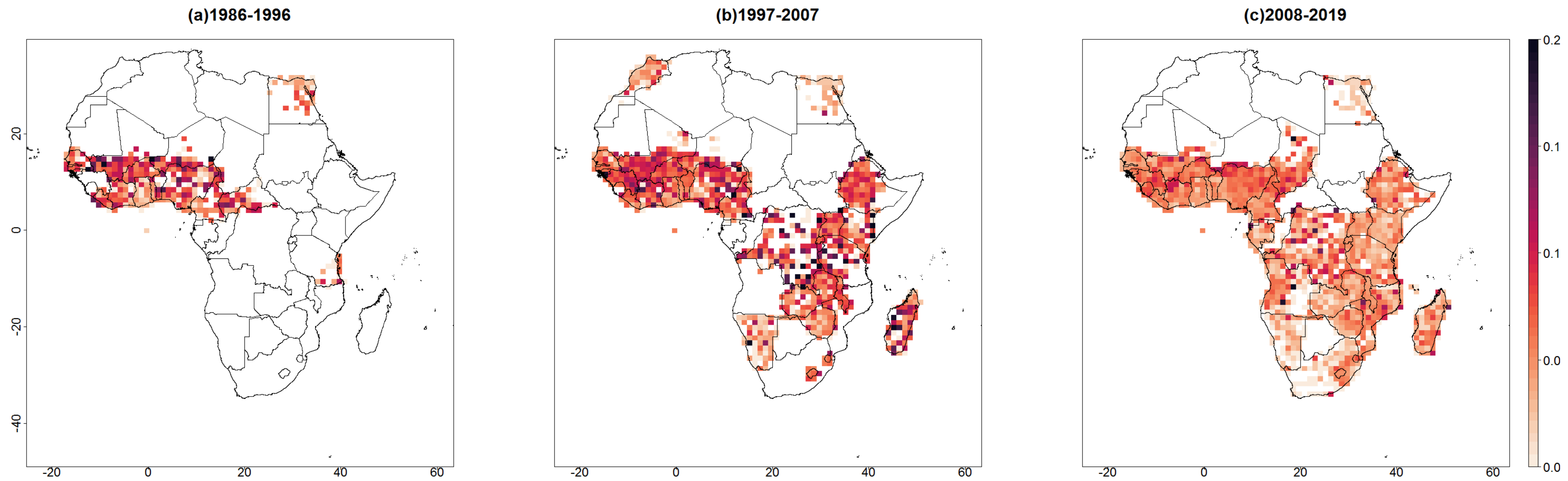
Sources: Authors' elaboration on DHS and SNL data.

Figure 2.3: Spatial variation of mine opening per period



Notes: The figures represent the number of mines that opened during the periods over the grid area (160 km on average). A red grid cell represents an area where no mine opened over the period, but where at least one mine open before the period. A grey cell represents an area where no mine opened over the period, but where at least one mine will open in the future.
Sources: Authors' elaboration on SNL data.

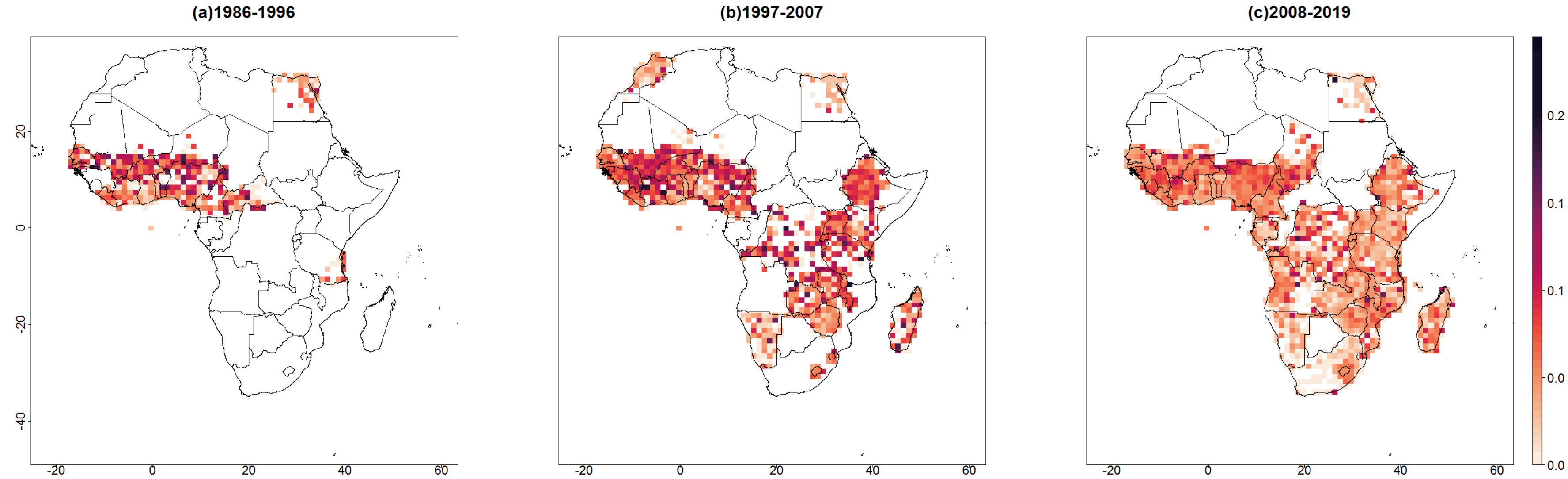
Figure 2.4: Spatial variation of 12-month mortality rates per period



Notes: The figures represent the means of 12-month mortality rates averaged at the grid level over (a) 1986-1996, (b) 1997-2008 and (c) 2008-2019. The mortality rates are estimated without the children that did not reach 12 months at the time of the survey.

Sources: Authors' elaboration on DHS data.

Figure 2.5: Spatial variation of 24-month mortality rates per period



Notes: The figures represent the means of 24-month mortality rates averaged at the grid level over (a) 1986-1996, (b) 1997-2008 and (c) 2008-2019. The mortality rates are estimated without the children that did not reach 24 months at the time of the survey.
Sources: Authors' elaboration on DHS data.

2.4 Empirical strategy

The main empirical strategy of this paper uses the relative topographic position of sub-basins as a proxy for exposure to mining activity pollution. It compares the effects on the health of individuals living downstream to those living upstream of a mine, before and after the opening of at least one site. It is a staggered design Difference-in-Difference analysis with two-way fixed effects at the mine's sub-basin and birth year level. This upstream-downstream strategy intends to identify the mechanism of water pollution.

As seen in Section 2.2.3.1, this strategy alleviates some endogeneity issues raised by treatments using the Euclidian distance as a proxy for exposure to the mine. First, it reduces the bias linked to unbalanced samples due to endogenous pairing. Second, it breaks the average effects based on distance buffers and highlights the heterogeneity of the effects of mining activity on health, and isolates the negative externalities linked to water degradation.

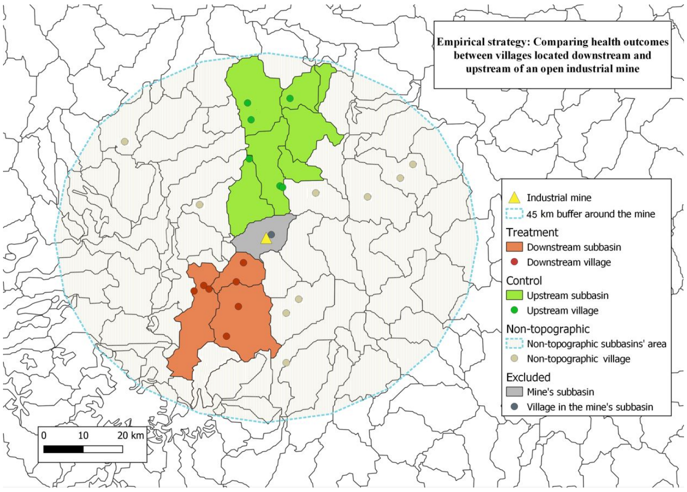
2.4.1 Measuring exposure to pollution

2.4.1.1 Pairing strategy

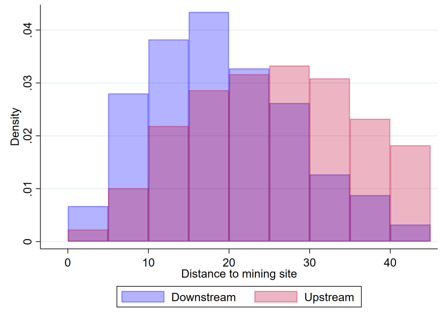
The pairing of DHS clusters to mines represents a significant challenge, as each DHS cluster can be downstream of and close to several industrial sites in major mining areas. It introduces endogeneity in the sample selection and raises the issue of unbalanced samples. In this analysis, we propose the following pairing to overcome this issue and thus be able to measure the exposure to pollution of each DHS cluster.

First, we construct a 100 km buffer around each DHS cluster and register all mines within this buffer (independently of their activity status). We then categorize the topographic position of the DHS cluster relative to the industrial site, using a dummy equal to 1 if the cluster is downstream of the mine and 0 if it is located upstream. This topographic position is defined using the relative position of each sub-basin. As each cluster and sites have GPS coordinates, they lie in a specific sub-basin, and we used the relative position of each sub-basin to classify the DHS according to the paired mine. Through such a process, we also have pairs that are located in the same sub-basin, and for which it is impossible to say exactly whether the cluster is downstream or upstream of the mine. At this stage, for these specific couples,

Figure 2.6: Pairing Strategy



(a) Scheme for pairing strategy



(b) Density of distance to the mine

Notes: Figure (a) is a scheme that illustrates the pairing, giving the example of a mine, its main sub-basin, its three closest downstream and upstream sub-basins, and DHS clusters that are in the treatment and control areas within 45 kilometers. Figure (b) plots the density of the distance (in km) to the mining site for DHS clusters across their upstream-downstream position.
Sources: Authors' elaboration on DHS, SNL, and HydroSheds data.

we consider the DHS to be downstream. Please note that, as explained in section 2.3.1.3, we used the finest Pfasftetter level 12 that breaks down sub-basins at an average area of $100km^2$ (the size of the sub-basin varies according to their shape, cf Figure 2.6a). At this stage, some villages can be paired with several mines and can have more than one occurrence in the sample. The difficulty of the strategy lies in choosing the mine that will be paired with the cluster.

Second, we restrict the group of downstream DHS clusters to the ones that lie within one of the three closest sub-basins downstream of the mine's sub-basin, to focus on the potentially most contaminated areas. Third, we pair each cluster with only one mine, proceeding as follows. If a DHS was in both groups (i.e downstream a mine A and upstream a mine B), then it is automatically assigned to the downstream group, and it is paired to the mine from which it is downstream (i.e it is paired to mine A), regardless of its activity status. At this stage, some clusters may still be counted twice, as they can be upstream of several mines, or in the three closest sub-basins downstream of several mines. To complete the uniqueness of the pairing, we paired each cluster to the nearest mine, regardless of its activity status as well.

In conclusion, the DHS clusters are attached to the nearest mine from which they are downstream up to the third sub-basin level, or else attached to the nearest mine upstream up to a radius of 100km. The final remaining problem relates to the clusters that are in the mine's same sub-basin, which we have so far identified as being downstream. We eliminated from the main analysis all DHS villages which are located in the same sub-basin of the mines from which they were paired. Also, this reduces the noise linked to the random displacement of DHS villages (cf Section 2.10.3.1) and avoids allocating villages as being downstream whereas they are upstream due to the displacement, as it drops the closest areas around the mine.

Once the pairing is done, we restrict the control group to upstream villages that are within 45 kilometers of the mine, to ensure the comparability of upstream and downstream villages. To choose this distance cut-off, we have calculated the mean of the maximal distance between a mine and the furthest extremity of its third downstream sub-basin, which was 44.7 kilometers. Figure 2.6b plots the distribution of the distance to the mine for both upstream and downstream villages. As downstream villages are prioritized in the pairing strategy, they are slightly closer to the mine, but the two distributions are comparable.

The pairing is illustrated in Figure 2.6a. It gives the example of a mine, its main sub-basin (grey), the downstream sub-basins (orange), and upstream sub-basins (green) up to 45 kilometers. The dashed area displays the sub-basins within 45 kilometers, with no topographic relationship to the mine, meaning they are neither downstream nor upstream. In the main strategy, we compare the villages within the green area to those in the orange area. In section 2.9 we run robustness tests checking whether the results hold allowing for further sub-basins and heterogeneity effects by distance to the mining site. In section 2.10.2.1 we discuss the results when including the non-topographic sub-basins.

2.4.2 Identification strategy

2.4.2.1 Main estimation

The main analysis relies on a Difference-in-Differences strategy using the topographic position of a DHS cluster relative to a mine deposit to indirectly identify the channel of water pollution. We propose a staggered Difference-in-Difference specification (DiD), with a sub-basin fixed effect panel for each mine. We isolate the mechanism of water pollution by building the treatment and control groups using an upstream-downstream comparison. We restrict our analysis using the pairing strategy explained in the previous section 2.4.1.1. We compare health outcomes in upstream-downstream areas, both before and after the opening of the paired mine. The empirical strategy can be formally written as follows:

$$\begin{aligned} Death_{i,v,c,SB} =& \alpha_0 + \alpha_1 Opened_{birthyear,i,v} + \alpha_2 Downstream_{v,SB} \\ &+ \alpha_3 Opened_{birthyear,i,v} \times Downstream_{v,SB} + \alpha_4 X_i \\ &+ \gamma_S B + \gamma_{SB-trend} + \gamma_{c,birthyear} + \epsilon_v \end{aligned} \tag{2.1}$$

With $Death_{i,v,c,SB}$ a dummy equal to one if child i from DHS village v of country c, has reached the n^{th} month and has died (n being 12 for the 12-month old mortality, same for 24 months). $Opened_{birthyear,i,v}$ is a dummy equal to 1 if the mine, which is located in sub-basin SB, has opened before child i's year of birth. $Downstream_{v,SB}$ is a dummy of relative position (equal to 1 if village DHS v is located in a sub-basin downstream of the mine sub-basin SB, and 0 if it is upstream), X_i a vector of child and mother level controls (mother's age, age square, years of education, urban residency). Finally, γ_{SB} is a mine sub-basin fixed effect, $\gamma_{SB-trend}$ a mine sub-basin linear birthyear trend and $\gamma_{c,birthyear}$ a country-birthyear fixed effect. This analysis is a staggered design as the treatment shock (mine opening) does not occur at the same time for each DHS cluster.

The main regression is run without the DHS clusters that lie within the same sub-basin as the mine they are coupled with, as discussed in the previous section. The list of countries and survey years used in the main regression are given in Table B.2, and the list of metals in Table B.6.

2.4.2.2 Identification assumption

The key assumption of a DiD is that the downstream group would have evolved as the upstream group in the absence of the opening of a mine. As we cannot test that upstream and downstream areas would have followed the same time trends, we test in Section 2.8 the common trend assumption using pre-treatment data.

However, the fact that pre-treatment data are parallel is neither a necessary nor a sufficient condition for the identification. Past trends can be identical but the upstream group may be affected by a group-specific shock at the period of the treatment. The estimation of this paper relies on the fact that the comparison between downstream and upstream villages is a proxy for exposure to water pollution. The major identification assumption is that the opening of a mine affects differently upstream and downstream areas only through the decrease in water quality. Throughout the paper, we will try to address the concerns of unobservable factors that might not be orthogonal to our treatment and Section 2.11 displays a final general discussion on the threats to the identifying assumption, and how they have been solved in the analysis.

2.4.3 Descriptive statistics

In this section, we describe the balance tables for the outcomes that play a key role in our analysis, out of parsimony.

Table 2.1: Balance Table

	Before Mine Opening					After Mine Opening					Within Up.	Within Dwn.	Within
	Upstream		Downstream		Diff	Upstream		Downstream		Diff			
	N	Mean /(SD)	N	Mean /(SD)	(4-2) /(p.v)	N	Mean /(SD)	N	Mean /(SD)	(9-7) /(p.v)	(7-2) /(p.v)	(9-4) /(p.v)	(12-11) /(p.v)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Dth < 12													
All	23,547	0.073	7,875	0.074	0.001	12,319	0.055	4,738	0.051	-0.004	-0.018	-0.023	-0.005
		(0.261)		(0.262)	(0.83)		(0.228)		(0.219)	(0.256)	(0)	(0)	(0.468)
Mines	244		237			179		183					
Dth < 24													
All	17,726	0.096	5,928	0.098	0.002	8,664	0.068	3,330	0.072	0.004	-0.028	-0.026	0.002
		(0.294)		(0.297)	(0.618)		(0.252)		(0.259)	(0.428)	(0)	(0)	(0.671)
Mines	244		236			168		168					

Notes: Standard errors and p-values in parentheses. Descriptive statistics of 12- and 24-month mortality outcomes, for villages located upstream and downstream of mining sites, for individuals born before and after the opening of the mine.

Balance Table 2.1 compares the changes in infant mortality before and after the opening of a mine, for places upstream *vs* downstream of the mining site, following the pairing strategy. It displays also the number of individuals and paired mines in each group of the analysis. On average, upstream and downstream areas have non-significant differences in terms of 12 and 24-month mortality (columns 5 and 10). For both upstream and downstream clusters, the opening of a mine significantly decreases the mortality probability (columns 11 and 12), which is in line with the result of Benshaul-Tolonen, 2018, and with the fact that mortality rates decrease over time in Africa, as trends are not included (Figures B.12 and B.13). Table 2.1 shows that this reduction is overall slightly more important in upstream areas than in downstream areas for under 24-month mortality (0.002), while it is the contrary for under 12-month mortality (-0.005) but they remain not significant differences (column 13). Table 2.1 does not include any controls and is only descriptive. Table B.7 from Section B.3 in the Appendix replicates this exercise for control variables.

Figure B.11 in the Appendix identifies the country with the biggest stock of open mines in our sample (Ghana, Zimbabwe, and Tanzania with the highest density of open mines nearby DHS), as well as insights on the variation in mine opening over the period per country.

2.5 Main results

This section displays the results of our main analysis. The first section describes the overall effects of mining opening on child mortality among the villages living downstream compared to those living upstream. The second section displays the effects of being downstream of an open mine on other child's health outcomes, while the third section focuses on women's outcomes.

2.5.1 Child mortality

This section displays the main results of this paper from equation 2.1 for the 12-month mortality rate and the 24-month mortality rate. Table 2.2 gathers our main results with mine sub-basin and country-birth-year fixed effects. We also include mine sub-basin and birthyear linear trends, adjusting for spatial and period-specific cofounders and trends, and commodity fixed effects. Columns (1) to (4) give the results for the 12-month mortality rate, while columns (5) to (8) for the 24-month mortality rate. Columns (1), (2), (5), and (6) display the results for the total population while columns (3), (4), (7), and (8) focus on the rural population. Control variables are birth order, mother's age, mother's age square, the mother's years of education, urban, and the intensity of the river network. [10]. Even columns include the number of open mines within 45km of the DHS cluster as control, which controls for the mining density.

[10]The variable intensity of the river network using the HydroRIVERS product. It is a continuous variable, which takes into account the area of the catchment that contributes directly to a river reach, and the Strahler order of the specific river segment. In our sample, the Strahler spans from 3 to 10.

Table 2.2: Effects of industrial mining opening on child mortality

	12-month mortality				24-month mortality			
	Total Population		Rural Population		Total Population		Rural Population	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Down×Open	-0.00352	-0.00506	0.00517	0.00510	0.0231**	0.0218**	0.0379***	0.0380***
	[0.00824]	[0.00831]	[0.0102]	[0.0102]	[0.0105]	[0.0108]	[0.0130]	[0.0130]
Downstream	-0.0140**	-0.0152**	-0.0203***	-0.0204***	-0.0202***	-0.0211***	-0.0287***	-0.0284***
	[0.00655]	[0.00665]	[0.00743]	[0.00762]	[0.00731]	[0.00739]	[0.00795]	[0.00810]
Open	0.0121*	0.00963	0.0106	0.0102	-0.00302	-0.00496	-0.00650	-0.00588
	[0.00722]	[0.00754]	[0.00858]	[0.00952]	[0.00986]	[0.0101]	[0.0115]	[0.0122]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nb open mines	No	Yes	No	Yes	No	Yes	No	Yes
Birthmth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ctry-bthyr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mine SB FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MineSB-bthyr trd	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Commodity FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	48,472	48,472	33,231	33,231	35,638	35,638	24,544	24544
R2	0.0378	0.0378	0.0476	0.0476	0.0511	0.0511	0.0633	0.0633
Outcome Mean	0.0666	0.0666	0.0716	0.0716	0.0873	0.0873	0.0945	0.0945

Notes: Standard errors clustered at the DHS village level, $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. The variables Downstream and Opened are dummies that indicate whether an individual lives in a village downstream of at least one mining site and whether the site opened before the year of birth. Each DHS village is paired to only one mining site so that each individual appears only once in the regression. Other variables are control variables. The sample focuses on heavy metal mines. Columns (1-3) give the results for the total population while columns (4-6) display the results for rural villages. Columns (2, 4, 6, 8) control for the number of open mines within 45 km. Control variables are birth order number, mother's age, mother's age square, mother's years of education and urban, number of open mines, and a continuous variable indicating the presence of rivers and their order.

The results show that being downstream of an open mine increases by 2.18 percentage points (p.p) the 24-month mortality rate [11]. This corresponds to an increase by 25% as the average 24-month mortality increases from 8.7% to 10.9%. The results are higher in terms of magnitude in rural areas, as being downstream an open mine increases by 3.8 p.p the 24-month mortality rate, which is associated to an increase by 40%, as the mortality increases from 9.4% to 13.2%. This is in line with the fact that rural populations have less access to facilities and infrastructure and are more exposed to unsafe water. The results are not significant concerning the 12-month mortality rate, and are very close to zero, showing no difference between individuals leaving upstream to those leaving downstream. This lag in the effect of water pollution on children's health may be explained by the higher probability of children under 12 months to be breastfed compared to children under 24-month, hence their decreased exposure to contaminated water and limitation of direct ingestion (VanDerSlice, Popkin, and Briscoe, 1994; Fängström et al., 2008). This mechanism explaining the different results on the 12-month mortality *vs* 24-month mortality is explored in Section 2.6.3.

2.5.2 Other health effects

Table 2.3 represents the effect of industrial mining on other children's health outcomes than mortality. Columns (1-3) display the results on anthropometric measures of children who were still living at the time of the survey, and are measured at the time of the survey. A child is affected by stunting if her height-for-age z-score is below minus 2 standard deviations below the mean on the World Health Organization Child Growth Standards. The same definition applies to underweight (weight-for-age) and wasting (weight-for-height). We find a negative and significant effect of industrial mining on underweight but not on stunting and wasting: living downstream of an open mine decreases wasting by 3.9 pp. This result could potentially be explained by the death of the most vulnerable children and the survival of the heaviest ones. We find no results on other diseases among living children: anemia (measured), diarrhea, cough, or fever (reported within the two weeks preceding the interview). We find no effect either of industrial mining on low weight at birth (below 2.5 kg) nor reported size at birth (reported as small or very small by the mother).

[11] 95 % Confidence interval: [0.000595; 0.042993]

Table 2.3: Effects of industrial mining opening on other child health outcomes

	Surviving children							All births	
	Stunting	Underweight	Wasting	Anemia	Diarrhea	Cough	Fever	$< 2.5kg$	Small
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Down×Open	-0.0167	-0.0389**	-0.00479	-0.0265	0.00146	-0.00824	-0.00219	-0.00925	-0.00337
	[0.0199]	[0.0169]	[0.0109]	[0.0277]	[0.0130]	[0.0176]	[0.0154]	[0.0180]	[0.0120]
Downstream	-0.0126	-0.00293	0.00330	0.0428**	0.00287	-0.0115	0.0141	-0.00951	0.00673
	[0.0172]	[0.0152]	[0.00897]	[0.0188]	[0.0108]	[0.0138]	[0.0144]	[0.0163]	[0.0107]
Open	-0.00618	0.0257*	0.00769	0.00582	-0.00545	0.00547	-0.00571	0.00571	0.0191
	[0.0162]	[0.0146]	[0.0106]	[0.0246]	[0.0111]	[0.0124]	[0.0127]	[0.00954]	[0.0159]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birthmonth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ctry-bthyr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mine SB FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MineSB-bthyr trd	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Commodity FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	37,393	37,043	37,903	19,331	55,162	54,958	54,955	29,162	58,338
R2	0.155	0.124	0.0895	0.215	0.0900	0.104	0.111	0.0608	0.0532
Outcome mean	0.308	0.246	0.0893	0.660	0.165	0.237	0.246	0.171	0.157

Notes: Standard errors clustered at the DHS village level, $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$. Columns (1-3) focus only on surviving children (due to variable construction in DHS), while the others encompass all children, including those who died before the survey. The same sample and controls as Table 2.2 Column 2 apply.

2.5.3 Women's outcomes

We make sure that the results found on child mortality are not due to a change of fertility among women [12]. We find no significant effect of industrial mining neither on whether women ever had a child (Table 2.4 column 1) nor on the total number of children she had (column 2). We find no effect either on whether women were pregnant during the time of the survey (column 3). Table 2.4 also displays results on women's other health outcomes: we find no effect of industrial mining on neither whether women ever had a miscarriage or on their anemia status.

[12] The analysis has been made using DHS Women Recode, which population sample is all women aged 15-49 years old.

Table 2.4: Effects of industrial mining opening on women outcomes

	Fertility			Health	
Outcome	Ever had a child	Total lifetime fertility	Currently pregnant	Ever had a miscarriage	Anemia
	(1)	(2)	(3)	(4)	(5)
Down × Open	0.0156	-0.0164	-0.0171	-0.00507	0.000806
	[0.00977]	[0.0720]	[0.0111]	[0.0138]	[0.0261]
Downstream	0.00886	0.0841	0.0160	0.00894	-0.00928
	[0.00952]	[0.0731]	[0.0118]	[0.0134]	[0.0233]
Open	-0.00161	0.0663	0.00607	-0.00136	-0.00417
	[0.00916]	[0.0595]	[0.00833]	[0.0119]	[0.0285]
Controls	Yes	Yes	Yes	Yes	Yes
Ctry-survey year FE	Yes	Yes	Yes	Yes	Yes
Mine SB FE	Yes	Yes	Yes	Yes	Yes
MineSB-svey year trd	Yes	Yes	Yes	Yes	Yes
Commodity FE	Yes	Yes	Yes	Yes	Yes
N	82,406	82,406	82,373	72,423	31,587
R2	0.510	0.659	0.0422	0.0906	0.122
Outcome mean	0.737	2.912	0.0939	0.136	0.396

Notes: Standard errors clustered at the DHS village level, $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$. Control variables are birth order number, woman's age, woman's age square, woman's years of education, urban, number of open mines and presence of rivers.

2.6 Mechanisms

2.6.1 Households' access to water and facilities

We deepen our analysis by studying whether the effects found on children's mortality are indeed due to water pollution downstream of mines and not driven by improved access to water and sanitation or facilities upstream. Under 24-month mortality is still increased significantly by 2 p.p. when adding the triple interaction with several facilities variables: whether a household has piped water as the main drinking source (Table 2.5 column 1), whether a household has a flushed toilet (column 2), whether it has access to electricity (column 3), and whether the mother had visited health facilities during the 12 months preceding the survey (column 4). We find no significant heterogeneity across the four facilities, which suggests that our result is not explained by an improvement of facilities upstream, which contradicts the findings of Dietler et al., 2021. Table B.8 in Section B.3 of the Appendix looks at the DiD estimator using the access to piped water and electricity as dependent variables and shows no difference after the opening of a mine between upstream and downstream villages.

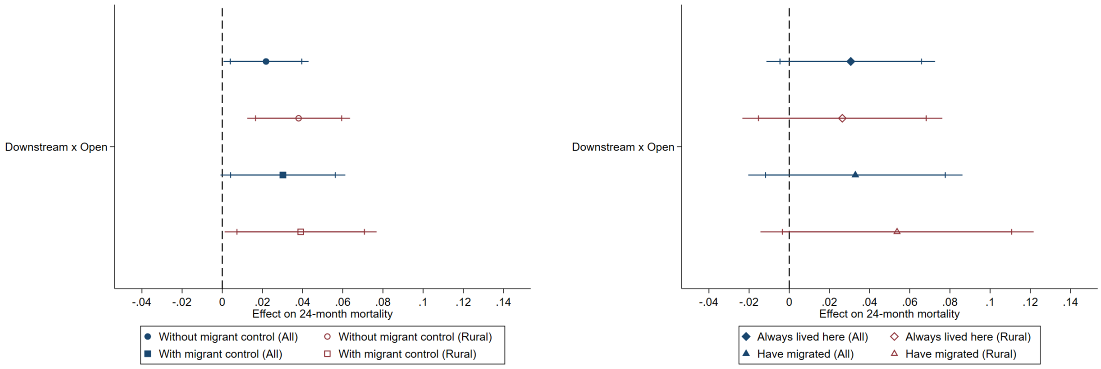
Table 2.5: Effects of industrial mining opening on access to water, sanitation and facilities

Outcome	24-month mortality			
Var.	Has piped water	Has flushed toilet	Has electricity	Visited health facilities
	(1)	(2)	(3)	(4)
Downstream×Open × Var.	0.000283	-0.0356	-0.0114	-0.0140
	[0.0195]	[0.0263]	[0.0192]	[0.0165]
Downstream×Open	0.0210*	0.0236**	0.0243**	0.0292*
	[0.0118]	[0.0110]	[0.0115]	[0.0159]
Var.	-0.00266	-0.0165*	-0.0157**	-0.00491
	[0.00637]	[0.00920]	[0.00695]	[0.00541]
Downstream	-0.0229***	-0.0215***	-0.0223***	-0.0170*
	[0.00770]	[0.00744]	[0.00764]	[0.00983]
Open	-0.000958	-0.00482	-0.00715	-0.00543
	[0.0103]	[0.0101]	[0.0103]	[0.0122]
Controls	Yes	Yes	Yes	Yes
Birthmonth FE	Yes	Yes	Yes	Yes
Country-birthyear FE	Yes	Yes	Yes	Yes
Mine SB FE	Yes	Yes	Yes	Yes
Mine SB-birthyear trend	Yes	Yes	Yes	Yes
Commodity FE	Yes	Yes	Yes	Yes
N	35,638	35,536	35,423	32,018
R2	0.0512	0.0513	0.0512	0.0512
Outcome mean	0.0873	0.0873	0.0873	0.0857

Notes: Standard errors clustered at the DHS village level, $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$. The same sample and controls as Table 2.2 Column 2 apply.

2.6.2 Migration

Figure 2.7: Migration analysis



(a) With and without migrant control (b) Migrant/Always lived here samples

Notes: Figure (a) plots the coefficients associated with being downstream of an open mine on under 24-month mortality when controlling for mothers' migration status or not, across the whole or rural sample. Figure (b) plots the coefficients of the same interaction but across the sample of mothers who have migrated or always lived here. *Sources:* Authors' elaboration on DHS and SNL data.

We pursue our analysis by making sure that our results on children mortality are not due to migration and do not suffer from selection bias. The migration information is retrieved from the variable indicating whether mothers have ever migrated to the actual place of residency, or if they have always lived there. The information is available among 60% of our sample (cf. Table B.4) and controls for in-migration, which is an important effect of the opening of a mine that attracts new working populations (cf Section B.3 for more discussion on bias linked to migration). Figure 2.7 displays the coefficient associated to the interaction term of being downstream of an open mine. The top coefficient on Figure 2.7a is our main specification when we do not control for migration, across the whole. We plot the same focusing on the rural sample. The bottom two coefficients are when we control for migration, across our whole and rural sample. We find that all are statistically positive and significant. We further our analysis by splitting the sample across mothers who have ever migrated and mothers who have always lived here (Figure 2.7b). The estimation suffers from lack of statistical power (see Appendix Table 2.6 for the drop of observations) but suggests no differential effect of industrial mining across the two samples.

Table 2.6: Effects of industrial mining activity, migration analysis

Outcome	Mortality under 24 months							
Spec.	Without migrant control		With migrant control		Migrant sample		Always lived here	
Sample	All	Rural	All	Rural	All	Rural	All	Rural
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Downstream x Open	0.0218**	0.0380***	0.0302*	0.0390**	0.0329	0.0537	0.0306	0.0264
	[0.0108]	[0.0130]	[0.0158]	[0.0193]	[0.0272]	[0.0347]	[0.0214]	[0.0254]
Downstream	-0.0211***	-0.0284***	-0.0249**	-0.0332***	-0.0229	-0.0304	-0.0301**	-0.0418***
	[0.00739]	[0.00810]	[0.0106]	[0.0119]	[0.0190]	[0.0226]	[0.0139]	[0.0147]
Open	-0.00496	-0.00588	-0.0255	-0.0235	0.0116	0.0187	-0.0409**	-0.0425*
	[0.0101]	[0.0122]	[0.0159]	[0.0194]	[0.0260]	[0.0335]	[0.0198]	[0.0256]
Migrant			0.00850*	0.00348				
			[0.00449]	[0.00594]				
N	35638	24544	22231	15060	8658	6007	13503	8982
R2	0.0511	0.0633	0.0634	0.0770	0.112	0.132	0.0797	0.107
Outcome mean	0.0873	0.0945	0.0946	0.104	0.0892	0.102	0.0983	0.107

Notes: Standard errors clustered at the DHS village level, $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$. The same sample and controls as Table 2.2 Column 2 apply.

2.6.3 Early life characteristics

We want to better understand the mechanism behind the results on 12- and 24-month mortality, and focus on children's nutrition and access to health care as main potential explaining factors. Table 2.7 gives the results of several triple interactions looking at the heterogeneity of the effect according to early life characteristics.

We find a significant increase of mortality among children living downstream of an open mine and who were given plain water 24 hours before the survey for both the 12-month mortality and 24-month mortality. For individuals living downstream an open mine and who consumed plain water, the 12-month mortality increases by 5.3 p.p. and the 24-month mortality increases by 6.5 p.p. (Columns (1) and (2)). Unfortunately, the DHS variable does not specify the source of plain water, and we cannot show that the given plain water is more polluted downstream than upstream. We find no significant effect of the triple interaction with breastfeeding behaviors on mortality: whether the child was ever breastfed (columns 3 and 4) or number of months during which the child was breastfed (columns 5 and 6). This absence of result can be explained by the low variability as 98 % of the children in the sample were breastfed. There is a larger variability of plain water consumption, as it was the case for 18.7% of children. We thus interpret the fact that drinking plain water as a child is a proxy for having non-exclusive breastfeeding [13].

We find no significant effect either of the triple interaction with access to health care: whether the mother received prenatal care (columns 7 and 8) or whether the child was ever vaccinated (columns 9 and 10).

[13] DHS questionnaire ask whether the children has been breastfed and has consumed plain water during the 24 hours before the survey

Table 2.7: Effects of industrial mining opening on explaining factors 12 vs. 24 months

	Child's nutrition						Child's access to health care			
Var.	Was given plain water		Ever breastfed		Breastfeed months		No prenatal care		Ever vaccinated	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Mortality outcome	12m	24m	12m	24m	12m	24m	12m	24m	12m	24m
Downstream× Open × Var.	0.0530**	0.0650*	0.000597	-0.0450	0.00106	0.00106	0.0165	0.0288	0.0114	0.0134
	[0.0244]	[0.0350]	[0.0519]	[0.0481]	[0.00176]	[0.00210]	[0.0272]	[0.0402]	[0.0191]	[0.0231]
Downstream	-0.0000982	-0.00344	-0.0104	-0.0161	-0.0125	-0.0293	-0.0140**	-0.0200**	0.0117	0.00258
	[0.00760]	[0.0138]	[0.0250]	[0.0305]	[0.0237]	[0.0300]	[0.00613]	[0.00871]	[0.0127]	[0.0126]
Open	0.0104	-0.00951	0.0172	0.0163	-0.0785***	-0.134***	0.00842	0.000268	0.00433	0.00929
	[0.00861]	[0.0189]	[0.0266]	[0.0345]	[0.0231]	[0.0324]	[0.00770]	[0.0117]	[0.0105]	[0.0175]
Downstream×Open	-0.0131	0.0193	0.00423	0.0702	-0.0213	-0.000897	-0.0114	-0.000663	-0.0119	-0.0105
	[0.0103]	[0.0214]	[0.0523]	[0.0488]	[0.0373]	[0.0516]	[0.00823]	[0.0121]	[0.0178]	[0.0211]
Var.	0.0338***	0.0277**	-0.921***	-0.880***	-0.0179***	-0.0201***	0.0299***	0.0398***	-0.0201***	-0.0257***
	[0.0102]	[0.0137]	[0.0115]	[0.0134]	[0.000595]	[0.000657]	[0.00774]	[0.0110]	[0.00728]	[0.00828]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birthmonth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-birthyear FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mine SB FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mine SB-birthyear trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Commodity FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	19,671	10,797	45,168	33,022	29,015	18,323	31,656	19,543	17,372	13,638
R2	0.0735	0.102	0.208	0.174	0.330	0.355	0.0558	0.0822	0.239	0.306
Outcome mean	0.0396	0.0758	0.0493	0.0694	0.0466	0.0768	0.0479	0.0639	0.00835	0.0121

Notes: Standard errors clustered at the DHS village level, $^{*}p < 0.1$,$^{**}p < 0.05$,$^{***}p < 0.01$. The same sample and controls as Table 2.2 Column 2 apply.

2.7 Heterogeneity

2.7.1 Individual characteristics

Table 2.8: Effects of industrial mining opening across children's location and gender

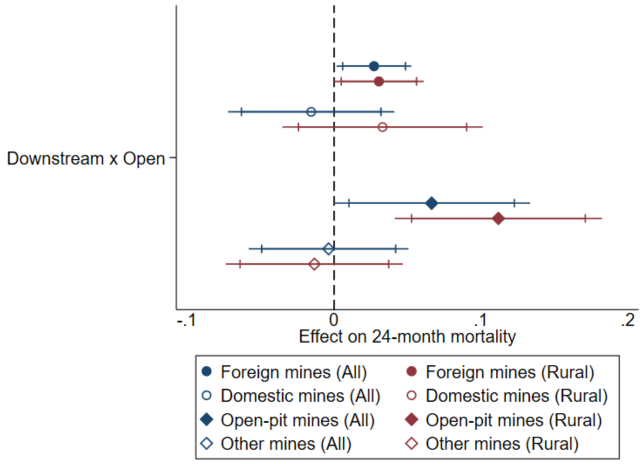
Outcome	24-month mortality					
Sample	All: urban and rural			Rural		
	All	Girls	Boys	All	Girls	Boys
	(1)	(2)	(3)	(4)	(5)	(6)
Downstream× Open	0.0218**	0.0120	0.0334**	0.0380***	0.0204	0.0677***
	[0.0108]	[0.0151]	[0.0167]	[0.0130]	[0.0186]	[0.0199]
Downstream	-0.0211***	-0.0203*	-0.0206*	-0.0284***	-0.0292**	-0.0292**
	[0.00739]	[0.0114]	[0.0111]	[0.00810]	[0.0126]	[0.0117]
Open	-0.00496	0.00364	-0.0178	-0.00588	0.00419	-0.0200
	[0.0101]	[0.0155]	[0.0143]	[0.0122]	[0.0186]	[0.0181]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Birthmonth FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-birthyear FE	Yes	Yes	Yes	Yes	Yes	Yes
Mine SB FE	Yes	Yes	Yes	Yes	Yes	Yes
Mine SB-birthyear trend	Yes	Yes	Yes	Yes	Yes	Yes
Commodity FE	Yes	Yes	Yes	Yes	Yes	Yes
N	35,638	17,452	18,142	24,544	12,009	12,481
R2	0.0511	0.0758	0.0762	0.0633	0.0942	0.0972
Outcome mean	0.0873	0.0805	0.0938	0.0945	0.0883	0.101

Notes: Standard errors clustered at the DHS village level, $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$. The same sample and controls as Table 2.2 Column 2 apply.

We conduct a heterogeneity analysis across children's location and gender (Table 2.8). We find that being downstream of an open mine is more critical in rural areas, (Column 4) as it increases the 24-month mortality by 3.8 p.p, which corresponds to a 40 % increase in the mortality rates. The heterogeneity by gender shows that our results are mainly driven by the mortality of males (columns 3 and 6), which remains consistent in rural areas.

2.7.2 Mining activity's characteristics

Figure 2.8: Heterogeneity across mines' characteristics



Notes: This graph represents the coefficients associated with the interaction of living downstream of an open mine when splitting the sample between mines that are owned by foreign companies and mines that are owned by at least one domestic company (in blue) and between mines that are open-pit and not open-pit (underground, placer, and in-situ leach) (in red).
Sources: Authors' elaboration.

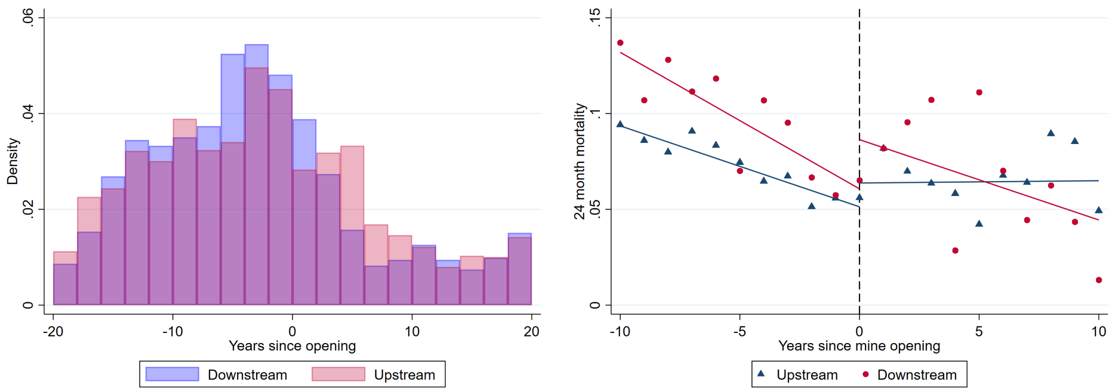
We pursue the heterogeneity analysis across mines' ownership and extraction methods. A mine was considered domestic if at least one of the owning companies is from the same country as the country of location, and they represent 17.8 percent of our mine sample. Figure 2.8 represents the coefficients associated with the interaction term of living downstream of an open mine. We find no effect of mine opening when we restrict the sample to domestically owned mines whereas our results hold when we restrict to the foreign-owned only mines (in blue). This could potentially be explained by improved management of a mine or a better consideration of the surrounding populations if a national company is involved. We then look at the open-pit nature of the industrial site, which concern 21.6 percent of our mine sample. We find that our results hold when restricting to open-pit mines but not when we only look at the sample of other extraction methods (underground, placer, and in-situ leach) (in red). This is consistent with the fact that open-pit mines are the most polluting mines due to the generation of large amounts of waste kept in tailing storage facilities.

2.8 Dynamic effects

In this section, we investigate the dynamic effects of the opening of an industrial mine, looking at pre-trends and at whether the effects on 24-month mortality occur within a short or long time, and during the mine activity.

2.8.1 Pre-trends and event-study

Figure 2.9: Linear trends of 24-month mortality



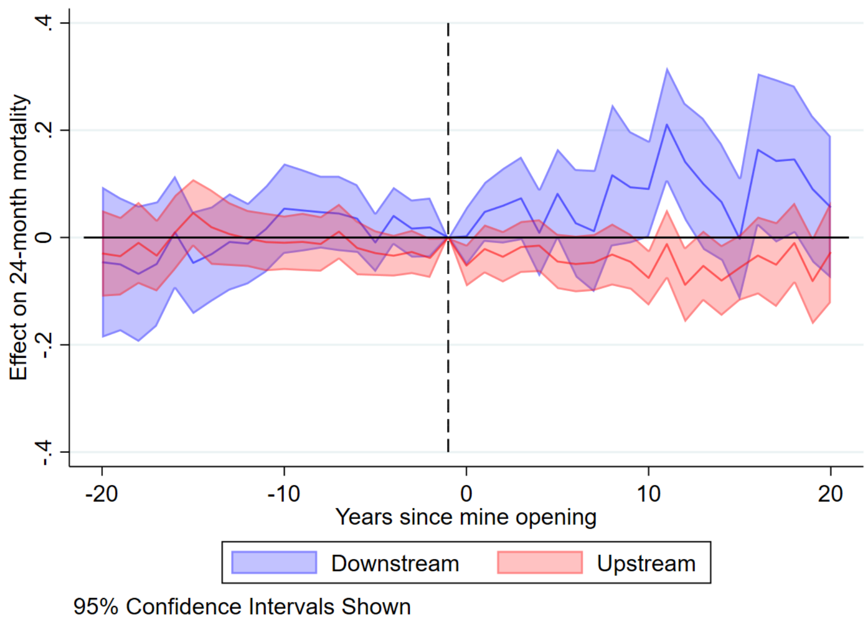
(a) All sample (b) All sample

Notes: Figure (a) gives the distribution of the number of observations per opening year. Figure (b) plots the trends of the 24-month mortality rates according to the year of opening. The figures are made for the whole sample and include neither control variables nor fixed effects. The reference point is -1, the year before the mine opening.
Sources: Authors' elaboration on DHS and SNL data.

The key assumption of the DiD strategy is that the outcome - the 24-month mortality - would follow the same time trend in the absence of the mine opening both in upstream and downstream areas. The common trends assumption cannot be tested. However, we can observe the pre-treatment data and the evolution of mortality rates before each mine opening according to the topographic position. Figure 2.9b plots the linear trends of the 24-month mortality rates and distinguishes between upstream and downstream DHS clusters, before and after the opening of the paired mine. For each year, it plots the average mortality rates over the sample, with no control nor fixed effect. Figure 2.9a plots the distribution of the years before and after the mine opening. Figure 2.9b shows non-exact parallel trends but is only descriptive, and we can see looking at the scatter plot that the downstream and upstream areas seem to follow a similar pattern of decreasing mortality before a mine opens. This decreasing pattern is triggered by temporal trends, as the years closest to the mine opening are more likely to be recent years, and the mortality rates are overall decreasing over the recent decades (cf Figure 2.5). This pattern is corrected in Figure 2.10.

Figure 2.10 plots the event study of the effect of mine opening, for both the upstream and downstream samples. It includes the same controls and fixed effects as the main analysis (cf Table 2.2), and thus corrects for previous trends as we include country and mine sub-basin trends. Both upstream and downstream villages do not display any pre-trends, which suggests that the common trend assumption is verified. We observe almost no effect of a mine opening on the mortality rates upstream, a slight decrease which is significant 10 years after the opening. Figure 2.10 shows that the infant mortality downstream increases once the mine opens. This effect is significant in the medium run, around a decade after the mine opening.

Figure 2.10: Event study - dynamic effect of mine opening on 24-month mortality



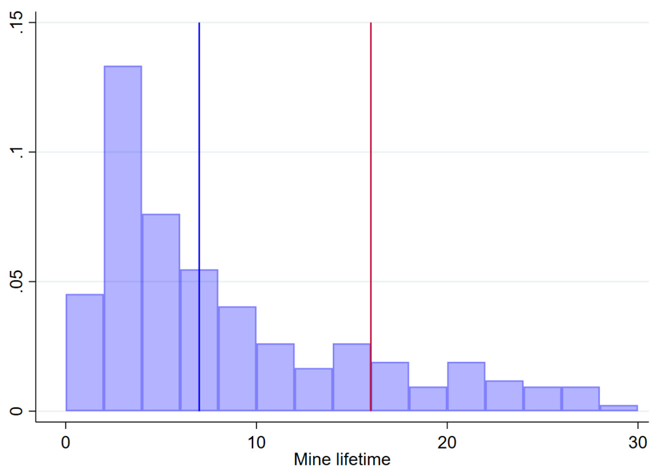
Notes: This Figure plots the event study of the effect of mine opening for downstream and upstream DHS villages, 10 years before the mine opening and 10 years after. The year before the mine opening, -1, is taken as the reference point.
Sources: Authors' elaboration on DHS and SNL data.

2.8.2 Mine closure

In the main analysis, we focus on mine opening without taking into account the closure year, since it is a piece of information harder to retrieve by hand. In this section, we focus on a restricted sample of mines for which the SNL database provides directly this information, to understand whether the closing date plays a role in our main effect.

Figure 2.11 gives the distribution of mines' lifetime, for the restricted sample of mines for which closing years are available. On average, a mine lasts 16 years, but the distribution is skewed to the right and the majority of mines close before 10 years. Please note that the closing date available in the SNL database for this restricted sample is not exact. Over its lifetime, a mine can be put on hold several times, for political or economic reasons. In Table 2.9 we look at the effects of being downstream of a mine that is active at the year of birth of the child. Columns (1) and (2) show no effect on the 12-months mortality rates. Column (3) shows that being downstream of a mine that is active the year of birth increases the mortality rate by 4 p.p, which corresponds to an increase of 40% in the mortality rate. This result suggests that the harmful effects of mining activity on the individuals living downstream are mainly critical while the mine is active.

Figure 2.11: Distribution of a mine lifetime



Notes: This figure gives the distribution of mines' lifetime. The red line y=16 plots the mean of a mine lifetime, while the blue line y=7 plots the median. The maximum of a mine lifetime in our sample is 138 years.
Sources: Authors' elaboration on SNL data.

Table 2.9: Average effects of mine activity on infantile mortality

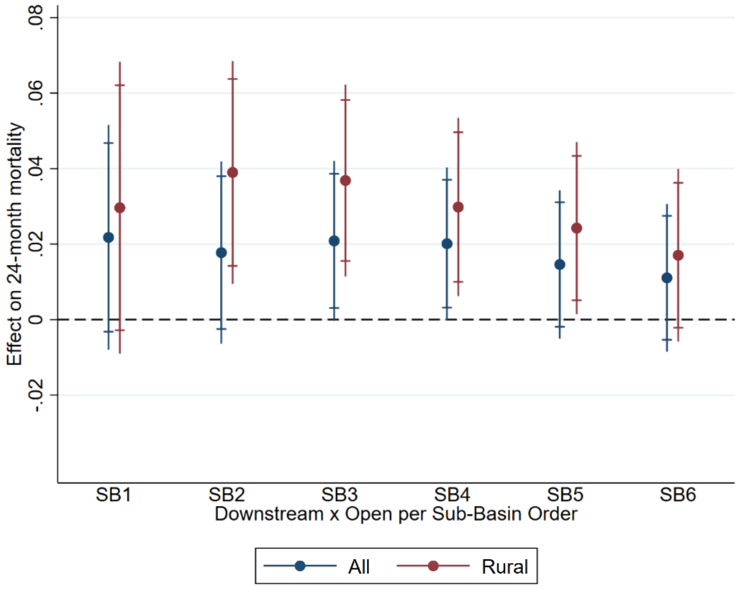
	Mortality under 12 months		Mortality under 24 months	
	All	Rural	All	Rural
	(1)	(2)	(3)	(4)
Downstream×Active	0.0112	0.0321	0.0409*	0.0488**
	[0.0222]	[0.0254]	[0.0248]	[0.0242]
Downstream	-0.0264*	-0.0434**	0.00877	-0.00721
	[0.0139]	[0.0184]	[0.0145]	[0.0184]
Active	0.000600	0.00420	-0.00842	-0.00345
	[0.0140]	[0.0173]	[0.0172]	[0.0193]
Controls	Yes	Yes	Yes	Yes
Nb open mines	Yes	Yes	Yes	Yes
Birthmonth FE	Yes	Yes	Yes	Yes
Country-birthyear FE	Yes	Yes	Yes	Yes
Mine SB FE	Yes	Yes	Yes	Yes
Mine SB-birthyear trend	Yes	Yes	Yes	Yes
Commodity FE	Yes	Yes	Yes	Yes
N	7,231	5,589	5,270	4,082
R2	0.0899	0.0960	0.0984	0.108
Outcome Mean	0.0756	0.0825	0.0981	0.104

Notes: Standard errors clustered at the DHS village level, $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. The variables Downstream and Active are dummies that indicate whether the individual lives in a village downstream of at least one mining site and whether the site is active during the year of birth. The same sample and controls as Table 2.2 Column 2 apply.

2.9 Intensive Margin

2.9.1 Spatial intensive margin

Figure 2.12: Effect of industrial mine opening according to the downstream sub-basin order

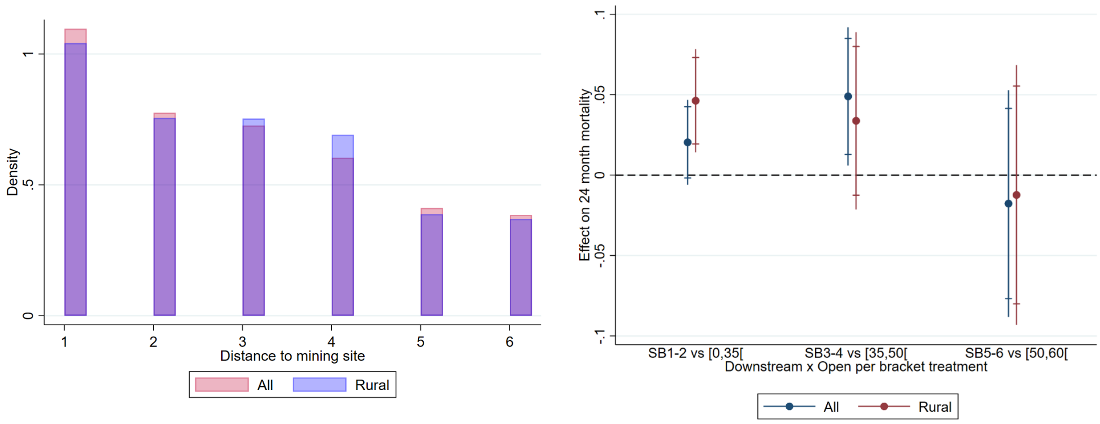


Notes: This Figure plots the treatment effect when changing the treatment group. SB 1 gives the DiD estimator when the control group includes DHS villages up to the first sub-basin, SB 2 up to the second, and then SB6 up to the sixth sub-basin. SB 3 gives the main result of the paper. *Sources:* Authors' elaboration on DHS and SNL data.

In this section, we change the cut-off for being treated and test the effect on different orders of downstream sub-basins. In Figure 2.12, we test whether the effect holds when allowing for further sub-basins downstream. It plots the coefficient on *Downstream* × *Open* for six different models. SB1 corresponds to the model where the treatment group includes only the first neighbouring downstream sub-basin, SB2 up to the second, and SB6 up to the sixth. SB3 gives the main results from Column (6) in Table 2.2. The Figure shows an attenuation of magnitude of the effect when including further sub-basins. For all the individuals, the results are significant at the 5% level up to the third sub-basin and up to the fourth, while for all rural areas it is significant from the second up to the fifth sub-basin. We interpret the non-significance of the result in the first sub-basins as being the consequence of statistical power (as the sample size is relatively low up to SB1 and SB2).

Figure 2.13 looks at the effect per distance brackets. To build the control group for each sub-basin, we determined which distances correspond to which sub-basin order.

Figure 2.13: Intensive margin - Effect of the number of mine opening on under 24 months mortality



(a) (b)

Notes: Figure (a) plots the distribution of observations downstream per sub-basin order. Figure (b) plots the interaction term on the 24-month mortality rates per distance brackets. The first coefficient on the left gives the effect for individuals living within the first and second sub-basins compared to individuals living up to 35 kilometers. The second coefficient gives the effect for individuals living downstream within the third and fourth sub-basins compared to those living upstream between 35 and 50 kilometers. The third coefficient gives the effect for individuals living downstream within the fifth and sixth sub-basins compared to those living upstream between 50 and 60 kilometers. The distances are chosen based on the mean of the distance between the mine and the extremity of the XXth sub-basin. [a]
Sources: Authors' elaboration on DHS and SNL data.

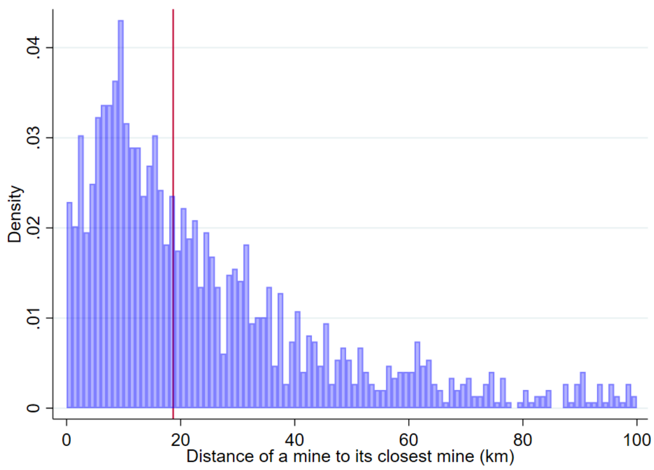
[a]The mean of the distance between the mine and the extremity of the first sub-basin is 27 km. It is 37 km for SB2, 45km for SB3, 46km for SB4, 58km for SB5 and 59km for SB6

We calculated the mean of the maximal distance between the mine and the furthest extremity of each sub-basin order. On average, a mine is at 27 kilometers of the furthest extremity of its first sub-basin, at 37 kilometers of its second sub-basin, 45 kilometers of sub-basin 3, 46 kilometers of sub-basin 4, 58 kilometers of sub-basin 5 and 59 kilometers of sub-basin 6. Following this indicator, we compare in Figure 2.13 the individuals living downstream within the first and second sub-basin to those living upstream within 35 kilometers of the mine (coefficient SB1-2). Then, we compare individuals living downstream within the third and fourth sub-basins to those living upstream within 35 to 50 kilometers of the mine (coefficient SB3-4). Finally, we compare individuals living downstream within the fifth and sixth sub-basin to those living within 50 to 60 kilometers of the mine. Figure 2.13 shows that our result is mainly driven by the effect within the third and fourth sub-basins, while in rural areas the effect is only significant within the closest sub-basins. This shows that the effect is critical close to the mine, where the pollution is supposed to be the highest.

The difference between the whole and rural samples might be explained by the fact that the location of mines close to urban areas suffers from lower precision (cf section 2.10.3.2).

2.9.2 Mine density

Figure 2.14: Distance of mines to each others

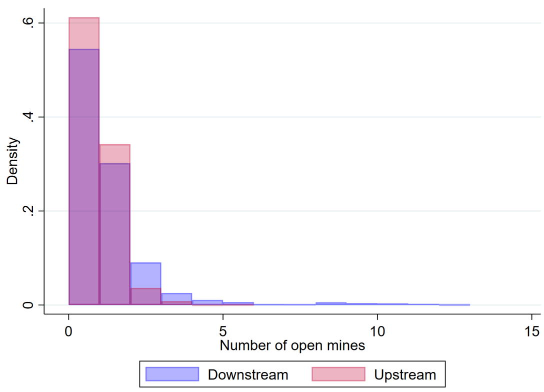


Notes: This Figure gives the distribution of the distance between each mine and its closest industrial mining site, giving insights of how far these mines are located from each other. In red is plot the median distance (18km), and the graph is given for distances under 100 km (please note that the maximum distance is up to 474 km).
Sources: Authors' elaboration on DHS and SNL data.

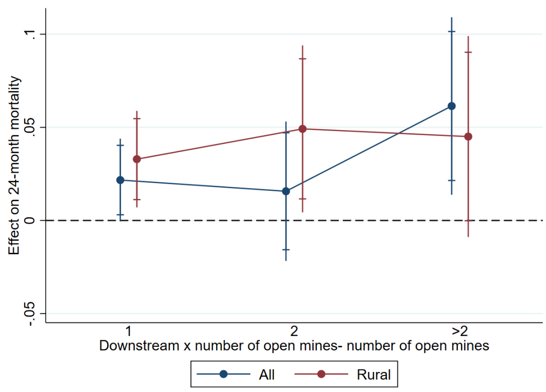
In this section, we explore the intensive margin of our result according to the mine density. Figure 2.14 gives insights of how far these mines are located from each other. It shows the distribution graph of the distance to the closest mine for each mines. It is made with no regards on the activity status of the mining site. On average, a mine is located at least at 31 kilometers to its closest mining site, while the median is 18 kilometers. The distribution is skewed to the right, showing that the majority of the mining sites are located in areas with a high density of mining activity. Few mines are isolated, up to 100 kilometers to the closest mining site. This graph shows the necessity first to control for the number of open mines within the area in the main analysis (Table 2.2), and the necessity to look at heterogeneous effect according to the intensity of the mining activity within the area.

Figure 2.15a plots the frequency of the number of open mines within our main sample, both for upstream and downstream areas, within 45 kilometers and up to the third sub-basin. As the number of observations falls starting at 3 open mines, we investigate in Figure 2.15b and Table 2.10 the statistical difference between being downstream of one opening site, two or more than two. For the whole sample, being downstream of one open mine increases the 24-month mortality by 2 p.p. The effect increases when the number of open mines increases, as being downstream of more than 2 open mines increases by 6 p.p the mortality rate in comparison to being downstream of only one open mine. Table 2.10 column (1) gives the DiD interaction term when open becomes a continuous variable and not a dummy, being the number of open mines. It shows that being downstream one additional mine that opens increases the mortality by 1.3 p.p, and by 2 p.p within rural areas.

Figure 2.15: Intensive margin - Effect of the number of mine openings on 24-month mortality



(a)



(b)

Notes: Figure (a) plots the distribution of the number of open mines across downstream and upstream villages. Figure (b) plots the interaction variable on the 24-month mortality rates. It gives the average treatment effects of the number of mine open on 24-month mortality.
Sources: Authors' elaboration on DHS and SNL data.

Table 2.10: Effects of the number mine opening on infantile mortality according to the number of open mine

	24-month mortality			
	All		Rural	
	(1)	(2)	(3)	(4)
Downstream×Nb open	0.0130*** [0.00484]		0.0205*** [0.00744]	
Downstream×Nb open=1		0.0217* [0.0113]		0.0329** [0.0132]
Downstream×Nb open=2		0.0157 [0.0191]		0.0492** [0.0228]
Downstream×Nb open ¿2		0.0614** [0.0243]		0.0451 [0.0275]
Downstream	-0.0214*** [0.00723]	-0.0208*** [0.00767]	-0.0295*** [0.00823]	-0.0308*** [0.00837]
Nb Open	-0.00419 [0.00526]		-0.00842 [0.00613]	
Nb Open =1		-0.0000134 [0.00785]		-0.00328 [0.00895]
Nb Open =2		-0.00850 [0.0129]		-0.0220 [0.0141]
Nb Open ¿2		-0.0407** [0.0190]		-0.0329 [0.0219]
Controls	Yes	Yes	Yes	Yes
Birthmonth FE	Yes	Yes	Yes	Yes
Country-birthyear FE	Yes	Yes	Yes	Yes
Mine SB FE	Yes	Yes	Yes	Yes
Mine SB-birthyear trend	Yes	Yes	Yes	Yes
Commodity FE	Yes	Yes	Yes	Yes
N	35,638	35,638	24,544	24,544
R2	0.0511	0.0511	0.0633	0.0634

Notes: Standard errors clustered at the DHS village level, $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$. Columns (1-3) give the results for the total population while columns (4-6) display the results for rural villages. Columns (2, 4, 6, 8) control for the number of open mines within 45 km. The same sample as Table 2.2 Column 2 applies. Control variables are birth order number, mother's age, mothers' age square, mother's years of education and urban, and a continuous variable indicating the presence of rivers and their order.

2.9.3 Production intensive margin

Table 2.11: Effects of industrial mining opening, across each commodity's price evolution.

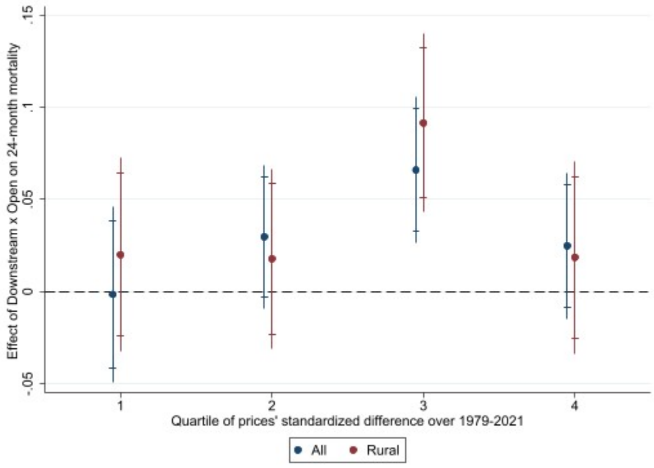
Outcome	24-month mortality	
Price var.	(1) Standardized difference	(2) Z-score
Downstream × Open× Price var	0.0160* [0.00823]	0.0101** [0.00463]
Downstream	-0.00244 [0.0104]	0.00102 [0.0110]
Controls	Yes	Yes
Country-survey year FE	Yes	Yes
Mine SB FE	Yes	Yes
Mine SB-survey year trend	Yes	Yes
Commodity FE	Yes	Yes
N	31,517	31,517
R2	0.0509	0.0509
Outcome mean	0.0907	0.0907

Notes: Standard errors clustered at the DHS village level, $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$. Standardized difference and Z-score of each commodity's price calculated over 1979-2021. The same sample and controls as Table 2.2 Column 2 apply.

We proxy the production intensity of each mine by using the global price of each mine's primary commodity as done in Berman et al., 2017 and Girard, Molina-Millan, and Vic, 2022. We presume the higher the prices, the more intense the production. Annual prices were retrieved from the SNL data (coal, gold, lead, nickel, platinum, silver and zinc) and the World bank pink sheet (copper). For each commodity, we calculate the average price over 1971-2021, and for each year we calculate the standardized difference ($\frac{Price_t - \overline{Price}_{[1971-2021]}}{\overline{Price}_{[1971-2021]}}$) and Z-score ($\frac{Price_t - \overline{Price}_{[1971-2021]}}{\sigma_{Price_{[1971-2021]}}}$). We find a positive and significant effect of the triple interaction (Table 2.11) with both price variables (column 1 for the standardized difference and column 2 for the Z-score).

We then plot the coefficients associated with the interaction term of being downstream of an open mine, across the quartiles of the change in the z-score (Figure 2.16). For both total and rural samples, we find that an increase in prices (going from the second to the third quartile) leads to an even higher effect of industrial mining on the 24-month mortality.

Figure 2.16: Effect of living downstream of an open mine across the evolution of the mine's primary commodity's price



Notes: This graph represents the coefficients associated with being downstream of an open mine across the evolution of each mine's primary commodity's price (available for coal, copper, gold, lead, nickel, platinum, silver and zinc). For each commodity, the standardized difference to the mean over the 1979-2021 period was calculated and then split across quartiles to grasp the relative price evolution specific to each type of commodity.
Sources: Authors' elaboration using DHS, SNL and World Bank pink sheet data.

2.10 Robustness checks

2.10.1 Balanced sample and de Chaisemartin and D'Haultfœuille, 2020

2.10.1.1 Balanced sample

One issue of working with DHS data is dealing with repetitive cross-sections instead of an exact panel. In this section, we define a balanced sample as a restricted sample for which each mine has observations before and after its opening, both upstream and downstream. In this sense, it is a balanced panel of mine, if we consider only two points in time which are (1) the period before the mine opens and (2) the period after its opening. Please note that, in this paper, it is possible to restrict the analysis to a balanced sample by the extension of the mines' sample size, and it underlines the limits of analyses looking at dynamic effects while using few mines. In this section, we first define the balanced sample and then we replicate the main analysis on this restricted sample.

First, let's define the construction of the balanced sample. A staggered DiD is driven by changes in mortality rates of switchers, which are observations that change treatment status, in comparison to those that do not change treatment status. In the case of a balanced sample, the design of this paper distinguishes three groups of observations :

- Group 1 "the switchers": the subgroup for which a mine has opened between two different years (for which there are DHS observations) and thus for which the treatment status changes from 0 to 1.
- Group 2 "the always treated": the subgroup of areas for which the mine has always been opened and are thus always treated, i.e. the treatment variable which is an interaction is always equal to 1.
- Group 3 "the never treated": the subgroup of areas where mines have not yet opened. The treatment variable is equal to 0. The third group is made of subgroups for which the mine has not opened yet in 2022 but the opening is planned in the future (the mine is projected to open), but also of mines where no DHS cluster was surveyed after it opened. This group is called "the never treated", but it includes both DHS villages that will never be treated or are not yet treated, because they will be treated in the future.

The balanced sample makes it possible to identify the three groups. Formally, it is defined as the following, for each group:

Let's consider observations that can be divided into G groups and T periods, for every $(g,t) \in \{1,...,G\} \times \{1,...T\}$, let $N_{g,t}$ denote the number of observations in the group g and period t, and let $N = \sum_{g,t} N_{g,t}$ be the total number of observations. For all $(g,t) \in \{1,...,G\} \times \{1,...,T\}$, let's call $D_{g,t}$ the $Downstream_{g,t}$ variable and $O_{g,t}$ the $Opened_{g,t}$ variable.

Definition 1 (Group 1- Balanced sample of "switchers"). *Let's call* $G_1 = \{g_0, ..., g_{n_1}\}$ *the set of Group 1. Group 1 is defined as the following:*
For all $g \in G_1, \exists (v_1, v_2, v_3, v_4) \times (t_1, t_2, t_3, t_4) \in g \times T$ *such as:*
(i) $N_{v_1,t_1} > 0 \land D_{v_1,t_1} = 0 \land O_{v_1,t_1} = 0$
(ii) $N_{v_2,t_2} > 0 \land D_{v_2,t_2} = 1 \land O_{v_2,t_2} = 0$
(iii) $N_{v_3,t_3} > 0 \land D_{v_3,t_3} = 1 \land O_{v_3,t_3} = 1$
(iv) $N_{v_4,t_4} > 0 \land D_{v_4,t_4} = 1 \land O_{v_4,t_4} = 1$
In our setting, g is the whole area associated with a mine, including both upstream and downstream observations, and is made of $k \in N$ *DHS clusters such as* $g = \{v_1, ..., v_k\}$.

Definition 2 (Group 2- Balanced sample of "always treated"). *Let's call* $G_2 =$

$\{g_0, ..., g_{n_2}\}$ *the set of Group 2. Group 2 is defined as the following:*
For all $g \in G_2, \exists(v_1, v_2) \times (t_1, t_2) \in g \times T$ *such as:*
(i) $N_{v_1,t_1} > 0 \wedge D_{v_1,t_1} = 0 \wedge O_{v_1,t_1} = 1$
(ii) $N_{v_2,t_2} > 0 \wedge D_{v_2,t_2} = 1 \wedge O_{v_2,t_2} = 1$

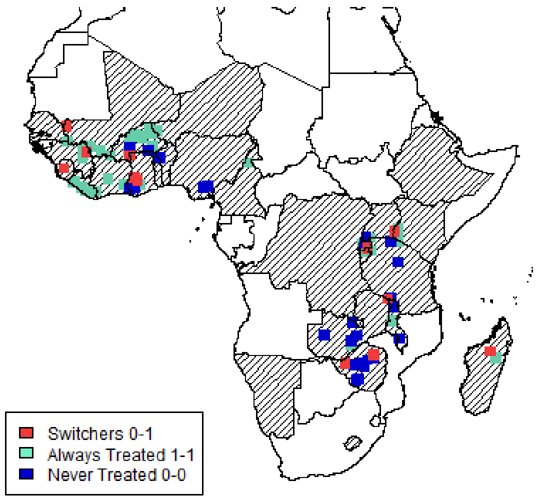
Definition 3 (Group 3- Balanced sample of "never treated")**.** *Let's call* $G_3 = \{g_0, ..., g_{n_3}\}$ *the set of Group 3. Group 3 is defined as the following:*
For all $g \in G_3, \exists(v_1, v_2) \times (t_1, t_2) \in g \times T$ *such as:*
(i) $N_{v_1,t_1} > 0 \wedge D_{v_1,t_1} = 0 \wedge O_{v_1,t_1} = 0$
(ii) $N_{v_2,t_2} > 0 \wedge D_{v_2,t_2} = 1 \wedge O_{v_2,t_2} = 0$

Definitions 1, 2, and 3 define the treatment group (Group 1) and the control groups (Group 2+3) in the setting of the mine balanced sample. For Group 1 switchers, we restrict the sample to areas that have DHS clusters surveyed both downstream and upstream both before and after the opening of the mine. This means that we select areas that have been surveyed at least in four different locations by DHS. For groups 2 and 3, meaning that the surveys have occurred only after the opening (Group 2) or before the opening (Group 3), we restrict to areas that have observations both upstream and downstream.

Figure 2.17 plots the different groups from the balanced sample and displays the group of switchers, the always-treated and the never treated groups. It displays the areas that are key to the main estimation, which are located in Western Africa, Zimbabwe, Western Kenya, Rwanda, Tanzania, and Madagascar. Table B.9 from Appendix plots our main estimator across the African sub-regions and shows that our results are mainly driven by Western Africa, and remain significant in Eastern Africa. Table 2.12 gives the size of the three groups in the balanced sample, as well as the associated number of mines. It shows that Group 1 switchers account for around 12% of the total balanced sample, and corresponds to the neighborhood of 13 mines. In total, the control groups gather 75 mines. We observe that the average mortality rates have decreased over time, before and after the opening of the mining site in the Switcher Group, linked to the decrease of infant mortality in Africa over time, which is in coherence with the Balance Table 2.1 and Figures 2.4 and 2.5, and which highlights the importance of controlling for trends.

Table 2.13 displays the balance table for the restricted sample. This table shows the within comparison before and after a mine opens both downstream and upstream. It is only descriptive statistics and neither account for control variables nor account for fixed effects. The table shows that there is a significant difference between upstream and downstream areas after a mine opens concerning both the 12 and 24-months mortality rates. From a descriptive point of view, being downstream of a mine increases the 12-month mortality by 2.7 p.p, and the 24-month mortality by 2.4 p.p (column (13)). This difference is explained by a significant decrease in mortality rates within upstream areas after a mine opening (column (11)).

Figure 2.17: Balanced Panel - Group identification



Notes: The Figure plots the groups' areas accross the three groups of the balanced panel, for the 24-month mortality rate.
Sources: Authors' elaboration on DHS and SNL data.

Table 2.12: Balanced Sample - Descriptive Statistics

	Group 1 : Switchers 0-1						Groups 2+3		Group 2 : 1-1		Group 3 : 0-0	
	All		Before Opening		After Opening							
	N	Mean (SD)	N	Mean (SD)	N	Mean (SD)	N	Mean (SD)	N	Mean (SD)	N	Mean (SD)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dth¡12												
All	1,191	0.07	894	0.069	297	0.071	8,423	0.07	2,368	0.056	6,055	0.076
		(0.255)		(0.254)		(0.257)		(0.256)		(0.23)		(0.265)
Mines	13		13		13		75		31		44	
Dth¡24												
All	1,191	0.089	894	0.091	297	0.084	8,423	0.091	2,368	0.072	6,055	0.099
		(0.285)		(0.287)		(0.278)		(0.288)		(0.258)		(0.298)
Mines	13		13		13		75		31		44	

Notes: Standard errors and p-values are in parentheses. Outcomes' descriptive statistics of under 12-and 24-month mortality, for villages within the Group 1 Switchers for individuals born before and after the opening of the mine, then Group 2 always treated and Group 3 never treated.

Table 2.13: Balance Table

	Before Mine Opening					After Mine Opening					Within Up.	Within Dwn.	Within
	Upstream		Downstream		Diff	Upstream		Downstream.		Diff			
	N	Mean /(SD)	N	Mean /(SD)	(4-2) /(p.v)	N	Mean /(SD)	N	Mean /(SD)	(9-7) /(p.v)	(7-2) /(p.v)	(9-4) /(p.v)	(12-11) /(p.v)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Dth¡12													
All	5,272	0.079	1677	0.063	-0.016	1,812	0.054	853	0.066	0.012	-0.025	0.002	0.027
		(0.27)		(0.243)	(0.025)		(0.226)		(0.248)	(0.248)	(0)	(0.814)	(0.005)
Mines	54		56			38		37					
Dth¡24													
All	5,272	0.101	1677	0.088	-0.012	1,812	0.07	853	0.081	0.011	-0.031	-0.007	0.024
		(0.301)		(0.284)	(0.123)		(0.254)		(0.273)	(0.306)	(0)	(0.527)	(0.03)
Mines	54		56			38		37					

Notes: Standard errors and p-values in parentheses. Descriptive statistics of 12-month and 24-month mortality outcomes, for villages upstream and downstream of mining sites, for individuals born before and after the opening of a mine, over the balanced sample.

2.10.1.2 Heterogeneous treatment effects with two-way fixed effects: de Chaisemartin and D'Haultfœuille, 2020

The main result of this paper estimates the effect of being downstream of an open mine by using standard difference-in-difference designs. However, recent developments in the estimation of difference-in-differences in staggered adoption designs (Borusyak, Jaravel, and Spiess, 2021; Goodman-Bacon, 2018; Callaway and Sant'Anna, 2021; de Chaisemartin and D'Haultfœuille, 2020) show that the estimated ATT[14] is a weighted sum of different ATTs with weights that may be negative. The negative weights are an issue when the treatment effect is heterogeneous between groups over time, as one could have the treatment coefficient in those regressions as negative while the treatment effect is positive in every group and time period. Using treated observations as controls creates these negative weights. In our design, the effect on Group 1 Switchers is compared to two control groups, Group 2 always treated and Group 3 never treated. The negative weights might come from the comparison of the effect of the Group 1 switchers to the Group 2 always treated. This biases the DiD estimator as it is an average of local treatment effects. In this section, we use the de Chaisemartin and D'Haultfœuille, 2020 estimator which deals with the issue of negative weights in a staggered adoption design.

Table 2.14 compares the two-way fixed effects (TWFE) used in the main result (odd columns), to the de Chaisemartin and D'Haultfœuille, 2020 estimator (dCDH) (even columns) [15]. Columns (1, 2, 5, 6) give the results for the entire sample, while columns (3, 4, 7, 8) for the balanced sample, defined in previous Section 2.10.1.1. Columns (1-4) give the results for the 12-months mortality rates, while columns (5-8) for the 24-months mortality rates.

First, let's look at the 24-months mortality rates. When looking at the TWFE estimator, we see that the results are stable on the balanced sample, even though it only represents 27% of the whole sample. This is coherent with the fact that the balanced sample keeps the villages that drive the main estimation's results. When focusing on the balanced sample, being downstream of an opened mine increases the 24 month-mortality rates by 3.19 p.p, which represents an increase of 36% of the mortality. Column (6) gives the dCDH estimator for the whole sample, while column (4) is for the balanced sample. We observe an increase in terms of the magnitude of

[14] Average Treatment on the Treated

[15] The Stata command *did_multiplegt* is used to run the dCDH estimator.

the effect when correcting for negative weights, as being downstream of an open mine increases the 24-month mortality rates by 11 p.p, which represents an increase of 129% of the mortality. If these magnitudes seem high, it is reassuring to observe the stability of the direction and significance of our main effect when using the dCDH estimator. Regarding the 12-month mortality rates, we observe that the restriction to the balanced sample displays a 2.8 p.p increase.

Table 2.14: Effects of industrial mining opening on 24-month mortality de Chaisemartin and D'Haultfœuille, 2020

	12-month mortality				24-month mortality			
	Whole Sample		Balanced Sample		Whole Sample		Balanced Sample	
	TWFE	dCDH	TWFE	dCDH	TWFE	dCDH	TWFE	dCDH
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Downstream×Open	-0.00506	0.0249	0.0286*	0.1457	0.0218**	0.1109**	0.0319**	0.1667*
	[0.00831]	[0.0262]	[0.00222]	[0.1132]	[0.0108]	[0.0405]	[0.0162]	[0.1112]
Downstream	-0.0152**		-0.0242***		-0.0211***		-0.0283***	
	[0.00665]		[0.00826]		[0.00739]		[0.00866]	
Open	0.00963		0.0347		-0.00496		0.0238	
	[0.00754]		[0.0320]		[0.0101]		[0.0347]	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birthmonth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-birthyear FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mine SB FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mine SB-birthyear trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Commodity FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	48, 472	48, 472	9, 606	9, 606	35, 638	35, 638	9, 606	9, 606
R2	0.0378		0.0523		0.0511		0.0599	

Notes: Standard errors clustered at the DHS village level, $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$. Column (1) gives the result of the main anlysis, the Two Way Fixed Effect (TWFE) for the whole sample, while Column (2) gives the de Chaisemartin and D'Haultfœuille, 2020 estimator. Columns (3) and (4) give the TWFE and de Chaisemartin and D'Haultfœuille, 2020 estimators for the balanced sample.

2.10.2 Sensitivity analysis

2.10.2.1 Including non topographic sub-basins

In this section, we replicate the main analysis from Table 2.2, adding within the control group, individuals living in a sub-basin with no topographic relation to the mine sub-basin, within 45 kilometers. This test can have several readings.

First, it strengthens the control for income effects linked to mining activity and enables to isolate more precisely the channel of water pollution and excludes other potential mechanisms. Indeed, villages close to the mine but located in a sub-basin with no topographic relationship with the mine, are allegedly less exposed to mining-induced water pollution and would be as exposed to income or labour effects, conflicts, or migration.

Yet, it also leads to the comparison of villages that do not necessarily share the same water resources, and this could blur the interpretation of our estimation. For example, other activities such as more intensive agriculture or livestock farming could aggregate around the mining site and could be responsible for other types of pollution. If these activities are located in a sub-basin with no topographic relationship to the mine, the estimated comparison would display the difference between the pollution of the mine and the pollution of these activities, rather than the pollution of the mine only, and this would lead to a downward bias to our analysis. Moreover, as mining activity is water intensive, the location of these activities might also be endogenous to the location of the mine, and this could induce an even larger downward bias.

Table 2.15 displays the results when including the non-topographic sub-basins within the control group. As expected, the table suggests that the main results on the 24-month mortality rates are downward biased, and only significant at the 10% level for the rural population.

Table 2.15: Effects of industrial mining opening on infantile mortality - including DHS with non-topographic relationship

	12-month mortality				24-month mortality			
	Total Population		Rural Population		Total Population		Rural Population	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Downstream×Open	-0.00266	-0.00227	0.00341	0.00381	0.00746	0.00804	0.0172*	0.0165*
	[0.00543]	[0.00544]	[0.00632]	[0.00632]	[0.00752]	[0.00753]	[0.00887]	[0.00888]
Downstream	-0.00490	-0.00472	-0.00904*	-0.00884*	-0.00486	-0.00455	-0.0103	-0.0106*
	[0.00445]	[0.00446]	[0.00506]	[0.00507]	[0.00561]	[0.00561]	[0.00637]	[0.00636]
Open	0.00364	0.00488	0.00318	0.00466	0.00115	0.00308	0.00283	0.000259
	[0.00292]	[0.00302]	[0.00345]	[0.00359]	[0.00377]	[0.00391]	[0.00457]	[0.00440]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nb open mines	No	Yes	No	Yes	No	Yes	No	Yes
Birthmonth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-bthyr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mine SB FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mine SB-bthyr trd	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Commodity FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	168,931	168,931	123,413	123,413	124,670	124,670	91,395	91395
R2	0.0214	0.0215	0.0252	0.0252	0.0305	0.0305	0.0356	0.0355
Outcome Mean	0.0638	0.0638	0.0670	0.0670	0.0824	0.0824	0.0872	0.0872

Notes: Standard errors clustered at the DHS village level, $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$. Columns (1-3) give the results for the total population while columns (4-6) display the results for rural villages. The same controls as Table 2.2 apply. Columns (2, 4, 6, 8) control for the number of open mines within 45 km. The sample includes individuals living in non-topographic sub-basins within 45km.

2.10.2.2 Dropping fixed effects and other tests

Table 2.16: Effects of industrial mining opening on 24 months mortality, while dropping fixed-effects.

Outcome	24-month mortality			
	(1)	(2)	(3)	(4)
Downstream×Open	0.0218**	0.0216**	0.0179*	0.0177*
	[0.0108]	[0.0108]	[0.0105]	[0.0104]
Downstream	-0.0211***	-0.0211***	-0.0218***	-0.0219***
	[0.00739]	[0.00738]	[0.00734]	[0.00733]
Open	-0.00496	-0.00494	-0.00459	-0.00466
	[0.0101]	[0.0101]	[0.00972]	[0.00962]
Controls	Yes	Yes	Yes	Yes
Mine SB FE	Yes	Yes	Yes	Yes
Country-birthyear FE	Yes	Yes	Yes	Yes
Birthmonth FE	Yes	No	No	No
Commodity FE	Yes	Yes	No	No
Mine SB-birthyear trend	Yes	Yes	Yes	No
N	35,638	35,638	35,638	35,638
R2	0.0511	0.0504	0.0503	0.0491
Outcome mean	0.0873	0.0873	0.0873	0.0873

Notes: Standard errors clustered at the DHS village level, $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. The same sample as Table 2.2 Column 2 apply.

We find stability in our results when dropping fixed effects one by one: birth month primary commodity, and sub-basins birth year trend (Table 2.16) until keeping the two-way fixed effects (i.e keeping the mine sub-basin fixed effect and the country-birthyear fixed effect).

Section B.5.1 runs other tests. Table B.10 shows that our result is stable when controlling for the hand work. Figure B.18 shows that the main results are stable when dropping countries one by one, and Figure B.17 when dropping metals one by one.

2.10.2.3 Spatial correlation

As an additional robustness check, we run our main result's specification while taking into account the spatial correlation of DHS clusters. We estimate the standards errors with a spatial HAC correction following the method developped by Conley, 1999 and using the Stata command introduced by Colella et al., 2020. Table 2.17 shows the stability of our results for different cut-off distances of spatial correlation (from 20 km to 200 km). We did not include directly the Conley, 1999 test in the main analysis as it does not allow for several fixed-effects. Table 2.17 corrects for spatial correlation for the results when using only Mine-Subbasin and country-birthyear fixed effects (result from Table 2.16 Column (4)).

Table 2.17: Effects of industrial mining activity, Conley spatial correction (acreg)

Outcome	Mortality under 24 months					
Conley spatial correction threshold	20 km	45 km	60 km	80 km	100 km	200 km
	(1)	(2)	(3)	(4)	(5)	(6)
Downstream×Open	0.0177*	0.0177*	0.0177*	0.0177*	0.0177*	0.0177*
	[0.0100]	[0.00999]	[0.0101]	[0.0101]	[0.00996]	[0.00916]
Downstream	-0.0219***	-0.0219***	-0.0219***	-0.0219***	-0.0219**	-0.0219**
	[0.00709]	[0.00746]	[0.00789]	[0.00847]	[0.00913]	[0.0106]
Open	-0.00466	-0.00466	-0.00466	-0.00466	-0.00466	-0.00466
	[0.00941]	[0.00932]	[0.00943]	[0.00960]	[0.00955]	[0.00938]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-birthyear FE	Yes	Yes	Yes	Yes	Yes	Yes
Mine SB FE	Yes	Yes	Yes	Yes	Yes	Yes
N	35,648	35,648	35,648	35,648	35,648	35,648
R2	0.00262	0.00262	0.00262	0.00262	0.00262	0.00262

Notes: Standard errors clustered at the DHS village level, $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$. The variables Downstream and Opened are dummies that indicate whether the individual lives in a village downstream of at least one mining site and whether the site opened before the birth year of the child. Each village DHS is paired to only one mining site so that each individual appears only once in the regression. Other variables are control variables. The sample focuses on heavy metal mines. Control variables are birth order number, mother's age, mother's age square, mother's years of education, urban, number of open mines, and presence of rivers.

2.10.3 Measurement errors

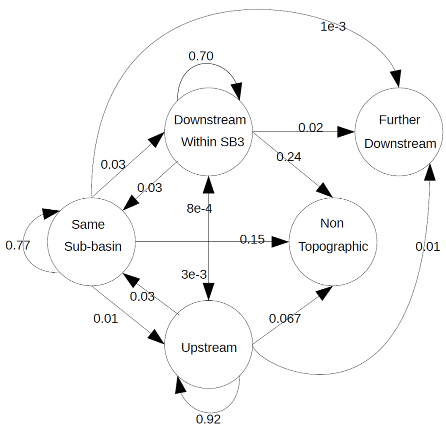
In this section, we deal with measurement errors that come from the nature of the data. Section 2.10.3.1 tests for the random displacement of DHS villages and section 2.10.3.2 tests our result according to the precision of the mine location.

2.10.3.1 DHS random displacement

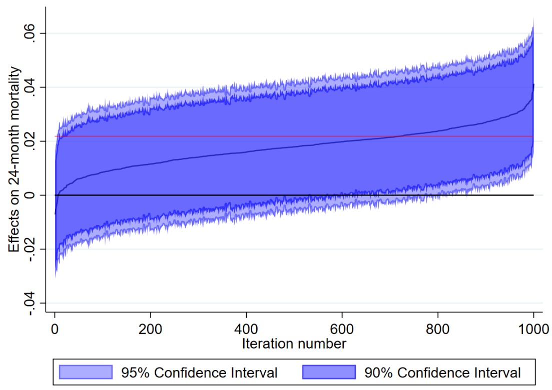
DHS randomly displaces the GPS coordinates of each village to protect the confidentiality of respondents. Urban locations are displaced within 2 kilometers, while rural clusters are displaced within 5 kilometers, with 1% of rural clusters moved up to 10 kilometers. Displacements are made within administrative districts. This random reshuffling of DHS villages introduces measurement errors in our main estimation, all the more important as our treatment allocation depends on the relative position of the DHS villages to the mine.

First, we randomly displace 1,000 times each DHS village within a buffer of 2 kilometers for urban clusters and 5 kilometers for rural clusters. Thus, each displaced village is located in a new sub-basin, which can be the initial sub-basin or not. Then, we determine the topographic relation of this sub-basin to the sub-basin of the mine, which gives the treatment of the DHS village: whether it falls into a sub-basin upstream, downstream, in the same sub-basin as the mine or in a sub-basin with no topographic relationship with the one of the mine. The topographic relation of the new sub-basin gives the new treatment status of the DHS village. We only reshuffled the position of DHS villages that have a topographic relation with the mine initially, and that were up to the third sub-basin downstream. This means that we can have some DHS villages that exit the main sample, for instance, if their newly assigned sub-basin has no topographic relation, or is downstream in the fourth sub-basin, or if it falls into the same sub-basin as the mine, as these cases are excluded from the main result. The only new observations that come within the sample are DHS villages that were initially within the same sub-basin as the mine and fall upstream, or downstream with the new iteration of the random displacement of their location. Please note that it is possible as well, but very rare, that a DHS village falls into the ocean.

Figure 2.18: DHS random displacement - 1,000 iterations



(a)



(b)

Notes: Figure (a) plots the transition probability graph for 1,000 random displacements of DHS clusters. Figure (b) plots the interaction term for 1,000 different regressions, each done for a new sample where DHS GPS coordinates have been randomly displaced. The red line y=0.0218 plots the coefficient from our main result. The coefficients are ordered, and we plot the 95% and 90% intervals.
Sources: Authors' elaboration.

Figure 2.18a gives the probability graph showing the transition probabilities of changing treatment status. For instance, after 1,000 iterations, a DHS village initially downstream within the third sub-basin has 70% chances to remain downstream up to sub-basin three, has 0.3% chances to be upstream the mine, 24% chances to fall into a sub-basin with no topographic relation (and be out of the sample), 3.5% chances to be in the same sub-basin of the mine and finally 2% chances to be downstream further than the third sub-basin (and be out of the sample). In the end, a DHS village treated in our initial sample has 25% chances to leave the sample. Please note that this random reshuffling is not perfect, as DHS villages should be reshuffled within administrative level 2 boundaries as made in the DHS procedure.

Figure 2.18b plots the interaction term $Donwstream \times Open$ of our main estimation for 1,000 random displacements of DHS GPS coordinates. The coefficients are ordered, and we plot the 95% and 90% intervals. As there is a higher probability that a DHS cluster leaves the sample rather than a new enters it, the number of observations varies for each iteration and is likely to be smaller than our main estimation.

2.10.3.2 Accuracy of mine location

We further test for potential measurement errors by looking at the precision of the mines' location. The SNL database provides information on the accuracy levels of each mine's GPS coordinates and enables us to restrict the analysis to mines with exact coordinates, precise at 1 km. Our main results are positive but no longer significant when restricting to the mines with exact coordinates but hold when focusing on rural households. This hints towards a higher effect of industrial mining activity on child mortality among rural households, and to a lack of precision in the location of mines close to urban areas.

Table 2.18: Effects of industrial mining opening, restriction to exact GPS coordinates.

Outcome	24-month mortality		
Accuracy level	All	Exact coordinates	
Sample	Urban and rural	Urban and rural	Rural
	(1)	(2)	(3)
Downstream×Open	0.0218**	0.0116	0.0294**
	[0.0108]	[0.0116]	[0.0143]
Downstream	-0.0211***	-0.0204**	-0.0239***
	[0.00739]	[0.00807]	[0.00888]
Open	-0.00496	0.00532	0.00805
	[0.0101]	[0.0104]	[0.0130]
Controls	Yes	Yes	Yes
Birthmonth FE	Yes	Yes	Yes
Country-birthyear FE	Yes	Yes	Yes
Mine SB FE	Yes	Yes	Yes
Mine SB-birthyear trend	Yes	Yes	Yes
Commodity FE	Yes	Yes	Yes
N	35,638	29,195	20,172
R2	0.0511	0.0517	0.0626
Outcome mean	0.0873	0.0858	0.0920

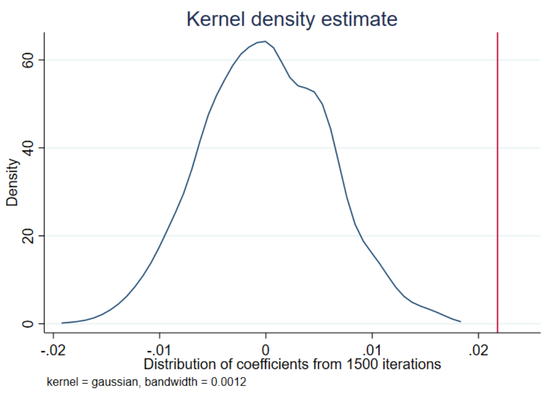
Notes: Standard errors clustered at the DHS village level, $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$. The same controls as Table 2.2 Column 2 apply.

2.10.4 Placebo tests

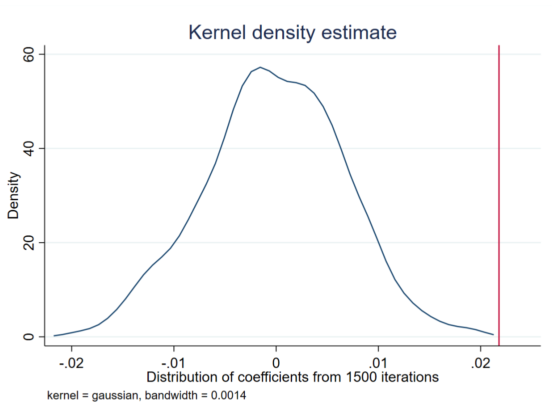
2.10.4.1 Randomization inference

To make sure that the assignment of each village to its topographic position relative to the mine is indeed what drives our result on child mortality, we run a randomization inference test. We draw randomly 1,500 permutations of the "Downstream" variable without changing the start-up year and 1,500 permutations of the "Open" variable without changing the downstream position [16]. The simulations show that the distribution of treatment effects (Downstream × Open) are shifted around zero (Figure 2.19). The red line represents the initial treatment effect using our main specification: we are sure at the 1 percent level that our main model is not misspecified.

Figure 2.19: Spatial and temporal randomization inference tests



(a) Randomization of the "Downstream" variable



(b) Randomization of the "Open" variable

Notes: The two figures represent the distribution of coefficients associated with the interaction term of being downstream of an open mine and its effect on under 24-month mortality when conducting 1,500 permutations of the "Downstream" position of each DHS sub-basin (Figure (a)) and 1,500 permutations of the "Open" variable (Figure (b)). The red line represents the initial treatment effect using our main specification.
Sources: Authors' elaboration using the Stata *ritest* command.

2.10.4.2 Placebo diseases

We conduct a placebo test on other potential diseases that could affect women's and thus children's mortality. We do not find significant industrial mining on the infection of any sexually transmitted disease among women living downstream of an open mine (Table 2.19 column 1) or among awareness of tuberculosis (column 2). This

[16] The randomization inference of the "Downstream" and "Open" treatment are within the sub-basin level, and are clustered at the DHS village level.

absence of differential results on women's health across upstream and downstream villages is reassuring for our identification of the water pollution channel.

Table 2.19: Effects of industrial mining opening on women, placebo diseases.

	(1)	(2)
Outcome	Any sexually transmitted infection	Heard of tuberculosis
Downstream × Open	0.00332 [0.00923]	-0.0387 [0.0259]
Downstream	0.00751 [0.00772]	0.0277 [0.0210]
Open	0.00766 [0.00913]	0.00469 [0.0314]
Controls	Yes	Yes
Country-survey year FE	Yes	Yes
Mine SB FE	Yes	Yes
Mine SB-survey year trend	Yes	Yes
Commodity FE	Yes	Yes
N	66,653	14,750
R2	0.0888	0.186
Outcome mean	0.0501	0.938

Notes: Standard errors clustered at the DHS village level, $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$. The same sample and controls as Table 2.4 apply.

2.11 Discussion and limits

2.11.1 Selection issues

Our study includes the best available data on mining and child health we have at the scale of a continent, but of course, is neither exhaustive nor represents the whole African continent. First, as we limited our sample to countries with at least two waves of DHS, we had to drop many countries with only one wave among which South Africa which has an intense mining activity. Future work will be possible once other survey waves will have been conducted. Our 26 countries represent about two-thirds of the total population of the continent[17].

Second, our mining data is also limited to industrial sites, and do not include artisanal or small-scale mining which information is much harder to retrieve at the scale of the continent. One possibility for another project is to use data on the suitability of artisanal gold mining (Girard, Molina-Millan, and Vic, 2022) and to compare their

[17]The proportion is stable between 1981 and 2020.

environmental impacts to industrial mining.

One remaining concern is about the exhaustivity of the SNL, and the heterogeneity of the sampling selection across countries. We tried our best to evaluate the exhaustivity of the SNL data by comparing it with other mining data and social sources (Ministries, USGS, mining website. . .) but it is out of our feasible means to get an exact proportion of representativity and to compete with the business-oriented activity of SNL.

2.11.2 Threats to the identifying assumption

2.11.2.1 Type of pollution

First, our study mainly focuses on water pollution through the lens of water subbasins while controlling for rivers, i.e. surface water. Yet, further work could also control for groundwater as their pollution may follow different dynamics than surface water: villages located in areas with low-depth groundwater could pump the water more easily and with more affordable water pumps than in areas with deeper groundwater. These former villages could therefore be more exposed to mining-induced water pollution than the latter ones. Moreover, groundwater could take more time to be contaminated by mining-induced pollution than surface water, but its contamination could also last more permanently.

This paper does not directly examine mining-induced air pollution. The main hypothesis is that wind direction is less correlated to the topographic position of the village than water pollution and that the comparison between upstream and downstream villages should exclude the effect of air pollution. Besides, as discussed in Section 2.2, the effects of air pollution seem to concern the mine workers more than the surrounding population, even though fine particles can be displaced over long distances. However, our main result is not entirely net off the impacts of air pollution. The best control included so far is adding the sub-basins with no topographic relationship to the mine, as they are allegedly exposed to air pollution only, while sub-basins with a topographic relationship would be exposed to both water and air pollution. It is beyond the scope of the current paper to take into account the direction of the wind to disentangle both sources of pollution, but empirically feasible for another paper. Our study is most likely an underestimation of the total pollution induced by industrial mining activity.

The same concern remains for soil pollution. An additional heterogeneity analysis would be to take into account areas prone to subsistence agriculture or livestock, as mining-induced water pollution could also contaminate soils and cattle in the long run and the subsequent food produced. We assume more harmful effects of industrial mining on local population health if both water and food are polluted. In another paper, one could study the heterogeneous effects across the global agroecological zones (GAEZ) and crop suitability, and test whether villages located near industrial mining sites in high-yield crop areas are more affected than villages with less suitable soils.

2.11.2.2 Threats to identification

A major threat to identification is that the opening of a mine may not be orthogonal to unobservable factors that affect health and water quality, in different ways for downstream and upstream areas.

Migration is a major methodological concern, as we show in Table B.8 of Appendix B.3 that migrants significantly settle downstream after a mine opening. Section 2.6.2 shows that our main result is robust when controlling for in-migration. A main violation of the identifying assumption would be if downstream villages anticipate the mine opening and strategically out-migrate within upstream areas to avoid pollution. In this case, there would be a selection bias, as the individuals surveyed downstream after the mine opening would be those that were not able to migrate or anticipate the pollution. Controlling for in-migration in DHS villages, we show that our result is robust to this specific strategic behavior. However, we cannot control for strategic out-migration outside of the study area, meaning individuals out-migrating to avoid pollution elsewhere than the upstream area. In this paper, we made the choice not to use mother fixed-effects and retrospective questions on birth history, to limit endogenous selection due to out-migration, and to account for children born up to five years prior to the year of the survey.

Accordingly, a threat to the identification would be a differed improved access to infrastructure associated with the opening of a mine between upstream and downstream areas. Table B.8 shows no difference in terms of access to electricity and piped water between downstream and upstream areas after a mine opening, and Section 2.6 shows that our result is robust controlling for improved access to facilities.

An important omitted variable in our current study is the increased presence of conflicts and violence around areas with mining activity, as shown by Berman et al., 2017 and that could also explain the increase in child mortality in the vicinity of mines. We do not directly control for conflict, but there would be an upward bias of our estimation only if conflicts systematically happen more downstream than upstream. As our results hold when including non-topographic subbasins in rural areas, it is a first-step approximation that water pollution is indeed the main explaining factor of increased child mortality. Further work could include the ACLED data to exclude this mechanism.

Another concern is that other industries could aggregate around the mining industry and be partly responsible for the pollution. More than a bias, this could be a threat to identification if the location of the industry is correlated to the topographic position of the mine. In another paper, we could look at the correlation between mining activity and other industry implementations. Controlling for them could enable us to isolate the pollution linked to the mining activity solely.

2.12 Policy discussion

In this section, we first try to compute how many deaths were related to the water pollution linked to industrial mining activity in the 26 countries of our sample. Then, we try to assess whether the Extractive Industries Transparency Initiative, a global standard for good governance in the extractive sector, has been successful to reduce this mortality.

2.12.1 Back-of-the-envelope calculation

In this section, we compute a back-of-the-envelope calculation to grasp how many deaths could have been averted had there been policies implemented to limit water pollution, over the 1981-2020 period and within the 26 Sub-Saharan countries of our analysis.

First, we consider that as DHS is representative at the national level, it is feasible to calculate the proportion of individuals living within 45 kilometers of a mine, the proportion of those living downstream, etc. Here are the probabilities computed using the DHS database:

- $x = 28\%$: Proportion of individuals living within 45 kilometers of a mine [18]
- $x = x_d + x_u + x_{nt} + x_{sb}$, with
  - $x_d = 1.94\%$: Proportion of individuals living downstream [19]
  - $x_u = 5.25\%$: Proportion of individuals living upstream
  - $x_{nt} = 17.93\%$: Proportion of individuals living with no topographic relation
  - $x_{sb} = 2.92\%$: Proportion of individuals living in the same sub-basin as a mine

Our analysis leads to an estimation of $e = 2.18\%$ the increased mortality rate because of industrial mining-induced water pollution. In our sample, 9,258 individuals live downstream of a mine and we count 822 deaths among them. The total number of additional deaths due to mining-induced water pollution is 9,258 $\times$ 2.18% = 202 deaths. We now look at the 880 million children who were aged 0-2 years over 1981-2020 in our 26 countries [20]. As we assume the representativity of the DHS surveys and the stable proportion of the population living in the vicinity of mines, this would mean that 1.94% $\times$ 880 million = 17 million children lived within 45 km downstream of a mine. This leads to 2.18% $\times$ 17 million = 370,600 deaths due to mining-induced water pollution over 1981-2020 in our 26 countries, i.e. 9,265 deaths per year, or 16 deaths per mine per year.[21] To grasp a better sense of the magnitude of this figure, there are on average 840,000 births per year and per country (average within the 26 countries over 1981-2020), which means that the number of deaths caused by mining-induced water pollution over 26 countries represents 1.1% of the number of births per country[22].

2.12.2 Extractive Industries Transparency Initiative members

We look at whether there is a significant difference across countries that have signed the Extractive Industries Transparency Initiative, launched in 2002 and which cur-

[18]Please note that, exactly, this is the proportion of individuals living within 45 kilometers of a mine and downstream up to the third sub-basin.

[19]up to the third sub-basin

[20]Source: World Bank data.

[21]There are 604 mines in total in our main results' regressions.

[22]As sampling weights are not considered in the calculation, we do not give a number per country.

Table 2.20: Effects of industrial mining opening, across EITI membership.

Outcome	24-month mortality					
Sample	All			Rural		
	Not an EITI member	EITI member		Not an EITI member—	EITI member	
	(1)	(2)	(3)	(4)	(5)	(6)
Downstream× Open	0.0179	0.0259**	0.0133	-0.0428	-0.0221	-0.0557
	[0.0210]	[0.0127]	[0.0190]	[0.0518]	[0.0416]	[0.0669]
Surveyed after joining EITI			0.0237			-0.0259
			[0.0303]			[0.0315]
D× O× Surv. after joining EITI			0.0243			0.0221
			[0.0236]			[0.0705]
Downstream	-0.0552***	-0.00934	-0.00446	0.00399	0.0356	0.0118
	[0.0140]	[0.00876]	[0.0107]	[0.0500]	[0.0381]	[0.0641]
Open	-0.00576	-0.00588	-0.00656	-0.0456	-0.00345	-0.0114
	[0.0246]	[0.0112]	[0.0163]	[0.0651]	[0.0268]	[0.0443]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Birthmonth FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-birthyear FE	Yes	Yes	Yes	Yes	Yes	Yes
Mine SB FE	Yes	Yes	Yes	Yes	Yes	Yes
Mine SB-birthyear trend	Yes	Yes	Yes	Yes	Yes	Yes
Commodity FE	Yes	Yes	Yes	Yes	Yes	Yes
N	8,434	26,810	26,810	2,251	8,685	8,685
R2	0.0373	0.0548	0.0548	0.0838	0.0677	0.0679
Outcome mean	0.0716	0.0920	0.0920	0.0604	0.0738	0.0738

Notes: Standard errors clustered at the DHS village level, $^{*}p < 0.1$,$^{**}p < 0.05$,$^{***}p < 0.01$. The same sample and controls as Table 2.2 Column 2 apply.

rently gathers 55 countries. Member countries commit to disclose information along the production value chain of oil, gas, and mining extraction and respect a common set of governing standards. We want to see if there is an effect of the EITI Rules signed by the member countries on the effect of industrial mining on child mortality. 18 out of the 26 countries included in our sample signed the EITI[23] which gather 76 percent of our sample of children.

We estimate our main specification across the sample of countries that are members of the EITI or not. We find that our results hold even for countries who committed to improved governance of their extractive industries (Table 2.20), but which are also countries heavily relying on this activity in their national economy. We find no significant effect of our results when looking at whether surveys were conducted before or after their country signed the EITI Standards (triple interaction Downstream × Open × Surveyed after joining EITI in columns (3) and (6)).

2.13 Conclusion

This paper identifies a negative externality of industrial mining on local population living standards, as we show that industrial mining sites increase infant mortality in surrounding villages, indirectly through the contamination of water resources. We match geocoded repeated-cross sectional household surveys to geocoded data on industrial mine openings obtained through intensive handwork. We propose a staggered Difference-in-Difference strategy and isolate the mechanism of water pollution by building the treatment and control groups using an upstream-downstream comparison. We compare the effect on the health of villages located upstream and downstream of a mine deposit, before and after its opening. We are the first, to the best of our knowledge, to take into account the topography of mining areas using an upstream-downstream comparison and to empirically quantify this effect at the scale of 604 mines in 26 countries of Sub-Saharan Africa over 1981-2020.

We find that the opening of industrial mines increases by 25% the 24-month mortality rate among villages located downstream compared to villages located upstream, and thus indirectly isolate the channel of water pollution. We find almost no effects on

[23]Burkina Faso, Cote d'Ivoire, Democratic Republic of the Congo, Ethiopia, Ghana, Guinea, Liberia, Madagascar, Malawi, Mali, Niger, Nigeria, Senegal, Sierra Leone, Tanzania, Togo, Uganda, and Zambia are EITI members. Benin, Burundi, Kenya, Namibia, Rwanda, and Zimbabwe have not joined the EITI.

other children's health outcomes, such as anthropometric measures, cough, fever, diarrhea, or anemia. We exploit the variation of the opening of a mine and show that our results are not driven by a change in women's fertility behavior, differential access to piped water, electricity, or health facilities but mainly by mining-induced water pollution, as children who were given plain water show increased mortality. The heterogeneity in the consumption of plain water seems to explain the null result on the 12-month mortality rates, as we observe a significant increase in the 12-month mortality rates exclusively for those who consume plain water. This can be interpreted as a proxy for having non-exclusive breastfeeding.

In an additional heterogeneity analysis, we show that our results are mainly driven by the pollution occurring during the time of mining activity. We find that the effects are even more harmful in rural areas, for open-pit and foreign-owned mines, and in places with a high density of mines. We also find that the effects increase with productivity intensity (proxied by international commodity prices). We run manyfold robustness checks and find that our results hold when controlling for in-migration, and when restricting to a balanced sample which deals with the issue of repeated cross-section surveys. Our results are also robust to the heterogeneous treatment effects estimator of de Chaisemartin and D'Haultfœuille, 2020, to measurement error tests, and a battery of placebo tests such as spatial and temporal randomization inference tests.

Bibliography

Africa Bank (2022). *Mining Industry Prospects in Africa.* https://blogs.afdb.org/fr/afdb-championing-inclusive-growth-across-africa/post. Accessed: 2022-04-28.

Ahlerup, Pelle, Thushyanthan Baskaran, and Arne Bigsten (2020). "Gold Mining and Education: A Long-run Resource Curse in Africa?" In: *The Journal of Development Studies* 56.9, pp. 1745–1762.

Aragón, Fernando M. and Juan Pablo Rud (2016). "Polluting Industries and Agricultural Productivity: Evidence from Mining in Ghana". In: *The Economic Journal* 126.597, pp. 1980–2011.

Atkin, David (2016). "Endogenous Skill Acquisition and Export Manufacturing in Mexico". In: *American Economic Review* 106.8, pp. 2046–85.

Bazillier, Remi and Victoire Girard (2020). "The gold digger and the machine. Evidence on the distributive effect of the artisanal and industrial gold rushes in Burkina Faso". In: *Journal of Development Economics* 143, p. 102411.

Benshaul-Tolonen, Anja (2018). "Local Industrial Shocks and Infant Mortality". In: *The Economic Journal* 129.620, pp. 1561–1592.

Berman, Nicolas et al. (2017). "This Mine Is Mine! How Minerals Fuel Conflicts in Africa". In: *American Economic Review* 107.6, pp. 1564–1610.

Bialetti, Anca et al. (2018). "Lease Splitting and Dirty Entrants: The Unintended Deforestation Consequences of India's Environmental Clearance Process Reform". In: *PEDL Research Papers*.

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess (2021). "Revisiting Event Study Designs: Robust and Efficient Estimation". In: *Revisions Requested from Review of Economic studies*.

Briffa, J, E Sinagra, and Blundell R (2020). "Heavy metal pollution in the environment and their toxicological effects on humans". In: *Heliyon*.

Callaway, Brantly and Pedro H.C. Sant'Anna (2021). "Difference-in-Differences with multiple time periods". In: *Journal of Econometrics* 225.2. Themed Issue: Treatment Effect 1, pp. 200–230.

Chuhan-Pole, Puna, Andrew L Dabalen, and Bryan Christopher Land (2017). “Mining in Africa : Are Local Communities Better Off?” In: *Africa Development Forum* Washington, DC: World Bank and Agence Francaise de developpement.

Cobbina, Kumi, and Myilla (2013). “Small Scale Gold Mining And Heavy Metal Pollution: Assessment of Drinking Water Sources In Datuku In The Talensi-Nabdam District.” In: *International Journal of Scientific and Technology Research* 2, pp. 96–100.

Coelho, PCS and JPF Texeira (2011). “Mining Activities: Health Impacts”. In: *Elsevier*.

Colella, Fabrizio et al. (2020). “Inference with Arbitrary Clustering”. IZA Discussion Paper n. 12584.

Conley, T. G. (Sept. 1999). “GMM estimation with cross sectional dependence”. In: *Journal of Econometrics* 92.1, pp. 1–45.

Corno, Lucia and Damien de Walque (Feb. 2012). “Mines, migration and HIV/AIDS in southern Africa”. In: *Journal of African Economies* 21.

Cossa, Hermínio et al. (2022). “Assessing the effects of mining projects on child health in sub-Saharan Africa: a multi-country analysis”. In: *Globalization and Health*.

Cust, James and Steven Poelhekke (2015). *The Local Economic Impacts of Natural Resource Extraction*. OxCarre Working Papers 156. Oxford Centre for the Analysis of Resource Rich Economies, University of Oxford.

de Chaisemartin, Clément and Xavier D’Haultfœuille (2020). “Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects”. In: *American Economic Review* 110.9, pp. 2964–96.

Dietler, Dominik et al. (2021). “Impact of mining projects on water and sanitation infrastructures and associated child health outcomes: a multi-country analysis of Demographic and Health Surveys (DHS) in Sub-Saharan Africa”. In: *Global Health*.

Dike, IC et al. (2020). “Evaluation of Pb concentrations in selected vegetables and portable drinking water, and intelligent quotients of school children in Ishiagu-a Pb mining community: health risk assessment using predictive modeling”. In: *Environ Monit Assess* 192(2):126.

Do, Quy-Toan, Shareen Joshi, and Samuel Stolper (2018). “Can environmental policy reduce infant mortality? Evidence from the Ganga Pollution Cases”. In: *Journal of Development Economics* 133, pp. 306–325.

Duflo, Esther and Rohini Pande (2007). “Dams*”. In: *The Quarterly Journal of Economics* 122.2, pp. 601–646.

Edwards, David et al. (2013). “Mining and the African Environment”. In: *Conservation Letters* 7.

Fängström, Bob et al. (2008). “Breast-feeding protects against arsenic exposure in Bangladeshi infants”. In: *Environmental health perspectives,*

Fourati, Maleke, Victoire Girard, and Jérémy Laurent-Lucchetti (2021). *Sexual violence as a weapon of war*. Tech. rep. Universidade Nova de Lisboa, Nova School of Business and Economics, NOVAFRICA.

Garg, Teevrat et al. (2018). “(Not so) gently down the stream: River pollution and health in Indonesia”. In: *Journal of Environmental Economics and Management* 92, pp. 35–53.

Girard, Victoire, Teresa Molina-Millan, and Guillaume Vic (2022). “Artisanal mining in Africa”.

Glöser, Simon et al. (2017). “The cobweb theorem and delays in adjusting supply in metals’ markets”. In: *System Dynamics Review* 32.

Goodman-Bacon, Andrew (2018). *Difference-in-Differences with Variation in Treatment Timing*. Working Paper 25018. National Bureau of Economic Research.

Greenstone, Michael and Rema Hanna (2014). “Environmental Regulations, Air and Water Pollution, and Infant Mortality in India”. In: *American Economic Review* 104.10, pp. 3038–72.

He, A et al. (2020). “Potentially toxic metals and the risk to children’s health in a coal mining city: An investigation of soil and dust levels, bioaccessibility and blood lead levels”. In: *Environ Int.*

El-Kady, Ahmed A and Mosaad Attia Abdel-Wahhab (2018). “Occurrence of trace metals in foodstuffs and their health impact”. In: *Trends in Food Science and Technology* 75, pp. 36–45.

Khan, Tehmina, Trang Nguyen, and Richard Ohnsorge Franziska an Schodde (2016). “From Commodity Discovery to Production”. In: *Policy Research Working Paper* World Bank, Washington, DC.7823.

Kotsadam, Andreas and Anja Tolonen (2016). “African Mining, Gender, and Local Employment”. In: *World Development* 83.C, pp. 325–339.

Madilonga, RT et al. (2021). “Water Quality Assessment and Evaluation of Human Health Risk in Mutangwi River, Limpopo Province, South Africa”. In: *Int J Environ Res Public Health* 18(13):6765.

Malpede, Maurizio (2021). “The Dark Side of Batteries: Education and Cobalt Mining in the Democratic Republic of the Congo”. In: *SSRN.*

Mamo, Nemera, Sambit Bhattacharyya, and Alexander Moradi (2019). “Intensive and extensive margins of mining and development: Evidence from Sub-Saharan Africa”. In: *Journal of Development Economics* 139, pp. 28–49.

McQuilken, James and Rachel Perks (2020). *2020 State of the Artisanal and SmallScale Mining Sector. Washington, D.C.: World Bank.* Tech. rep. World Bank.

Obasi, NA et al. (2020). “Metal pollution and human health risk assessment of soils and edible plants in farmlands around Enyigba lead-zinc mining site, Ebonyi State, Nigeria”. In: *Environ Monit Assess* 192(5):292.

Oje, OA et al. (2010). “Environmental pollution levels of lead and zinc in Ishiagu and Uburu communities of Ebonyi State, Nigeria”. In: *Bull Environ Contam Toxicol.*

Ploeg, Frederick van der (2011). “Natural Resources: Curse or Blessing?” In: *Journal of Economic Literature* 49.2, pp. 366–420.

Saha, Shubhayu et al. (2011). “Under-mining health: Environmental justice and mining in India”. In: *Health Place* 17.1. Health Geographies of Voluntarism, pp. 140–148.

Strobl, Eric and Robert O. Strobl (2011). “The distributional impact of large dams: Evidence from cropland productivity in Africa”. In: *Journal of Development Economics* 96.2, pp. 432–450.

Taylor, Cliff D et al. (2009). “Geology and Nonfuel Mineral Deposits of Africa and the Middle East”. In: *U.S. Geological Survey.*

UN Environment Program (2022). *Our work in Africa*. https://www.unep.org/regions/africa. Accessed: 2022-04-28.

UNESCO (2019). *The United Nations world water development report 2019: leaving no one behind*. UNESCO World Water Assessment Programme.

VanDerSlice, John, Bob Popkin, and John Briscoe (1994). “Drinking-water quality, sanitation, and breast-feeding: their interactive effects on infant health.” In: *Bulletin of the World Health Organization, 72(4), 589–601.*

Venables, Anthony J. (2016). “Using Natural Resources for Development: Why Has It Proven So Difficult?” In: *Journal of Economic Perspectives* 30.1, pp. 161–84.

Von der Goltz, Jan and Prabhat Barnwal (2019). “Mines: The local wealth and health effects of mineral mining in developing countries”. In: *Journal of Development Economics* 139, pp. 1–16.

Chapter 3

Raw Materials Diplomacy, Official Development Finance and the Industrial Exploitation of Natural Resources in Africa [1]

Abstract

This paper investigates how official development finance from traditional and emerging donors influences the industrial exploitation of natural resources in Africa. Willingly or not, loans contribute to the local influence a donor country can have in a recipient country, and its companies can benefit from easier access to extract the recipient's natural resources. Using development finance flows panel data from the OECD countries, China and India on the one side, and novel data on industrial extraction of natural resources on the other side. The first step of the study aims at showing that the larger the donor's influence, the more natural resources activity it can achieve. Through an extended descriptive analysis, I find that official development flows from DAC and non-DAC countries are positively associated with their capacity to conclude large-scale land acquisitions in Africa, over the 2000-2014 period. Moreover, a stronger association is found among OECD-DAC donors and former colonial countries and heterogeneity is exhibited among DAC and non-DAC donors across recipient countries' property rights levels. This association is higher among DAC

[1] I would like to thank Mélanie Gittard, Lionel Fontagné, Pierre Bachas, Sylvie Lambert, Jérémy Laurent-Lucchetti, Céline Nauges, Luc Behaghel, Nathalie Ferrière, Akiko Suwa-Eisenmann, Karen Macours and Quy-Toan Do, for helpful comments and discussion. I am also grateful to the participants of the Casual Development Seminar (CFDS) and the GPET day 2022 at PSE.

donors in countries with high property rights index and on the contrary, is higher among Non-DAC donors in countries with low property rights index. In the second step, the study shows that a donor's official development flows affect the influence of other donors on their capacity to conclude land deals. Financial flows from the USA and the UK complement the activity of other DAC land investors, while financial flows from China and India substitute DAC flows and reduce the capacity for their investors to conclude land deals.

3.1 Introduction and literature review

The rich endowment of Africa in natural resources combined with the increasing global demand for raw materials make Africa an opportunity for investors. The African continent is estimated to hold 65% of the world's uncultivated arable land (AFDB, 2019), hold 30% of the global mineral reserves (Chuhan-Pole, Dabalen, and Land, 2017) and contributed to 8.4 % of the total sea catch world wide in 2020.[1] This abundant and often weakly regulated natural resources can make Africa of the utmost interest for foreign powers, from Western countries to emerging countries such as China, India, and Gulf countries, to invest in and secure their domestic needs for raw materials.

Foreign investors acquiring land or opening a mining site can need a relatively strong bargaining power with the host country's government to get access to property or usage rights. They may well rely on their national government's connections with local authorities, and the information they provide on existing risks and opportunities to achieve their project. If OECD-Development Assistance Committee (DAC) countries' companies mostly rely on international and competitive bidding to gain a deal, it may not be the case for non-OECD-DAC countries' companies. Therefore, competition can arise quite expectedly in the market of foreign aid influence across DAC and non-DAC donors due to these different practices. This paper aims at looking at the possible consequences of such competition by focusing on the market of natural resource extraction.

The main contributions of this paper are twofold. First, I build a new dataset that combines yearly bilateral official finance flows with three datasets on large-scale land acquisitions, industrial mining, and industrial fishing at the scale of the African continent over 2000-2014. This dataset identifies the origin of the companies conducting these natural resources activities and matches them with each OECD-DAC countries, China, India, and the Gulf countries.

Second, I provide an in-depth descriptive analysis and comparison of the raw materials diplomacy and competition between DAC and non-DAC donors that has been so far lacking in the economics literature. Using share-model regressions, this paper analyses the association between bilateral official development finance flows of donor countries and their natural extraction activities within a recipient country. In the first step, I

[1]Estimation using FAO's application FishstatJ, available at https://www.fao.org/fishery/en/statistics/software/fishstatj/en. Selection criteria used: wild fish catch among the maritime seas of all the African countries, and at the global level. This figure is most likely an underestimation as the continent is subject to the highest levels of Illegal, Unreported, or Unregulated (IUU) fishing on the global scale (Cabral et al., 2018)

find a positive and significant correlation between the share of cumulative official finance flows from donor countries within the recipient country the previous year, and the share of the cumulative number of land deals conducted by an investor from the donor country. An increase of 1 percent of a donor's share of cumulative official financial flows is associated with an increase of 0.067 p.p. (with 95% Confidence interval: [0.017; 0.118]) of the share of land deals in the recipient country. I find a stronger association among OECD-DAC donors, even when introducing donor, recipient, and year-fixed effects, and controlling for many factors among which past colonial or dependency relationship. I find strong heterogeneity among DAC and non-DAC donors across recipient countries' property rights levels. This association is stronger among DAC donors in countries with high property rights index[2] and on the contrary, is stronger among Non-DAC donors in countries with low property rights index. In the second step, the estimation shows that a donor's official development flows affect the influence of other donors on their capacity to conclude land deals. I find that financial flows from the USA and the UK complement the activity of other DAC land investors, while financial flows from China and India substitute DAC flows, and reduce the capacity for their investors to conclude land deals. A replication exercise is undertaken in the cases of industrial mining and industrial fishing but with less significant results. This study provides suggestive evidence that donors' relative share of official development finance in a recipient country has an important role in their capacity to acquire land, and that it is the share of official finance - rather than the absolute level - that is at play.

This paper is at the frontier of several literature. It first relates to the literature drawing a parallel between the revenue of natural resources extraction and foreign aid that could both act as a "curse" for resource-rich countries (Robinson, Torvik, and Verdier, 2006; Bermeo, 2011; Robinson and Verdier, 2013), (Robinson, Torvik, and Verdier, 2017; Mehmood and Seror, 2019). The "resource curse", is characterized by increased indebtedness and high volatility of revenues (Sachs and Warner, 2001; Manzano and Rigobon, 2001; Humphreys, Sandbu, and Soros, 2007; Ravetti, Sarr, and Swanson, 2018a) and the "aid curse" that could exist especially in politically unstable environments where external liquidity can disincentivize the investment in the general domestic economy (Djankov, Montalvo, and Reynal-Querol, 2008). Both types of liquidity highly depend on factors outside the national government's control such as global commodity prices and the decisions of international donors (Ravetti, Sarr, and Swanson, 2018b). This could also increase higher rent-seeking behaviors and corruption (Leite and Weidmann, 2002), conflicts (Collier and Hoeffler,

[2]The index is described in more detail later in the paper.

2004), weaker accountability and poor institutions (Ross, 2001). I here provide suggestive empirical evidence on the strong relationship between foreign aid and the exploitation of natural resources, and how it must be taken into account to deal with either of the "curses". It also contributes to the strand of the literature studying the determinants and motivations of foreign aid, and more precisely to the donor interest model. The latter is based on the assumption that donor countries pursue their interest when deciding on the allocation of aid and that aid is a tool of foreign policy (McKinley and Little, 1979). In such a way, donors expect recipients to act on their political interest or economic benefits on their country (Dudley and Montmarquette, 1976). More recent empirical studies have shown that foreign aid was also driven by political and strategic considerations (Alesina and Dollar, 2000) and that both DAC and non-DAC donors used official development finance to pursue their commercial self-interest (Dreher, Nunnenkamp, and Thiele, 2011). The current study builds on an extended empirical test of the donor interest model using novel data including a larger set of non-DAC countries and by matching them with donor-recipient level natural resources extraction information. This paper aslo closely relates to the flourishing literature on donors' competition, which mainly studied how to improve the cooperation among foreign aid flows to achieve improved effectiveness for recipient countries (Torsvik, 2005; Bourguignon and Platteau, 2013; Bourguignon and Platteau, 2015; Bourguignon and Platteau, 2017) as many moral hazard issues can impede the optimal allocation of aid (Svensson, 2000; Azam and Laffont, 2003). The Paris Declaration (2005) and Accra Agenda for Action in 2008 aimed at improving the quality of aid by increasing cooperation and coordination, and reducing the fragmentation of aid among DAC donors. Yet, the latest papers found no effect of improved coordination (Nunnenkamp, Ohler, and Thiele, 2013; Nunnenkamp, Sotirova, and Thiele, 2016; Steinwand and Reinsberg, 2020) and still note crowding-in and herding effects (Mascarenhas and Sandler, 2006; Frot and Santiso, 2011). Thus, countries receiving significant flows of aid have been called "aid darlings" compared to "aid orphans" (Davies and Klasen, 2019). Out of data availability issues, most papers have focused on the competition among OECD-DAC donors. The literature including "emerging" donors has bloomed only recently with the public release made by AidData whose first versions date back to 2011 for the Gulf countries, to 2013 for China, and to 2022 for India[3]. I here exploit the recently available data on non-DAC donors to expand the scope of the strategic behaviors of donors among recipient countries to build on the qualitative work of Fraser and

[3]No comparable standardized and publically-available data exist yet for Brazil, Russia, and South Africa.

Whitfield, 2008 who have emphasized the importance of ownership of aid policies in the decision-making process in Africa, and how ”emerging” donors like China could increase sovereign rights by implementing demand-driven development projects. More recently, Kilama, 2016 has studied the competition between G7 donors and China in Africa and has provided evidence of increased volumes of aid from G7 donors in response to Chinese official finance flows in countries with natural resources. The current paper aims at shedding light on this DAC and non-DAC competition not by looking only at the reaction (complement or substitute) of donors' financial flows between each other but also at its associated consequences on the natural resources extraction market. Recipients' decision-making and power when looking at the competition across donors is not studied in the current paper, yet it goes without saying that recipients' governments may take advantage of the proposition of multiple donor countries to bargain their own political and economic agenda.

At last, this paper contributes to the growing literature studying the characteristics of Chinese official development finance in particular and how the country became the main competitor of ”traditional donors”. The recent literature has not yet reached a consensus. Humphrey and Michaelowa, 2019 found that Chinese official development finance did not have a ”game-changing” impact on the way the World Bank and the African Development Bank allocate their concessional lending in Africa. Watkins, 2021 argues that Chinese development assistance decreased the likelihood of Sub-Saharan African countries' complying with World Bank project agreements. In his qualitative study, Swedlund, 2017 shows that claims that China is radically reshaping bargaining relations between OECD-DAC donors and recipient countries in Sub-Saharan Africa are overstated since aid from OECD-DAC remains such a significant source of income for many governments. Vadlamannati et al., 2019 found that the US votes on the Executive Board of Multilateral Development Bank programs were more favorable to countries that have signed the Belt and Road initiative, suggesting the US competitive practice to maintain its influence. The current paper focuses on bilateral rather than multilateral donors' flow to grasp solely the country-to-country influence, yet soft power can also be spread through multilateral organizations, NGOs, or private foundations. So far, the closest study is Dreher, Fuchs, Parks, et al., 2022 which argues that China does not disproportionally commit more ODA or OOF flows to countries abundant in natural resources. They measure the latter with oil-producing country dummies, the percentage of oil rents in the recipient country's GDP, the percentage that fuel, ore and metals, and agricultural products represent in total exports, as well as energy and mineral depletions in the percentage of GNI. The authors do not precise the sources of the data, but it is likely to be taken from the World Bank data.[4] In this paper, I provide alternative ways of measuring natural resource extraction, that has the primary advantage to identify the origin of the investors for all the main donors for which we have available official finance flows.

The remainder of the paper is organized as follows. Section 3.2 details the context and the two main hypotheses and mechanisms. Section 2.3 presents and describes the data. Section 3.4 introduces the results on the influence of donors' official finance flows on land acquisitions, while section 3.5 displays the results on the complement/substitute effects across competing donors. Section 3.6.1 provides an heterogeneity analysis across the level of property rights in recipient countries and looks at two other types of natural resources. Finally, a lengthy discussion is provided in section 3.7 and eventually, section 3.8 concludes.

3.2 Context and hypotheses

This section describes the main characteristics of the difference between official flows of DAC and non-DAC donors, and details the main data sources used for this study.

3.2.1 Context

This section provides some historical insights to shed light on the contemporary foreign aid strategy of the two main non-DAC and "emerging" donors: China and India, and how they compare with DAC donors.

3.2.1.1 Comparison between BRICS and OECD-DAC countries

The official finance flows from OECD Development Assistance Committee (DAC) donors must go through a peer review process to make sure their expenditures comply with the regulatory framework established with recipient countries (Ben-Artzi, 2017). Although BRICS countries signed the Paris Declaration on Aid Effectiveness in 2005, they are not bound by these rules and norms (Asmus, Fuchs, and Müller, 2020) as it was mostly as recipients and not donors of aid (Chaturvedi, 2008; Brautigam, 2009).

[4] Energy and mineral depletions are defined as "the ratios of the present value of rents, discounted at 4% to exhaustion time of the resource. Mineral rent is calculated as the product of unit resource rents and the physical quantities of minerals extracted. It covers tin, gold, lead, zinc, iron, copper, nickel, silver, bauxite, and phosphate". Energy rent is calculated as the product of unit resource rents and the physical quantities of energy resources extracted. It covers coal, crude oil, and natural gas." (WorldBank, 2011)

China refused to join the information sharing and coordination mechanism of the OECD Creditor Reporting System (CRS) in 2009 and still considers its foreign aid program as a "state secret" (Brautigam, 2009; Dreher, Fuchs, Parks, et al., 2022). Second, the BRICS (except Russia) have anchored their foreign aid philosophy in the Non-Aligned Movement and in the framework of South-South Cooperation which put forward the principle of non-interference in internal affairs, while OECD-DAC and Western donors most often introduce policy conditionality in their aid programs. In particular, the Chinese narrative emphasized its "no-strings-attached" fundings, and its increased flexibility compared to OECD-DAC members' Official Development Assistant (ODA) flows (see definitions in section 3.3.1). More specifically, China adopted a demand-driven approach to source, select and implement development projects: recipient country politicians have to express their political and commercial needs and make a formal request to contract a loan or apply for a grant, in line with the principle of local ownership. On its side, India also claims that its development finance is more need-oriented than DAC donors (Fuchs and Vadlamannati, 2013).

3.2.1.2 Historical insights on the two main non-DAC donors

China's and India's historical and geopolitical roles can shed light on their current official finance flows toward developing countries. In 1954, Chinese and Indian prime ministers Zhou Enlai and Jawaharlal Nehru introduced the "Five Principles of Peaceful Coexistence"(mutual respect for states' territorial integrity and sovereignty, mutual non-aggression, mutual non-interference in states' internal affairs, equality, and co-operation for mutual benefits and peaceful coexistence). These principles were later retaken at the Bandung Conference between Asian and African states in 1955. The latter represented an important step in the creation of the Non-Aligned Movement (NAM).

China

China's current official finance strategy is also drawn upon its own experience as an aid recipient from the late 1970s to mid-2000 when China became a net donor (Chin, 2012). In particular, Japanese donors and creditors left a strong influence (Kragelund, 2011; Johnston and Rudyak, 2017) through their "request-based" system to identify, approve and conduct large-scale development projects: Japanese companies would propose projects to the host government, and if interests matched, the host government would ask the Japanese development finance institutions to support them. Current Chinese development finance embraced a similar approach and its aid agencies and state-owned banks would only fund general projects that received a formal request from the host government. This project approval system is supposed to ensure that Chinese government-funded projects are answering the needs and preferences of host countries' political leaders. Yet, it also creates the vulnerability of being subject to political capture, corruption, and artificially inflated costs (Dreher, Fuchs, Parks, et al., 2022). The Japanese aid program also inspired China to commodity-backed loans: the aftermath of the 1973 oil crisis pushed Japan to secure access to reliable supplies in China, and thus Japanese concessional loans financed the export of Japanese technologies which were repaid with oil exports (Brautigam, 2009). In 1982, China's prime minister Deng Xiaoping introduced a reform of foreign aid and encouraged Chinese state-owned enterprises to partner with host country firms to develop and operate projects. These joint ventures, in majority owned by the state-owned enterprises, were then contracting loans from Beijing, which enabled the latter to better manage loan repayment risks.

In 1999, the "Going Out" diplomatic strategy was introduced to cope with several challenges (Dreher, Fuchs, Parks, et al., 2022): (i) an excess domestic industrial production that represented a threat to long-term growth and a potential source of social unrest and political instability if industries had to lay-off workers; (ii) a foreign exchange oversupply problem due to annual trade surpluses (Yuhui, 2011) that created a risk of macroeconomic instability if these reserves were allowed into the domestic economy; (iii) a need to secure access to natural resources lacking domestically to sustain high levels of economic growth. The Chinese government thus gave a formal mandate to its policy banks to support overseas projects focused on industrial production, infrastructure, and natural resources acquisitions. It facilitated the participation of Chinese firms in these projects and combined the investment of the foreign exchange reserves in the "Going Out" of Chinese enterprises through overseas lending (Dreher, Fuchs, Parks, et al., 2022). In response to these challenges, China's policy banks made several changes: (i) they increased foreign currency-denominated lending at or near market rates; (ii) contractualized overseas borrowers to source project inputs from China (i.e. steel, cement, etc.); (iii) facilitated countries loans and repayments with commodity sales to China (Dreher, Fuchs, Parks, et al., 2022).

The global financial crisis of 2008 was an inflection point for China as Western countries faced economic recession and had to decrease their foreign aid budget. China took the opportunity to fill the vacuum by expanding its overseas financial flows and becoming a reliable source of development finance for low and middle-income countries (Dreher, Fuchs, Parks, et al., 2022). The aftermath of the 2008 global financial crisis was also concomitant with the request from the Chinese authorities for policy banks to seek profitable investments in the natural resource sector (Kong and Gallagher, 2017).

In 2013, Chinese President Xi Jinping launched the "One Belt, One Road" (OBOR) initiative aimed at building "five connectivities": (i) physical connectivity via infrastructure buildings; (ii) policy coordination; (3) unimpeded trade; (4) financial integration; (5) people-to-people exchanges. The OBOR was first targeted towards integrating Europe and Asia with initially 31 countries during its first three years. In 2016, the OBOR changed its name to the Belt and Road Initiative (BRI) and significantly expanded its geographical scope to Africa, Latin America, the Middle East, and Oceania to the extent of encompassing 140 countries in 2021 (Dreher, Fuchs, Parks, et al., 2022). The initiative was framed by President Xi as *"a new option for other countries and nations who want to speed up their development while preserving their independence"* [5], and emphasized the "hardware" investments contrasting with the "software" investments of the Western model of development.

India

The start of Indian development aid originates in the Colombo Plan of 1950 which gathered a group of Commonwealth countries that declared their goal of providing assistance to developing countries. The main recipients of Indian aid after its independence were primarily neighboring countries (Bhutan, Myanmar, and Nepal), and aid was mostly provided through the form of grants and loans, but also through technical assistance (Fuchs and Vadlamannati, 2013). India's aid program towards developing countries extended with the country's growth over the years, and especially increased since the mid-1990s. A turning point was taken at the beginning of the 21^{st} century. The 2003-2004 budget speech enacted the will of India to be mostly perceived as an aid donor and not as a recipient. The launch of the India Development Initiative consisted of extending debt cancellations for a part of Highly Indebted Poor countries, and was accompanied by an increase in grant and project assistance (Fuchs and Vadlamannati, 2013). Its main sources of development finance are on the one side the Ministry of External Affairs (MEA) and the Export-Import (Exim) Bank of India. While the MEA projects are closer to the OECD's criteria of ODA, the Exim Bank flows are mostly non- or semi-concessional loans and export credits (Asmus, Eichenauer, et al., 2021).

[5] Belt and Road Forum for International Cooperation, 2017.

After having presented the different rules and practices that DAC and non-DAC donors follow to send their development finance flows, the next section describes how these differences could affect the extraction of natural resources in Africa.

3.2.2 Hypotheses and mechanisms

The first hypothesis to test empirically is the existence and effectiveness of the diplomacy of raw materials, i.e. whether official finance flows from donors increase the likelihood for a company from the donor country, to achieve a project in the natural resources sector.

National governments through their development programs can help to foster and support a business-friendly environment in the recipient country and can have increased involvement and connections with local government and institutions to collect information to disseminate to their companies and share their advice on the existing risks and opportunities. More directly, donor countries' investors can also be involved through public-private partnerships. Garriga and Phillips, 2014 found a positive effect of development aid on FDI in post-conflict countries and argue that foreign aid acts as an accessible signal in a low-information environment. Yet Li et al., 2013 emphasize the difference between Western countries and China in particular: if Western countries can sign bilateral investment agreements to promote their domestic companies, and provide financial, technical, or material assistance to increase their bargaining position (Asiedu, Jin, and Nandwa, 2009; Buckley et al., 2010; Dunning, Van Hoesel, and Narula, 1997; Ramamurti, 2001), their governments are not as involved as the Chinese state which looks for investment opportunities for specific firms. A salient illustration is the Forum on China–Africa Cooperation (FOCAC) first held in Beijing in 2000, where government-to-government deals are discussed, but where the Chinese government most often proposes packages with aid closely tied to investment projects of its state-owned enterprises (Li et al., 2013).Through their qualitative surveys in the oil, mining, and agricultural sectors in Tanzania, Nigeria, Zambia, and Angola, the authors argue that it is common practice for the Chinese government to propose multi-purpose packaged loans attached to natural resources investments with a focus on developing infrastructures such as roads, ports, and communications.

The second hypothesis to test is whether the strategy implemented by DAC and non-DAC donors compete with or support other donors' natural resources extraction projects and if so whether there are different effects according to the type of flows adopted (aid or credit), as well as across the type of natural resources, as they are subject to different regulation stringency.

Foreign investors have to deal with recipient countries' land tenure regimes and may need the political support of the ruling elite to transfer land rights or land-use rights and minimize the uncertainty of their investment (Buur et al., 2020). If foreign aid from DAC-donors can be subject to patronage (Mehmood and Seror, 2019), another characteristic of non-DAC flows is to be less transparent compared to OECD-DAC flows, which makes them, even more, subject to political capture, clientelism, or favoritism (Dreher, Fuchs, Hodler, et al., 2021) that could help to conclude a land deal or a mining concession.

This section has presented the contextual framework and hypothesis to test in this study, and the next section will present the data that will be used to test them empirically.

3.3 Data

This section describes the main data sources used for studying official finance flows and industrial extraction of natural resources, and the final sample. Descriptive statistics and stylized facts are also conducted to better understand the outcome and explanatory variables used in the empirical strategy.

3.3.1 Official finance flows

Data on official finance flows were assembled and harmonized using three publically available datasets from AidData. Official finance flows from OECD and Gulf countries come from AidData's Core Research Release Version 3.1 published in 2016, which provides information on commitment at the project level between 1947 and 2013. The first version of the database was introduced by Tierney et al., 2011 and built from multiple sources to compile comparable categories of financial flows across donors and recipients: Official Development Assistance (ODA) and Official Financial Flows (OOF) (definitions below). The database excludes funding from nongovernmental organizations (NGOs), private investors, and military assistance.
Chinese flows came from AidData's Global Chinese Development Finance Dataset, Version 2.0 published in September 2021 by Custer et al., 2021 which records commitments from 2000 to 2017 over more than 165 countries, using the Tracking

Underreported Financial Flows (TUFF) methodology. Indian flows were retrieved from the Indian Development Finance Dataset, Version 1.0 published in April 2022 by AidData[6] and described in Asmus, Eichenauer, et al., 2021. It contains all Indian development cooperation projects reported by India's Ministry of External Affairs and the Export-Import Bank of India between 2007 and 2014 in over 169 countries. All flows were converted in constant 2011 USD. The authors of the databases admit the potential bias, likely to be smaller in observable sectors (such as transportation infrastructure) and larger in less observable sectors (such as general budget support and debt forgiveness).

Flow class definitions

The three datasets published by AidData provide comparable variables of flow classes, based on OECD-DAC guidelines for Official Development Assistance (ODA) and Other Official Flows (OOF). The main added-value of the datasets on Chinese and Indian flows is to have finely analyzed and created "ODA-like" and "OOF-like" flows, as neither the two countries are OECD-DAC members.

- **Official Development Assistance (ODA)**: the project counts as Official Development Assistance as categorized by the OECD-DAC if it meets three criteria: (i) the promotion of the economic development and welfare of developing countries as its main objective ; (ii) a sufficient concessionality level with a grant element of at least 25 percent (using a fixed 10 percent rate of discount); (iii) the recipient country must qualify for ODA based on its income level.
- **Other Offical Flows (OOF)**: according to the Creditor Reporting System (CRS) of the OECD-DAC, this category includes official sector transactions which do not meet the ODA criteria. This category is only used when specified by the reporting organization. For China and India, the authors of the databases counted as OOF "all financing to developing countries for (i) representational or essentially commercial purposes; (ii) Official bilateral transactions intended to promote development but having a grant element of less than 25 percent; (iii) Official bilateral transactions, whatever their grant element, that are primarily export-facilitating in purpose. This category includes by definition export credits extended directly to an aid recipient by an official agency or institution ("official direct export credits"); (iv) The net acquisition by governments and central monetary institutions of securities issued by multilateral development

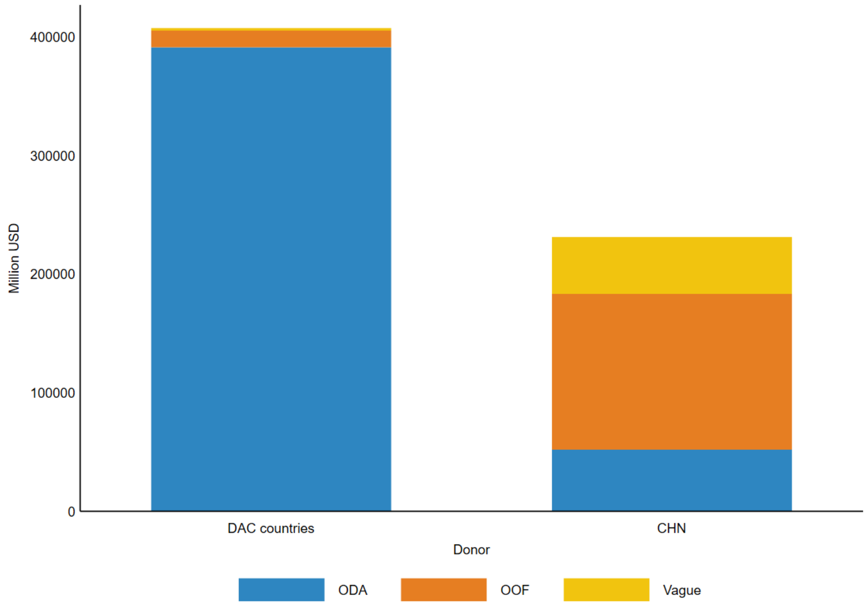
[6] Aiddata jointly worked with the ETH Zurich, Heidelberg University, the University of Göttingen, the Kiel Institute

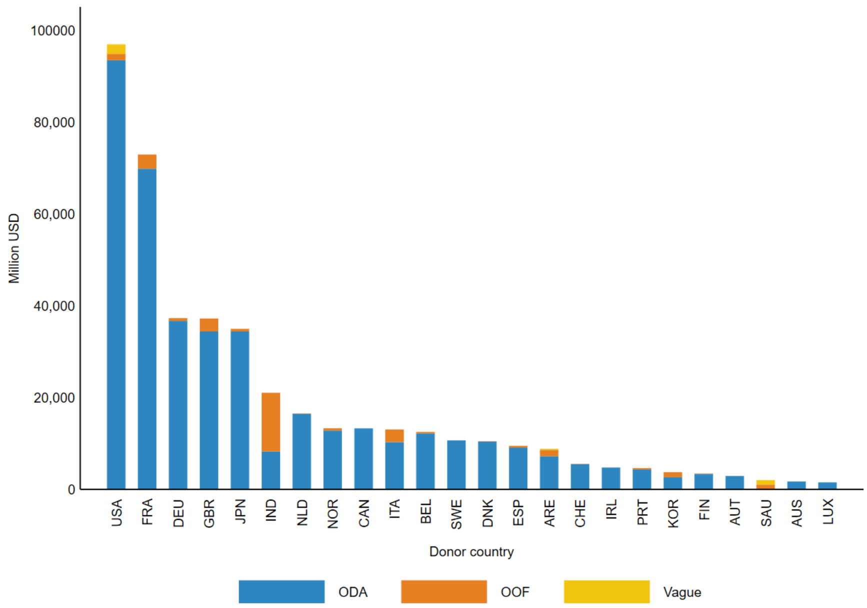
banks at market terms; (v) Subsidies (grants) to the private sector to soften its credits to developing countries; (vi) Funds in support of private investment." In our context, the latter type of funds is most likely closely related to the extraction of natural resources as OOF could directly support a project aiming at extracting natural resources, by building roads, telecommunications, or constructing a harbour.

- **Vague flows**: the datasets also include a third category entitled "Vague" official finance that represents flows backed by an official commitment but cannot fall into the ODA-like or OOF-like category out of insufficient information.

In other words, OOF are loans issued at or near market rates, seeking bankable and commercially profitable projects, and are more likely to be commodity-backed. On the other hand, ODA are more concessional and more likely to be used to gain foreign policy goals (Kuziemko and Werker, 2006; Kilby, 2011; Vreeland and Dreher, 2014). In total, ODA, OOF, and vague add up to total flows that will be essential in the analysis. Figure 3.1 plots the repartition between these flows types across each donor. Chinese and Indian finnacial flows are strikingly more composed of OOF compared to DAC donors. Figure C.1 in Appendix provides a scheme for the classification of official finance flows.

Figure 3.1: Class decomposition of financial flows from donor countries towards Africa over 2000-2013





Notes: These graphs represent the official finance flows from each donor country to all African country recipients over the 2000-2013 period. The upper graph compares China with all DAC countries, and the lower graph represent all individual countries but without China, for a matter of scale. Distinction is made between flow classes: Official Development Assistance (ODA), Other Official Finance (OOF), and Vague flows.
Source: Own elaboration using Core, China, and India Aiddata.

3.3.2 Natural resources

Large-scale land acquisitions

Data on large-scale land acquisitions come from the Land Matrix Initiative[7] and gathers transnational "transactions that entail (i) a transfer of rights to use, control, or own land through sale, lease, or concession; (ii) that cover 200 hectares or more; and (iii) that have been concluded since the year 2000 " (Lay et al., 2021). The data are compiled by local focal points and National Land Observatories, and information is provided by civil society organisations, research institutions, and the media from the host countries. Deals are published if there is information on at least one investor (name and country of registration), one data source, and the intended, contracted, or operational size. Therefore, the database has limitations[8] in its exhaustivity, yet it is the most comprehensive available so far that has been used in the empirical literature to study the determinants and consequences of large-scale land acquisitions (Deininger et al., 2011; Cotula, 2013; Arezki, Deininger, and Selod, 2015; Giovannetti and Ticci, 2016; Conigliani, Cuffaro, and D'Agostino, 2018; Balestri and Maggioni, 2021).

In the main analysis, land deals are restricted to the agricultural or biofuel sector and focus on deals that have been concluded "with credible reports about an oral agreement or a signed contract" (Lay et al., 2021) between 2000 and 2014. Intended and failed deals are so far excluded from the analysis (possibility to add them in future work). In total, the final sample includes 900 LSLA deals that have been concluded over all Africa (see Tables 3.1, C.1 and Figures 3.2, 3.3). We take the information on the investing company's country of registration and match it with each of our donor countries. If a land deal was concluded between several companies from different countries, we attributed the deal to each country. As we calculate the share of deals owned by each country at the end, we make sure not to double count the deals by aggregating only the total number of deals by recipient country and not by investing country. Figure C.18 in the Appendix represents the number of deals for all the investors between 2000 and 2014. In the final sample, we do not include countries with an investing company for which we do not have official finance flows information.

[7] Publically available at https://landmatrix.org/, downloaded on November 9th, 2021. The Land Matrix Initiative is a partnership between the Centre for Development and Environment (CDE) at the University of Bern, Centre de coopération Internationale en recherche Agronomique pour le développement (CIRAD), German Institute for Global and Area Studies (GIGA), Gesellschaft für Internationale Zusammenarbeit (GIZ) and International Land Coalition (ILC) at global level, and the University of Pretoria at the regional level.

[8] Under-reporting issues have been noted in five countries of Africa: Equatorial Guinea, Eritrea, Guinea-Bissau, Morocco, and Togo (Lay et al., 2021).

Industrial fishing

The measure of industrial fishing activity is derived from Kroodsma et al., 2018 which is the most recent and comprehensive geocoded dataset to measure fishing activity (see Appendix for more details). Different distances to the coast are used to aggregate the industrial fishing effort at the yearly level: (i) a maritime zone up to 36 NM to match with the average length of the continental shelves where the most important fishing grounds are located (Karleskint, Turner, and Small, 2013); (ii) the limit of the Exclusive Economic Zone (EEZ), namely 200 nautical miles (about 370 km). Industrial fishing is prohibited in inshores water which exclusion zones vary from 0 to 24 NM from the shore and the Exclusive Economic Zone (EEZ) is supposed to have regulated access for trespassing and conducting any type of extractive activity.

Each industrial fishing effort activity is associated with a vessel, and the vessels sailing through an identified flag with African countries' EEZ represented 97.1% of the total activity recorded over the 2012-2018 period. The main analysis will look at the country of origin of each available flag[9]. The final sample records more than 1 million hours of industrial fishing activity within the African EEZ between 2012 and 2014, with a third within 36 NM of the coastline (see Tables 3.1, C.1 and Figures 3.2, 3.3).

Industrial mining

Information on industrial mining comes from the SNL Metals and Mining database, which is privately owned by *S&P Global* and on license [10]. Overall, the database gathers 3,815 industrial mines in Africa opening from as early as the 19^{th} century up to 2021. The analysis looks at the start-up years of production, directly available for 1,193 mines in the dataset, and hand-checked for 1,738 mines [11] and take into account the nationality of owning companies (both foreign and domestic owners). The sample was restricted to the mines that opened between 2000-2014 (i.e. 871 mines, see Tables 3.1, C.1 and Figures 3.2, 3.3). As for land deals, if an industrial mining site was owned by several companies from different countries, we attributed

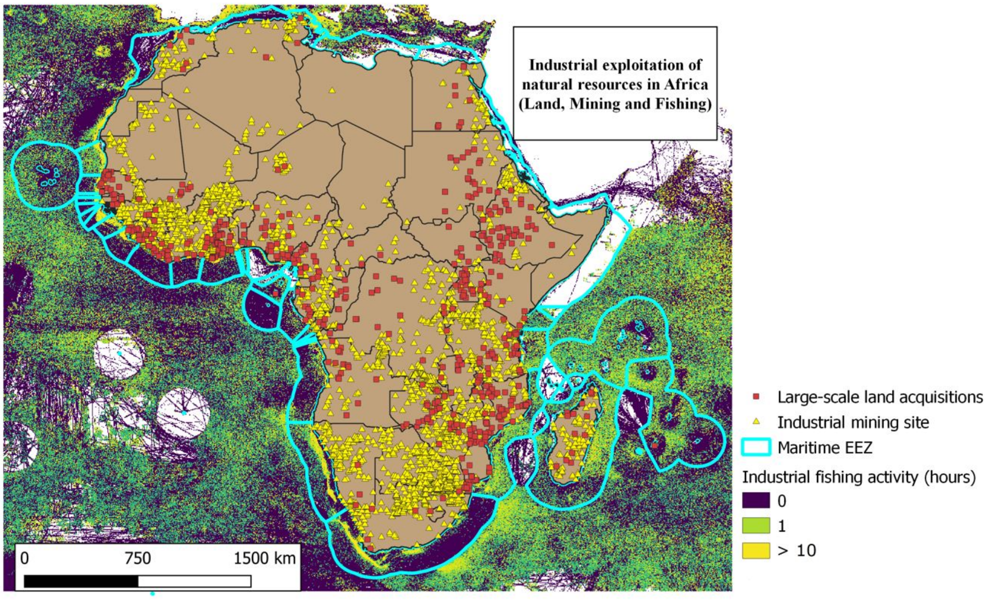
[9]The flag under which a vessel is sailing may not be truthful to the real origin of the vessel or company in charge as a flag can be bought (among which flags of compliance, but also local flags that already have the authorization to access and exploit the EEZ of their country) but it represents the best proxy.

[10]I am grateful to CEPREMAP, PjSE, EHESS, and the GPET thematic group of PSE, for their financial support and their help in purchasing the access to the data.

[11]The start-up year has been retrieved through handwork undertaken by Mélanie Gittard (PSE/CIRED/ENPC) and I, see Gittard and Hu, 2022 for more details on the 26 countries.

the mine to each investing country, and aggregated only the total number of mines by recipient country and not investing country to calculate the shares.

Figure 3.2: Three types of natural resources exploited industrially in Africa



Notes: This map represents the total number of industrial mines (19^{th} Century - 2022), large-scale land acquisitions (2000-2017), and industrial fishing activity (2012-2018). The latest data on LSLA mines and industrial fishing are included to grasp the most recent reality, but the current paper so far focuses on natural resources between 2000 and 2014.

Sources: Own elaboration using SNL mining and Metals, the Land matrix, and Global Fishing Watch.

3.3.3 Descriptive statistics

Table 3.1: Summary statistics of main variables, aggregated over each time period and overall Africa

	Time span	
Nb. large-scale land acquisitions deals	2000-2014	900
Nb. industrial mining site openings	2000-2014	871
Nb. industrial fishing hours	2012-2014	
within 36 NM		381,728
within EEZ		1,017,056
Total ODA (in millions, constant USD 2011)	2000-2013	459,890
Total OOF (in millions, constant USD 2011)	2000-2013	164,305
Total Vague (in millions, constant USD 2011)	2000-2013	51,874
Total Flows (=ODA+OOF+ vague) (in millions, constant USD 2011)	2000-2013	676,070

Notes: This table represents the main variables aggregated over all donors and recipients for the indicated time span. LSLA = large-scale land acquisitions. EEZ = Exclusive Economic Zone. ODA = Official Development Assistance. OOF = Other Official Flows.

Table 3.1 displays the summary statistics of the main outcome and explanatory variables. Over 2000-2014, 900 large-scale land acquisitions were concluded in Africa, 871 industrial mines opened and more than 1 million of hours of industrial fishing were detected along the African EEZ. In total, ODA represent 68% of the total official finance flows received by African countries between 2000 and 2013. Figure 3.3 shows the temporal evolution of natural resource exploitation in Africa since the beginning of the 21st century. The final sample includes the period of 2000-2014 which encompasses the mining boom (2011-2014) corresponding to the rise in international commodity prices, as well as the rush in large-scale land acquisitions (2007-2011) (Lay et al., 2021). The global financial crisis of 2008 was associated with a drop in the opening of industrial mining sites but with an increase in the acquisitions of land. The increasing industrial fishing activity since 2012 also represents an improvement in the industrial fishing data. The full lines in figure 3.3 represent the natural resources activity over the raw data, and the dashed lines represent the activity restricted to the sample of countries with official development finance data that constitute the final sample.

Figure 3.4 shows the temporal evolution of finance flows commitments by the main donors between 2000 and 2013, over the whole continent. Chinese official flows have surged since 2005 to reach a peak in 2010 and Indian flows kept increasing (from 2007, the start of data availability), while the official flows from other DAC countries decreased or stagnated with the 2008 global financial crisis, suggesting the growing implication and influence of mostly China, but also India, in Africa.

Figures 3.5, C.3 and C.4 show the allocation of the exploitation of the three types of natural resources by each donor and recipient countries. Eight African countries[12] concentrate 540 land deals, i.e. 60 % percent of the LSLA. Nine countries[13] concentrated 650 mine openings between 2000 and 2014, which represented 75% of the total industrial mine opening in the sample of countries. Finally, seven countries[14] recorded 600,000 hours of fishing hours within their EEZ in three years, i.e. 60% of the industrial fishing activity.

Figure 3.6 shows the Lorenz curve of development finance flows across the sub-sample of countries with each type of natural resource extraction. The top 20 percent of countries gather about a quarter of the OOF and half of the ODA across all three natural resources samples. Considering this high concentration of financial flows and natural resources extraction activity, we now delve deeper into the shares across donor countries.

Table 3.2 shows the main donor countries to Africa between 2000 and 2013: China, the United States of America, France, Germany, the United Kingdom, Japan, and India, as well as their respective main recipient countries. The different structures of official flows across China, India, and the other five DAC countries are striking: 57 percent of Chinese flows and 61 percent of Indian flows are OOF, while more than 90 percent of DAC countries' flows are ODA. Over the whole period and across the whole continent, Chinese ODA and OOF summed up, were about twice the amount of American official flows (183 trillion constant 2011 USD and 95 trillion constant 2011 USD respectively).

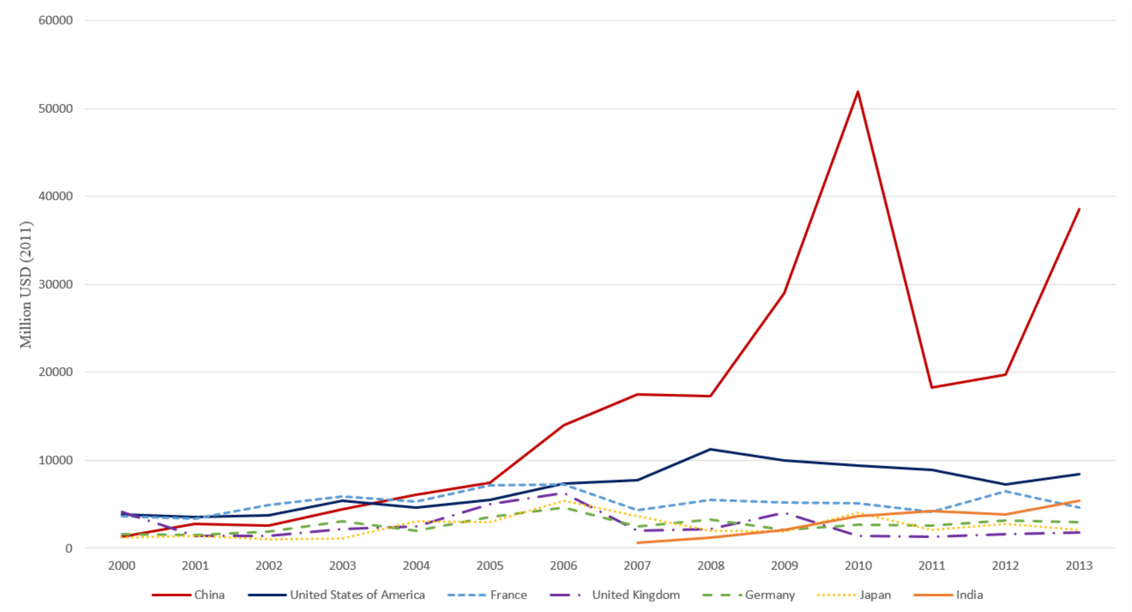
Table 3.3 represents the official flows received by the six largest recipient countries of Africa during 2000-2013. Nigeria received a total of 72 trillion USD 2011 over the period, way ahead of Angola (46 trillion constant 2011 USD), Ethiopia (39 trillion constant 2011 USD), the Democratic Republic of the Congo (36 trillion constant 2011 USD), Sudan (35 trillion constant 2011 USD) and Ghana (34 trillion constant 2011 USD). The importance of donors and their flow types varies greatly across recipient countries. In Nigeria, the United Kingdom is the first ODA donor (26 percent of received ODA) while China is the main OOF donor (90 percent). In Angola, the main ODA donors are the United States of America and Portugal (both 23 percent)

[12] Mozambique, Ethiopia, DRC, Tanzania, Ghana, Zambia, Sudan and Uganda.
[13] South Africa, DRC, Burkina Faso, Mali, Ghana, Tanzania, Namibia, Zambia, and Guinea.
[14] Tunisia, Mauritania, South Africa, Mozambique, Namibia, Madagascar, and Angola.

Figure 3.3: Temporal evolution of industrial exploitation of natural resources in Africa

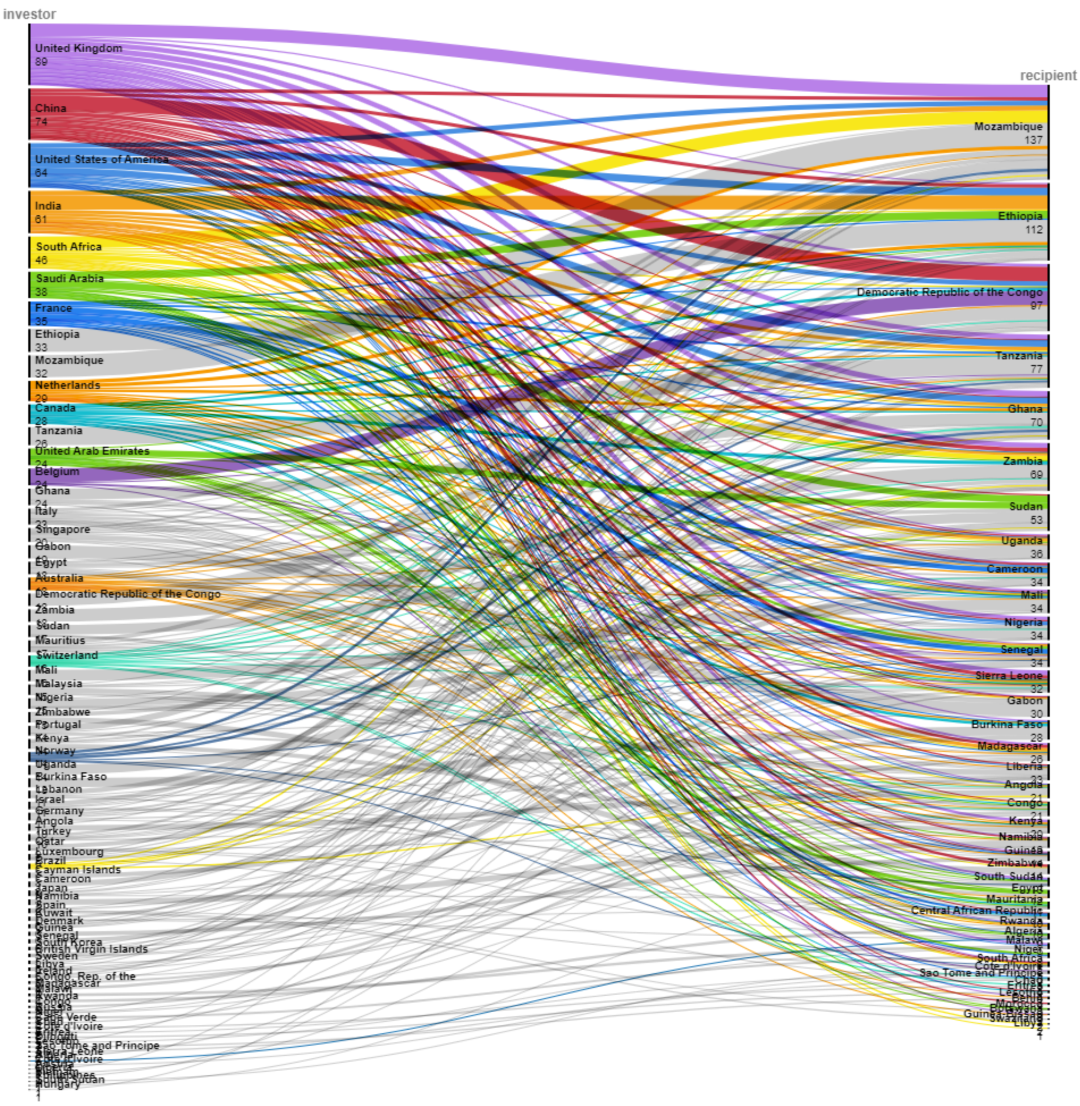
Notes: This graph represents the number of large-scale land acquisitions industrial mine openings, and industrial fishing hours with recipient countries' EEZ, across the whole sample (full lines) and the subsample of donor countries with Official Development Finance flows data (dashed lines).
Source: Own elaboration using SNL mining and Metals, the Land matrix, and Global Fishing Watch.

Figure 3.4: Temporal evolution of total official finance flows in Africa across main donors



Notes: This graph represents the total bilateral official finance flows of the main donor countries to African recipient countries between 2000 and 2013. Total financial flows include ODA, OOF, and Vague flows.
Source: Own elaboration using Core, China, and India Aiddata.

Figure 3.5: Bilateral large-scale land acquisitions in Africa (2000-2014)



Notes: This graph represents the total number of land deals concluded by investing companies registered in a country (left nodes) in a recipient country (right nodes) over the 2000-2014 period. If a land deal was concluded by companies registered in different countries than each country had a deal recorded.
Sources: Own elaboration using the Land Matrix.

Table 3.2: Largest donors' main recipients (2000-2013)

China				United States of America			
Main recipients	% ODA	% OOF	Total	Main recipients	% ODA	% OOF	Total
Angola	1	**99**	40,918	Ethiopia	100	0	8,559
Nigeria	1	**82**	39,921	Egypt	93	**7**	8,301
Ghana	**27**	8	19,299	Sudan	100	0	7,202
Sudan	15	68	17,574	Kenya	99	1	6,876
Ethiopia	**45**	52	16,482	Dem. Rep. Of the Congo	99	1	6,589
Total recipients	**22**	**57**	**231,080**	Total recipients	**96**	1	**96,885**

France				Germany			
Main recipients	% ODA	% OOF	Total	Main recipients	% ODA	% OOF	Total
Morocco	98	2	7,989	Nigeria	99	1	4,074
Cote d'Ivoire	94	**6**	7,042	Cameroon	100	0	3,362
Cameroon	99	1	4,718	Morocco	99	1	2,718
Nigeria	97	3	4,670	Egypt	99	1	2,585
Senegal	95	5	4,051	Dem. Rep. Of the Congo	100	0	2,356
Total recipients	**96**	4	72,895	Total recipients	**92**	8	37,280

United Kingdom				Japan			
Main recipients	% ODA	% OOF	Total	Main recipients	% ODA	% OOF	Total
Nigeria	97	3	8,009	Nigeria	100	0	3,467
Tanzania	94	6	3,438	Tanzania	100	0	3,185
Uganda	67	**33**	2,750	Egypt	100	0	2,770
Ethiopia	99	1	2,406	Kenya	100	0	2,769
Ghana	98	2	2,317	Morocco	100	0	2,291
Total recipients	**92**	8	37,181	Total recipients	**98**	2	34,947

India			
Main recipients	% ODA	% OOF	Total
Liberia	**83**	17	1,962
Mozambique	7	**93**	1,847
Ethiopia	26	74	1,825
Mali	10	**90**	1,123
Malawi	17	**83**	955
Total recipients	39	**61**	21,037

Note: This table describes the main country donors ranked by volume of total official finance flows and their respective main recipients over 2000-2013. ODA = Official Development Assistance. OOF = Other Official Flows. For each recipient, we indicate the share represented by ODA or OOF flows, compared to total flows which include vague flows. We also provide each donor's total flows towards all African countries over 2000-2013. All flows are expressed in millions constant 2011 USD.

Table 3.3: Largest recipients' main donors (2000-2013)

Nigeria

Main donors	ODA	Share rec. total ODA	OOF	Share rec. total OOF	flows	Share rec. total flows
China	5,079	0.17	31,973	**0.90**	57,883	**0.81**
United Kingdom	7,735	**0.26**	274	0.01	8,009	0.12
United States of America	4,919	0.17	25	0.00	4,944	0.08
France	4,527	0.15	143	0.00	4,670	0.07
Italy	1,597	0.05	2,570	0.07	4,167	0.06
All donors	29,497	1	35,590	1	71,663	1

Angola

Main donors	ODA	Share rec. total ODA	OOF	Share rec. total OOF	flows	Share rec. total flows
China	246	0.05	31,889	**0.99**	40,918	**0.88**
United States of America	1,203	**0.23**	6	0.00	1,209	0.03
Portugal	1,200	**0.23**	0	0.00	1,200	0.03
Spain	216	0.04	294	0.01	510	0.01
Norway	388	0.08	12	0.00	400	0.01
All donors	5,150	1	32,301	1	46,257	1

Ethiopia

Main donors	ODA	Share rec. total ODA	OOF	Share rec. total OOF	flows	Share rec. total flows
China	7,463	**0.26**	8,515	**0.85**	22,986	**0.59**
United States of America	8,559	**0.30**	0	0.00	8,559	0.22
United Kingdom	2,391	0.08	15	0.00	2,406	0.06
India	483	0.02	1,342	0.13	1,825	0.05
Canada	1,494	0.05	0	0.00	1,494	0.04
All donors	28,598	1	10,049	1	38,647	1

Democratic Republic of the Congo

Main donors	ODA	Share rec. total ODA	OOF	Share rec. total OOF	flows	Share rec. total flows
China	789	0.03	8,702	**0.94**	9,491	**0.26**
United States of America	6,506	**0.24**	83	0.01	6,589	0.18
Belgium	4,170	0.16	13	0.00	4,183	0.12
France	3,902	0.15	0	0.00	3,902	0.11
Germany	2,354	0.09	2	0.00	2,356	0.07
All donors	26,721	1	9,291	1	36,012	1

Sudan

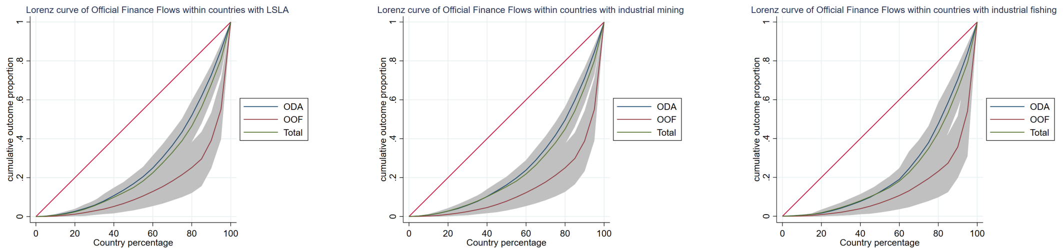
Main donors	ODA	Share rec. total ODA	OOF	Share rec. total OOF	flows	Share rec. total flows
China	3,658	0.19	12,054	**0.92**	18,893	**0.46**
United States of America	7,202	**0.38**	0	0.00	7,202	**0.23**
United Kingdom	1,536	0.08	17	0.00	1,553	0.05
Netherlands	1,374	0.07	0	0.00	1,374	0.04
Norway	1,315	0.07	1	0.00	1,316	0.04
All donors	18,870	1	13,068	1	35, 212	1

Ghana

Main donors	ODA	Share rec. total ODA	OOF	Share rec. total OOF	flows	Share rec. total flows
China	5,343	**0.28**	1,613	**0.66**	31,312	**0.92**
United States of America	2,335	0.12	48	0.02	2,392	0.07
United Kingdom	2,267	0.12	50	0.02	2,317	0.07
Japan	2,076	0.08	0	0	2,076	0.06
Netherlands	1,619	0.08	55	0.02	1,674	0.05
All donors	19,294	1	2,439	1	34,097	1

Note: This table describes the main African recipient countries ranked by their total volume of financial flows and their respective main donors, ranked by total flows over 2000-2013. ODA = Official Development Assistance. OOF = Other Official Flows. For each recipient (rec.), we indicate the levels and the shares represented by ODA or OOF flows, compared to the total flows they receive. We also provide each recipient's total flows from all donors (OECD, Gulf countries, India and China). All official finance flows are expressed in millions constant 2011 USD.

Figure 3.6: Lorenz curves of financial flows, across types of natural resources



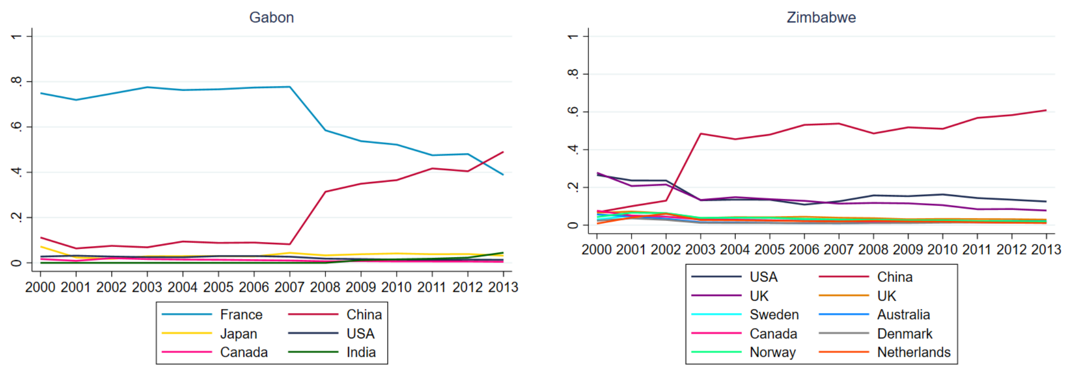
Note: These graphs display the Lorenz curve of the cumulated official finance flows from donor countries (until 2013) within the subset of countries with each type of natural resources. The top 20 percent of African countries is receiving about a quarter of the OOF and half of the ODA across all three natural resources' samples. Official finance flows are thus more concentrated among countries with industrial fishing activity (seven countries), and LSLA deals (eight countries) than mining activity (nine countries).
Source: Own elaboration using Aiddata.

while China gives 99 percent of the OOF. If China represents a non-negligible share of ODA donors among all these recipient countries, it is only in Ghana that it is the main provider (28 percent).

Figures 3.7, 3.8, 3.9 and 3.10 plot the shares of each donor's official finance flows cumulated until each year within the recipient country. Figure 3.7 shows the increasing share of Chinese official finance flows between 2000 and 2013: in Gabon, the share of China's cumulated flows has became greater than the one of France in 2013; while it took place as early as 2003 for China to outpace the United Kingdom and the United States of America in Zimbabwe. Figure 3.8 displays the slow but steading increasing shares of the USA in Kenya and Uganda. Figure 3.9 depicts an additional dimension of the heterogeneity of donors' share across recipients: the persistency of donors' shares and ranking across time in the case of France in Morocco and Côte d'Ivoire. Finally, Figure 3.10 shows that the shares of flows are rather competitive across many donors in Mozambique and Zambia. The share of the cumulative official finance flows that a donor has among a recipient country can well mirror the persistency of its influence, both diplomatic and economic. It seems to be more appropriate in the case of natural resources extraction to control for the longer-term influence of a foreign country rather than its punctual one, as it can take several years to conclude a land deal or to start operating an industrial mine.

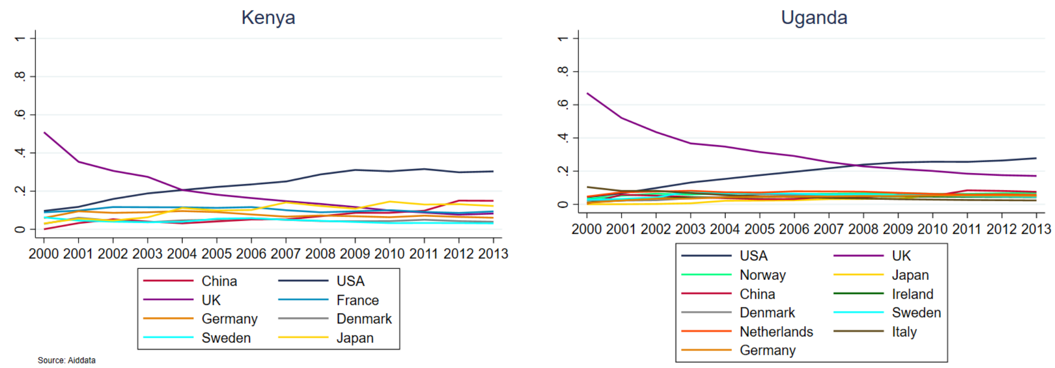
This section has provided a description of the main characteristics of DAC and non-DAC donors' financial flows and industrial extraction of African natural resources in the early 21st century and showed the concentration of these activity flows among a few protagonists. The next section details the results of the first hypothesis to test, i.e. whether official finance flows from donors increase the likelihood for a company from the donor country, to conclude land deals.

Figure 3.7: Change of shares of cumulative official finance flows: the rise of China



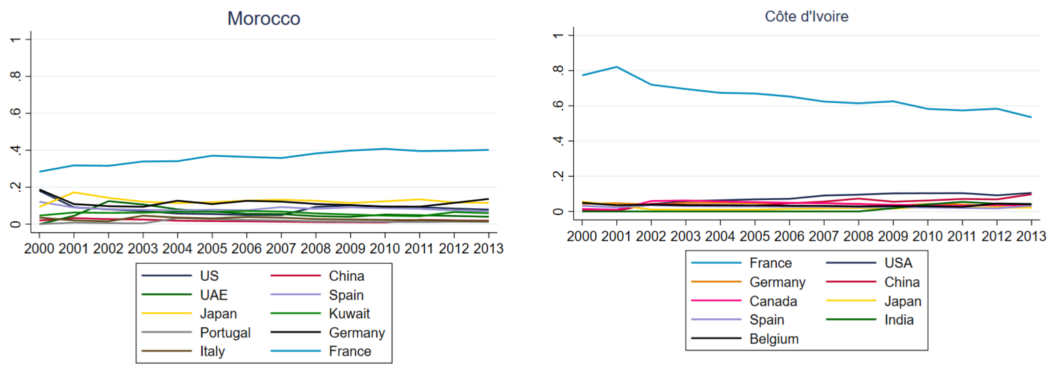
Notes: These graphs represent each recipient country's main donors and the share of their cumulative official finance flows up to each year within the recipient country.
Source: Own elaboration using Aiddata.

Figure 3.8: Change of shares of cumulative official finance flows: the rise of the USA



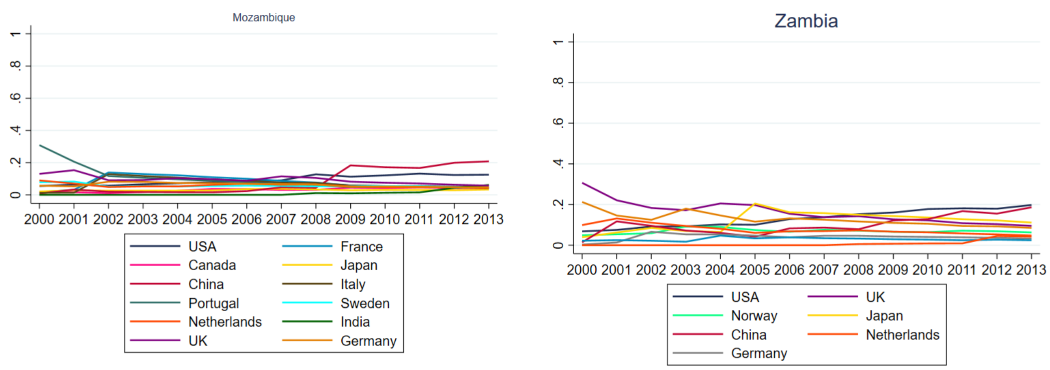
Notes: These graphs represent each recipient country's main donors and the share of their cumulative official finance flows up to each year within the recipient country.
Source: Own elaboration using Aiddata

Figure 3.9: Persistency of shares of cumulative official finance flows: the case of France



Notes: Thes graphs represent represent each recipient country's main donors and the share of their cumulative official finance flows up to each year.
Source: Own elaboration using Aiddata.

Figure 3.10: Competitive shares of cumulative official finance flows



Notes: Thes graphs represent represent each recipient country's main donors and the share of their cumulative official finance flows up to each year.
Source: Own elaboration using Aiddata.

3.4 Donors' influence on land acquisitions

This section describes the empirical strategy to test for the first hypothesis on the relevance of Raw materials diplomacy, i.e. whether official finance flows from donors increase the likelihood for a company from the donor country, to conclude land deals. Then, the section presents the results.

3.4.1 Empirical strategy

The main empirical strategy relies on a share model. It is well-suited in the context given the persistence and inertia of the influence of official finance flows over the years (Fuchs, Dreher, and Nunnenkamp, 2014). This class of models also deals with the large number of zero flows in both our main dependent and independent variables (see Table C.5 for the proportion of zeros for each variable in our final sample, and Figures C.6, C.7, C.8, C.9, C.10, and C.11) for the distribution of non-zero shares for each variable). Working on yearly flows instead of cumulated flows would emphasize punctual influence but would leave aside longer-term strategies. Moreover, this model also enables to capture the influence of the relative importance, rather than the absolute level of flows. For each type of natural resources, the following specification (equation 3.1) is run:

$$Share(CumActivity)_{d,r,t} = \alpha_0 + \alpha Share(CumOF)_{d,r,t-1} + \beta X_{d,r,t-1} + \delta_d + \delta_r + \gamma_t + \epsilon_v \tag{3.1}$$

with $CumActivity$ the total number of land deals concluded between a recipient country r, a donor country d until year t. The share is the ratio of each donor's cumulated activity in the recipient country until year t, on the recipient's total cumulated activity by all investors until year t, even the activity of investors for which we do not have official finance flows on, and domestic investors. The denominator enables us to capture the total activity present in the recipient country and not only those of the donors. $CumOF$ represents the cumulated bilateral flows from donor country d to recipient country r until year $t-1$, to capture the influence until the previous year and not the contemporary one, as the extraction of natural resources takes time to be agreed on. For each type of finance flow within country r, we calculate the share represented by this flow from each country d until year t among the received flows from the same type, from all donors. α will enable us to test the influence of official finance flows on the industrial extraction of natural resources activity: $\alpha > 0$ will represent a positive influence of official finance flows on the extraction activity. More precisely, we are interested in the share of cumulated flows since 2000 represented by each donor within a recipient country, which proxies the cumulated influence since this period. In an additional specification, we will also control for the levels and not only the shares of bilateral financial flows. This will enable us to distinguish the influence of donors among recipient countries receiving high volumes of development assistance (”aid darlings”) from countries receiving much less (”aid orphans”). Actual levels of cumulated extraction activity within the recipient country until year t will also be controlled for in this additional specification to differentiate countries with higher or lower natural resources activity. Both controls enable to separate the shares of influence and natural resources activity from the actual levels. It is the proportion of the influence played by each donor within a recipient country that is of interest in this study. The past colonial or dependency relationship and the distance between the most populous cities between donor and recipient countries are used as a proxy of more historical inertia and geographical characteristics. When data enables, we will also control for the original stock of natural resource activity that the donor has been conducting in the recipient country at the beginning of our period of interest in 2000. This enables us to capture the more recent activity and influence of official development finance, and make sure that it is not explained by past natural resources activity. The specifications also control for the GDP per capita of the recipient country during the year t as donors can prioritize recipient countries with higher needs in terms of poverty alleviation to deliver aid (more altruistic donors). We can also imagine that countries with lower GDP per capita have more incentives to extract their natural resources immediately and be more subject to bargain for an access to their natural resources with donors' official financial flows.

For each regression, I restrict the sample to recipient countries with at least one land deal over the period 2000-2014 and donor countries with at least one official finance flow to the recipient country, over the period 2000-2013. Therefore, I so far exclude countries without official finance flows, but that could be acquiring land. Their latter activity is taken into account in the shares of $CumActivity$ but we cannot make the distinction across these investing countries.

Table C.4 gives the summary statistics of all our outcome and control variables included in the estimation of the empirical strategy. Using shares of cumulative flows also enables dealing with the otherwise much higher proportion of zero yearly bilateral flows, as not all donors give official finance flows to each recipient country each year (see Table C.5 in the Appendix for the proportion of zeros for each variable in our final sample).

Section 3.7 will discuss the limits and threats of this empirical strategy.

3.4.2 Results

This section aims at shedding light on the importance of the role of official finance from donor countries to evolve in recipient countries' land market, and shows the positive association between the influence gained by donor countries on their capacity to buy land. Table 3.4. displays the results of equation 3.1 for large-scale land acquisitions.

The outcome variable is the share of each donor country d's cumulated number of land deals concluded with the recipient country r from 2000 until year t. The first column gives the result bare of any control and fixed effect for the sample of all donors and recipients which had at least one bilateral official finance flow and land deal (29 donors and 42 recipients, see Tables C.3 and C.2 for the exact list of recipient and donor countries). The correlation is positive and significant at the one percent level. Column (2) adds time-invariant donor country and recipient country-related explanatory factors of large-scale land acquisitions, and yearly variations that are common to all countries, whether they are correlated with land deals or official finance flows. In columns (3) to (6), I add, one by one, bilateral characteristics commonly used in gravity models and taken from the CEPII Gravity Database (Conte, Cotterlas, and Mayer, 2021). I include the log of the GDP per capita and the log of the population of the recipient country during the year t as independent variables to control for the need of recipients for aid or natural resources extraction, as well as the distance and the existence of a colonial or dependency relationship between each donor and recipient countries pair. Column (7) accounts for the total number of land deals cumulated by the recipient country (since 2000) to ensure that results are not driven by recipient countries that encountered particularly low or high transnational land deals and which market could be either at the beginning or already saturated. Column (8) controls for the yearly level of each financial flows' class (ODA, OOF, and vague) sent to the recipient country, to make sure that results are not driven by "aid darlings" or "aid orphans". These latter controls also enable us to take into account any exceptionally high flow that could happen during one year and that could explain the punctual bargaining effect it could play on the donor's natural resources extraction activity. Standard errors are clustered at the recipient-year level to enable correlation within each recipient country and year pair. At last, column (9), presents the results when using the Stata *acreg* command treating for arbitrary clustering with panel data (Colella et al., 2020), and clusters standard errors at the recipient and donor pair level.

This first analysis exhibits the positive correlation between bilateral official finance flows and land deals by donor countries in recipient countries while controlling for donor, recipient, and yearly fixed effect, taking into account the socio and economic characteristics of the recipient countries, and the historical links between donor and recipient countries. The latter control captures a strong effect (0.097 percent with 95% Confidence interval: [0.068; 0.126]) and cuts the coefficient of official finance by nearly half (column (5) to (6)). At a given share of financial flows, a former colonial power has on average 9.7 percentage point more share of land deals within a recipient country than countries that did not have this past link. This exhibits the persisting strength of the historical links that still weigh on the capacity of former colonial powers to buy pieces of land in their past colonies. The stability of the magnitude and significance of the main effect of donors' share (columns 6 to 8) when taking into account additional controls on financial flows and the total number of land deals within a recipient country, and seeing that they do not change radically the coefficient, reassure for the absence of flagrand omitted variable bias (Altonji, Elder, and Taber, 2005).

All in all, I find a positive and significant correlation between the share of cumulative official finance flows from donor countries within the recipient country the previous year, on the share of the cumulative number of land deals conducted by an investor from the donor country. An increase of 1 percent of a donor's share of cumulative official finance flows is associated with an increase of 0.067 p.p. (with 95% Confidence interval: [0.017; 0.118]) of the share of land deals in the recipient country. To give a sense of the magnitude of the correlation of all donors' flows, it would mean that, at the average share of cumulative total flows (3.42%), an increase of one standard deviation (7.82%), i.e going from 3.42% to 11.24%, would be associated with an increase of 0.52 p.p. of the donor's share of land deals. If the relation is assumed linear, it would mean that the average share of the donor's cumulative land deals within a recipient country during the following year would go from 2.79% to 3.28%.

Table 3.4: Hypothesis 1: Influence of Official Finance on land deals

Outcome	Share (Donor's cumulated land deals)$_t$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sh(Donor Cum.OF)$_{t-1}$	0.220***	0.155***	0.160***	0.160***	0.158***	0.0677***	0.0677***	0.0673***	0.0673***
	[0.0122]	[0.0220]	[0.0228]	[0.0228]	[0.0228]	[0.0257]	[0.0257]	[0.0257]	[0.0239]
Log(GDPcap)$_{rt}$			0.00316	0.00322	0.00329	0.00334	0.00326	0.00130	0.00130
			[0.00473]	[0.00480]	[0.00480]	[0.00483]	[0.00480]	[0.00505]	[0.0111]
Log(Pop)$_{rt}$				0.0196	0.0193	0.0214	0.0219	0.0219	0.0219
				[0.0168]	[0.0167]	[0.0171]	[0.0173]	[0.0166]	[0.0367]
Log(Dist)					-0.0201**	-0.0186**	-0.0186**	-0.0186**	-0.0186**
					[0.00796]	[0.00811]	[0.00811]	[0.00811]	[0.00786]
Col. or dep. ever						0.0967***	0.0967***	0.0966***	0.0966***
						[0.0148]	[0.0148]	[0.0148]	[0.0134]
Cum. deals$_{rt}$							-0.0000157	0.0000194	0.0000194
							[0.0000408]	[0.0000456]	[0.000103]
Log(Cum. ODA)$_{r,t-1}$								0.00332	0.00332
								[0.00223]	[0.00309]
Log(Cum. OOF)$_{r,t-1}$								0.000296	0.000296
								[0.000520]	[0.000943]
Log(Cum. Vague)$_{r,t-1}$								-0.000432	-0.000432
								[0.000466]	[0.000764]
Donor FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Recipient FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.0265	0.0922	0.0954	0.0954	0.0976	0.113	0.113	0.113	0.0292
Outcome mean	0.0280	0.0280	0.0279	0.0279	0.0279	0.0279	0.0279	0.0279	0.0284
N	11,915	11,915	11,547	11,547	11,547	11,547	11,547	11,543	11,543

Notes: This table presents the results from regression 3.1 for land deals. The main coefficient of interest is α_1, associated to Sh(Donor Cum.OF). All cumulated total official finance flows (Cum. OF) and large-scale land acquisitions (LSLA) deals are at the recipient-year level. The cumulative land deals start in 2000 and stop in 2014. Standard errors are clustered at the recipient-year level from columns (1) to (8), and at the donor-recipient level for column (9). $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

Heterogeneity across DAC and non-DAC donors. I run the preferred specification (column 8 of Table 3.5 with standard errors clustered at the recipient-year level, to enable more flexibility of donors' influence within each recipient) on different samples of donor countries to describe the different effects across groups (Table 3.5 and Figure 3.11 for a visual comparison). I find that this influence is higher among DAC countries (0.085 with 95% CI [0.013; 0.157]) and not significant for non-DAC countries. The correlation is especially high among former colonial powers[15] (0.139 percent with 95% CI [0.030;0.247]) and this is already when controlling for the existence of past colonial or dependency relationships. This piece of evidence is in line with the previous findings of Table 3.4 and highlights the special role that still pertains to these former colonial countries, and how they are still actively engaged in both sending financial flows and buying land. The correlation between financial flows from Japan and South Korea and their land acquisitions within recipient countries is also positive and significant (0.121 percent with 95% CI [0.049; 0.193]). On the contrary, the effect among Nordic countries (Denmark, Norway, and Sweden) is negative (-0.044 percent with 95% CI [-0.082;-0.006]). Other DAC donor groups between Australia-Canada-USA and Switzerland-Luxembourg do not have a significant correlation. All these results highlight the heterogeneity of official finance flows strategies among DAC countries. The share of official finance flows from non-DAC countries (Brazil, China, India, South Africa, Kuwait, Saudi Arabia, and the United Arab Emirates) is not significant either, which could at first be surprising given that these groups encompass many financial flows and land deals. The next section will look at countries at the individual level and not in groups.

This section has shown the positive and significant correlation between donor countries' financial flows and the share of land deals they can achieve in a recipient country. It has also exhibited the difference in this relationship across DAC and non-DAC donors.

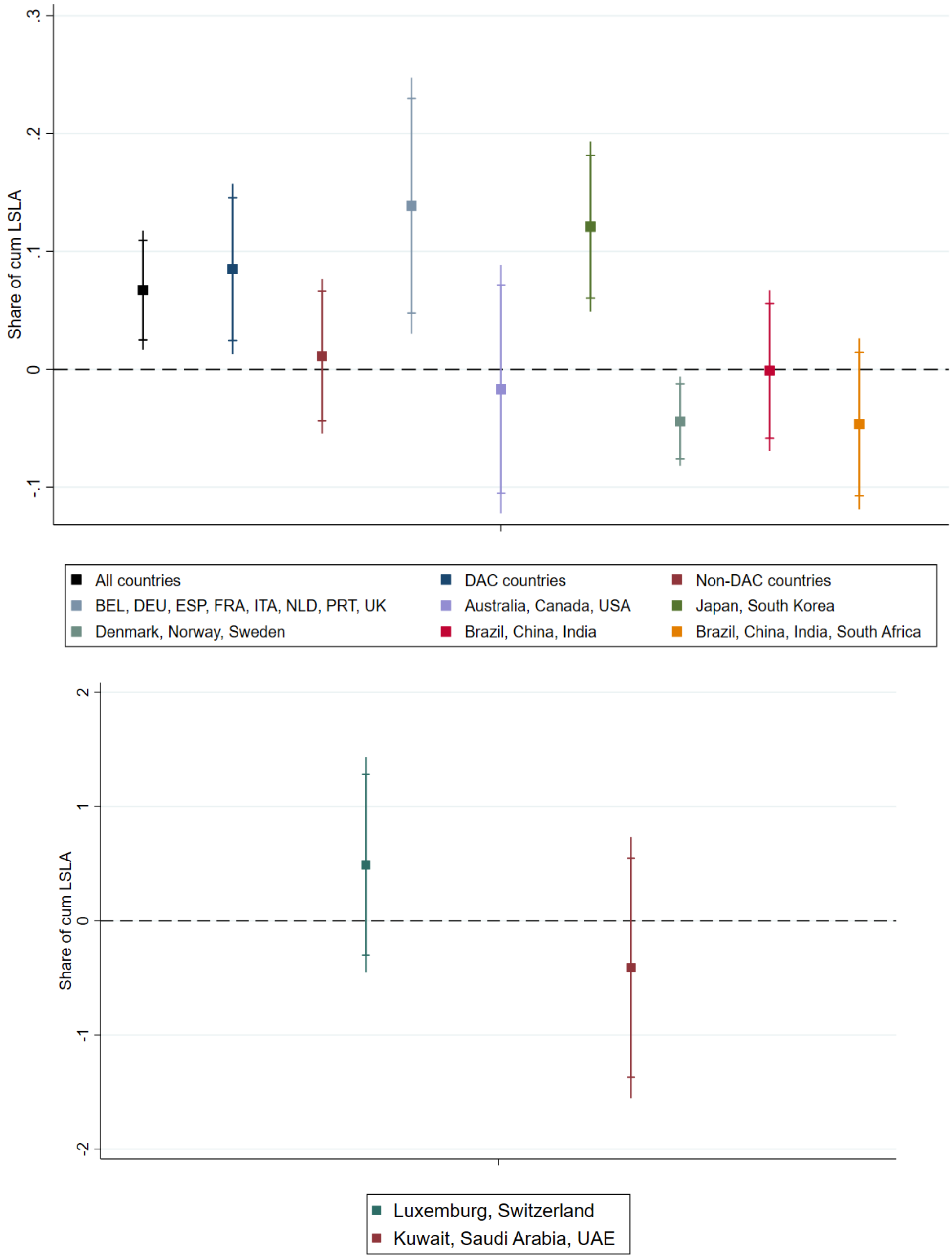
[15] Belgium, France, Germany, Italy, Netherlands, Portugal, Spain, and the United Kingdom.

Table 3.5: Hypothesis 1: Influence of Official Finance on land deals, across group of donor countries

Outcome	Share (Donor's cumulated land deals)$_t$										
				DAC					Non-DAC		
Group of countries	All	DAC	Non-DAC	BEL, DEU ESP, FRA ITA, NLD PRT, UK	Australia Canada USA	Japan S. Korea	Denmark Norway Sweden	Switz. Lux.	Brazil China India	Brazil China India S. Africa	Kuwait Saudi Ar. UAE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Sh(Donor Cum. OF)$_{t-1}$	0.0673***	0.0851**	0.0113	0.139**	-0.0167	0.121***	-0.0440**	0.489	-0.00110	-0.0462	-0.410
	[0.0257]	[0.0368]	[0.0333]	[0.0553]	[0.0536]	[0.0367]	[0.0192]	[0.480]	[0.0346]	[0.0369]	[0.582]
Cum. deals$_{rt}$	0.0000194	0.0000701	-0.000159	-0.000167	0.000917***	-0.00000317	0.00000182	-0.0000491	0.000552***	0.000450***	-0.00105***
	[0.0000456]	[0.0000630]	[0.000162]	[0.000138]	[0.000271]	[0.0000603]	[0.0000574]	[0.000144]	[0.000196]	[0.000162]	[0.000287]
Log(Cum. ODA)$_{r,t-1}$	0.00332	0.00330	0.00327	-0.00119	0.0337**	-0.00195	-0.00347**	0.00334	0.00733	0.00567	-0.00578
	[0.00223]	[0.00279]	[0.00590]	[0.00416]	[0.0147]	[0.00207]	[0.00152]	[0.00512]	[0.00867]	[0.00740]	[0.00881]
Log(Cum. OOF)$_{r,t-1}$	0.000296	0.000660	-0.000584	0.00232**	-0.00139	0.000653	0.000421	-0.00190	-0.000496	-0.00115	-0.000399
	[0.000520]	[0.000630]	[0.00116]	[0.00115]	[0.00313]	[0.000499]	[0.000506]	[0.00272]	[0.00214]	[0.00172]	[0.00134]
Log(Cum. Vague)$_{r,t-1}$	-0.000432	-0.000876	0.00106	-0.000429	-0.00594*	0.000616	0.000308	0.00115	-0.000946	-0.0000396	0.00241*
	[0.000466]	[0.000558]	[0.00110]	[0.000937]	[0.00336]	[0.000462]	[0.000337]	[0.00103]	[0.00153]	[0.00135]	[0.00145]
Constant	-0.0504	0.0373	0.277	0.576	0.322	-1.552	0.494***	0.849	-0.169	-0.0820	-5.823***
	[0.170]	[0.157]	[0.476]	[0.372]	[0.883]	[1.614]	[0.183]	[1.131]	[0.935]	[0.718]	[1.621]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Donor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Recipient FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.113	0.162	0.136	0.240	0.245	0.293	0.286	0.624	0.257	0.230	0.360
Outcome mean	0.0279	0.0238	0.0408	0.0394	0.0507	0.00450	0.00548	0.0157	0.0417	0.0466	0.0331
N	11,543	8,755	2,788	3,184	1,189	794	1,206	794	1,194	1,597	1,191

Notes: This table presents the results from regression 3.1 for land deals. The main coefficient of interest is α_1, associated to Sh(Donor Cum.OF). All cumulated total official finance flows (Cum. OF) and large-scale land acquisitions (LSLA) deals are at the recipient-year level. The cumulative land deals start in 2000 and stop in 2014. Controls include the log distance between recipient and donor countries, the existence of a colonial or dependency relationship, the GDP per capita and the log of the population at the recipient level during year t. Standard errors are clustered at the recipient-year level, $^{*}p < 0.1$,** $p < 0.05$,*** $p < 0.01$.

Figure 3.11: Hypothesis 1: Influence of official finance flows and large-scale land acquisitions by group of donor countries



Notes: These graphs display the coefficients α_1 in equation 3.1, i.e. the correlation between each donor's share of cumulated official finance flows and their share of the cumulated number of land deals within a recipient country. Each coefficient comes from a separate regression ran across each subset of donor countries.

3.5 Complementarity and substitution between DAC and non-DAC donors

This section compares the complement/substitute effects of different flow types across donors. The aim is to compare the different tools and strategies adopted by each country, which the main goal may not be to evict on purpose, but that are associated with a complementary or substitution effect towards the extractive activities engaged by other donors. These results bring suggestive evidence of the effects but do not claim causality or purposiveness of the flows. The first part consists in comparing the interaction effect of a specific competing donor across its different flow classes (Total, ODA, and OOF flows). The second part describes the heterogeneous effects across DAC and non-DAC countries to proxy the presence or absence of coordination or cooperation among donors or groups of donors.

3.5.1 Empirical strategy

The second hypothesis to test is whether a competing donor increases or reduces the influence of other donors' financial flows on their capacity to conduct natural resources extraction activity. I run the following specification (equation 3.2) and introduce a distinction between flow classes.

$$\begin{aligned} Share(CumActivity)_{d,r,t} =& \alpha_1 Share(CumOF)_{d,r,t-1} \\ &+ \alpha_2 Share(CumCompetFlowType)_{r,t-1} \\ &+ \alpha_3 Share(CumOF)_{d,r,t-1} \times Share(CumCompetFlowType)_{r,t-1} \\ &+ \beta X_{d,r,t-1} + \alpha_0 + \delta_d + \delta_r + \gamma_t + \epsilon_v \end{aligned} \tag{3.2}$$

For each of the main donor countries that is also a main protagonist of the natural resources sector, we calculate $Share(CumCompetFlowType)$, the share represented by one of its specific financial flow (Total, ODA or OOF) in a recipient country on the total type of same flows it has received. We look at the effect of the share of this specific competing flow, on other donors' total flows. We expect α_1 to be positive for land deals as in the previous regression. A negative interaction effect ($\alpha_3 < 0$) suggests that flows from a specific competing donor diminish the influence of donors' financial flows to conduct an extractive industry in a recipient country, and will further be called a substitute effect. A positive interaction effect ($\alpha_3 > 0$)

conveys the idea that flows from a specific competing donor have positive spill-over effects on other donors' to extract natural resources in a recipient country. This marks a complemementary effect. This positive interaction effect could capture the contribution to the development of public infrastructures or facilities (such as roads, electricity grids or water facilities, etc.) or the participation in a business enabling environment, prone to land acquisitions for other donors.

3.5.2 Results

Tables 3.6 and 3.7 display the results of the analysis (equation 3.2) for the main competing donor countries investing and acquiring land in Africa. All specifications included the same controls and fixed effects as column 8 of Table 3.5. Table 3.6 details the effects of Chinese and Indian financial flows on other donors, and Table 3.7 lays out the effects of financial flows from the USA, the UK, and France on other donors. For each of these competing countries, I run a regression with its total flows (columns 1 to 3), its ODA (columns 4 to 6), and OOF flows (columns 7 to 9) separately. For each of these flow types, I run the analysis on the sample of all the other donors while excluding the "competing" country (columns 1, 4, and 7), the sample of all the other DAC (columns 2, 5, and 8) and non-DAC donors donors[16] (columns 3, 6 and 9).

Table 3.6 displays evidence of the existence of an substitution effect of all Chinese flows and Indian ODA. The results from column (2) show that in countries not receiving any Chinese flow, the increase of 1 percent of the share of an average DAC donor's official finance flows, is associated with an increase of 0.11 p.p. of their land acquisitions' share. In comparison, when China is sending official flows, this influence is diminished by 0.29 p.p. Overall, for countries receiving Chinese flows, the influence of an average DAC donor would be (0.11-0.29=) -0.18 p.p. This eviction effect is even higher when looking solely at Chinese ODA: the increase of 1 percent of the share of Chinese ODA, is associated with a decrease of 0.56 p.p of DAC donors' ODA influence on land acquisitions. On the contrary, Chinese flows complement the financial flows from other non-DAC donors. Similarly, columns 4 to 6 show the strong eviction effect of Indian ODA on all other donors, both DAC and non-DAC countries. This result is in line with the competition of development flows from India with Chinese projects in developing countries (Asmus, Eichenauer, et al., 2021).

[16]excluding the competing country as well.

Table 3.7 shows that the OOF flows from the USA, only complement OOF from other DAC countries. Overall, flows from the United Kingdom have a complementary effect on DAC flows only, especially for ODA. On the contrary, British OOF have a substitute effect on Non-DAC OOF flows. French financial flows do not play a significant effect on other countries. Figures 3.12 and 3.13 summarize these interaction coefficients and enable us to compare their magnitude. Figure 3.12 lays out the effect of the main competing countries on all the other donors, and Figure 3.13 makes the distinction across DAC and non-DAC countries.

This section provided suggestive evidence of the heterogeneity of the strategies adopted by the main donor countries regarding their transnational land deals in Africa and compared their effects on other donors. The results hint towards the existence of a complementary effect of the USA and the UK with other DAC donors, while China and India seem to substitute for DAC countries' influence. China's ODA and OOF flows have the most important substitute effect, while it is the case for Indian ODA solely. After distinguishing the effects across other donors, the next section describes the heterogeneity analysis across recipient countries.

Table 3.6: Hypothesis 2: Complementary and substitution effects of the main competing non-DAC donors

Outcome	Share (Donor's cumulated land deals)$_t$								
Competing Flow type	Total			ODA			OOF		
Sample of other donors	All	DAC	Non-DAC	All	DAC	Non-DAC	All	DAC	Non-DAC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Competing country									
China									
Sh(DonorCum.OF)$_{t-1}\times$Sh(CompetFlowType)$_{t-1}$	-0.216	-0.291*	3.061*	-0.428*	-0.564**	3.245**	-0.135*	-0.179**	0.596
	[0.159]	[0.159]	[1.804]	[0.241]	[0.244]	[1.638]	[0.0702]	[0.0723]	[0.605]
Sh(DonorCum.OF)$_{t-1}$	0.125***	0.109***	-0.283	0.130***	0.116***	-0.0321	0.133***	0.118***	-0.279
	[0.0389]	[0.0400]	[0.296]	[0.0388]	[0.0404]	[0.174]	[0.0394]	[0.0402]	[0.290]
Sh(CompetFlowType)$_{t-1}$	0.00477	0.00128	0.0185	0.0251***	0.00214	0.0970**	0.00424	0.00890**	-0.00689
	[0.00538]	[0.00731]	[0.0177]	[0.00928]	[0.0115]	[0.0410]	[0.00286]	[0.00356]	[0.00681]
Outcome mean	0.0261	0.0238	0.0346	0.0261	0.0238	0.0346	0.0261	0.0238	0.0346
N	11,151	8,758	2,393	11,151	8,758	2,393	11,151	8,758	2,393
India									
Sh(DonorCum.OF)$_{t-1}\times$Sh(CompetFlowType)$_{t-1}$	-0.224	-0.184	-0.227	-2.026***	-2.066***	-2.889***	0.153*	0.148	0.201
	[0.399]	[0.455]	[0.945]	[0.501]	[0.567]	[1.079]	[0.0831]	[0.0949]	[0.259]
Sh(DonorCum.OF)$_{t-1}$	0.0746***	0.0879**	0.00300	0.0933***	0.106***	0.0361	0.0660**	0.0777**	-0.00201
	[0.0277]	[0.0385]	[0.0358]	[0.0285]	[0.0387]	[0.0370]	[0.0266]	[0.0374]	[0.0364]
Sh(CompetFlowType)$_{t-1}$	-0.0459	-0.0220	-0.166*	-0.00169	0.0417	-0.118	-0.00580	-0.00517	-0.0142
	[0.0341]	[0.0510]	[0.0881]	[0.0540]	[0.0477]	[0.150]	[0.00446]	[0.00661]	[0.00956]
Outcome mean	0.0274	0.0238	0.0407	0.0274	0.0238	0.0407	0.0274	0.0238	0.0407
N	11,149	8,758	2,391	11,149	8,758	2,391	11,149	8,758	2,391

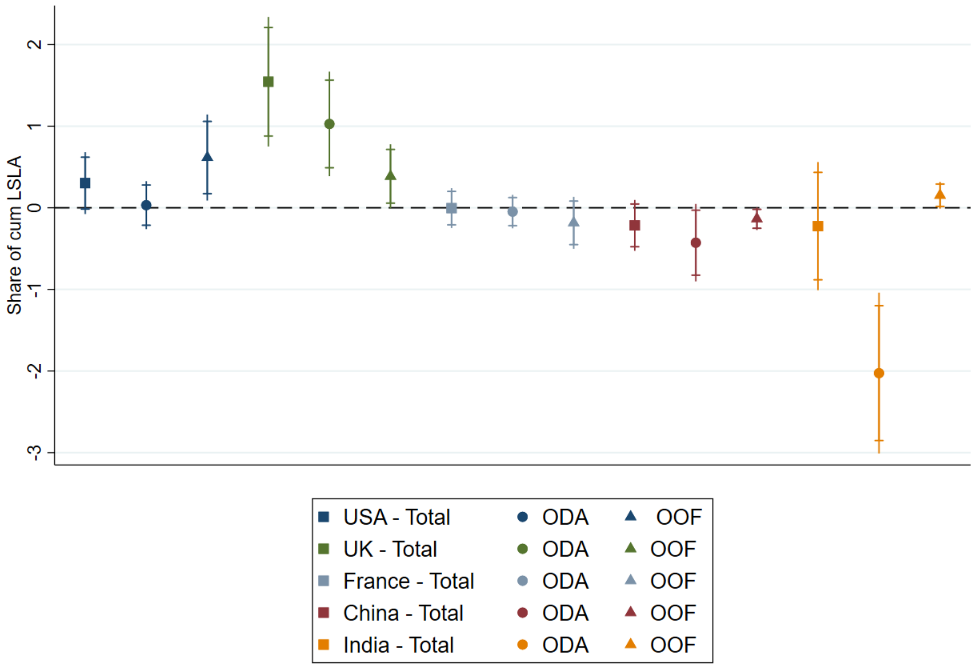
Notes: This table presents the results from regression 3.2 to test Hypothesis 2 for land deals. The main coefficient of interest is α_3 associated with $Sh(DonorCum.OF)_{t-1}\times$Sh(CompetFlowType)$_{t-1}$. $\alpha_3 < 0$ notes a substitution effect and $\alpha_3 > 0$ marks a complementary effect. All cumulated total official finance flows (Cum. OF) and large-scale land acquisitions (LSLA) deals are at the recipient-year level. The cumulative land deals start in 2000 and stop in 2014. Controls include the log distance between recipient and donor countries, the existence of a colonial or dependency relationship, the GDP per capita and the log of the population at the recipient level during year t. Standard errors are clustered at the recipient-year level, $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

Table 3.7: Hypothesis 2: Complementary and substitution effects of the main competing DAC donors

Outcome	Share (Donor's cumulated land deals)$_t$								
Competing Flow type		Total			ODA			OOF	
Sample of other donors	All	DAC	Non-DAC	All	DAC	Non-DAC	All	DAC	Non-DAC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Competing country									
United States of America									
Sh(DonorCum.OF)$_{t-1}$×Sh(CompetFlowType)$_{t-1}$	0.302	0.231	0.343	0.0326	0.441*	-0.210	0.616**	0.708**	-0.703
	[0.193]	[0.266]	[0.255]	[0.149]	[0.234]	[0.162]	[0.268]	[0.293]	[0.670]
Sh(DonorCum.OF)$_{t-1}$	0.0545*	0.0936	-0.0178	0.0774**	0.0720	0.0483	0.0629**	0.0732	0.0120
	[0.0325]	[0.0579]	[0.0304]	[0.0361]	[0.0546]	[0.0391]	[0.0284]	[0.0459]	[0.0335]
Sh(CompetFlowType)$_{t-1}$	-0.0241**	-0.0181	-0.0407	-0.0324***	-0.0220**	-0.0794**	-0.00973	-0.0213**	0.0275**
	[0.0104]	[0.0119]	[0.0368]	[0.0110]	[0.0111]	[0.0380]	[0.00622]	[0.00841]	[0.0125]
Outcome mean	0.0268	0.0222	0.0408	0.0268	0.0222	0.0408	0.0268	0.0222	0.0408
N	11,150	8,361	2,789	11,150	8,361	2,789	11,150	8,361	2,789
United Kingdom									
Sh(D.Cum.OF)$_{t-1}$×Sh(CompetFlowType)$_{t-1}$	1.545***	1.662***	0.257	1.028***	1.468***	0.187	0.386*	0.318	-1.101***
	[0.404]	[0.503]	[0.484]	[0.326]	[0.492]	[0.278]	[0.200]	[0.218]	[0.424]
Sh(DonorCum.OF)$_{t-1}$	0.0215	0.0428	0.00365	0.0281	0.0500	0.00110	0.0677***	0.100***	0.00516
	[0.0246]	[0.0349]	[0.0312]	[0.0251]	[0.0337]	[0.0323]	[0.0223]	[0.0305]	[0.0339]
Sh(CompetFlowType)$_{t-1}$	0.0142	0.0358**	-0.0658	0.00612	0.0340*	-0.100	-0.000728	0.00411	-0.000471
	[0.0135]	[0.0144]	[0.0464]	[0.0217]	[0.0204]	[0.0749]	[0.00532]	[0.00445]	[0.0210]
Outcome mean	0.0244	0.0189	0.0408	0.0244	0.0189	0.0408	0.0244	0.0189	0.0408
N	11,148	8,359	2,789	11,148	8,359	2,789	11,148	8,359	2,789
France									
Sh(D.Cum.OF)$_{t-1}$×Sh(CompetFlowType)$_{t-1}$	-0.00683	-0.242	0.307*	-0.0492	-0.177	0.115	-0.214	-0.216	-0.130
	[0.125]	[0.174]	[0.171]	[0.105]	[0.151]	[0.139]	[0.167]	[0.217]	[0.271]
Sh(DonorCum.OF)$_{t-1}$	0.0447	0.0693	-0.0155	0.0503	0.0646	-0.00413	0.0507*	0.0496	0.0164
	[0.0327]	[0.0512]	[0.0403]	[0.0339]	[0.0508]	[0.0423]	[0.0281]	[0.0430]	[0.0364]
Sh(CompetFlowType)$_{t-1}$	0.0107	-0.0111	0.0804***	0.0139	-0.0145	0.0972***	0.00998	0.00496	0.0200
	[0.0113]	[0.0133]	[0.0306]	[0.0109]	[0.0150]	[0.0303]	[0.00719]	[0.00881]	[0.0189]
Outcome mean	0.0266	0.0219	0.0408	0.0266	0.0219	0.0408	0.0266	0.0219	0.0408
N	11,148	8,359	2,789	11,148	8,359	2,789	11,148	8,359	2,789

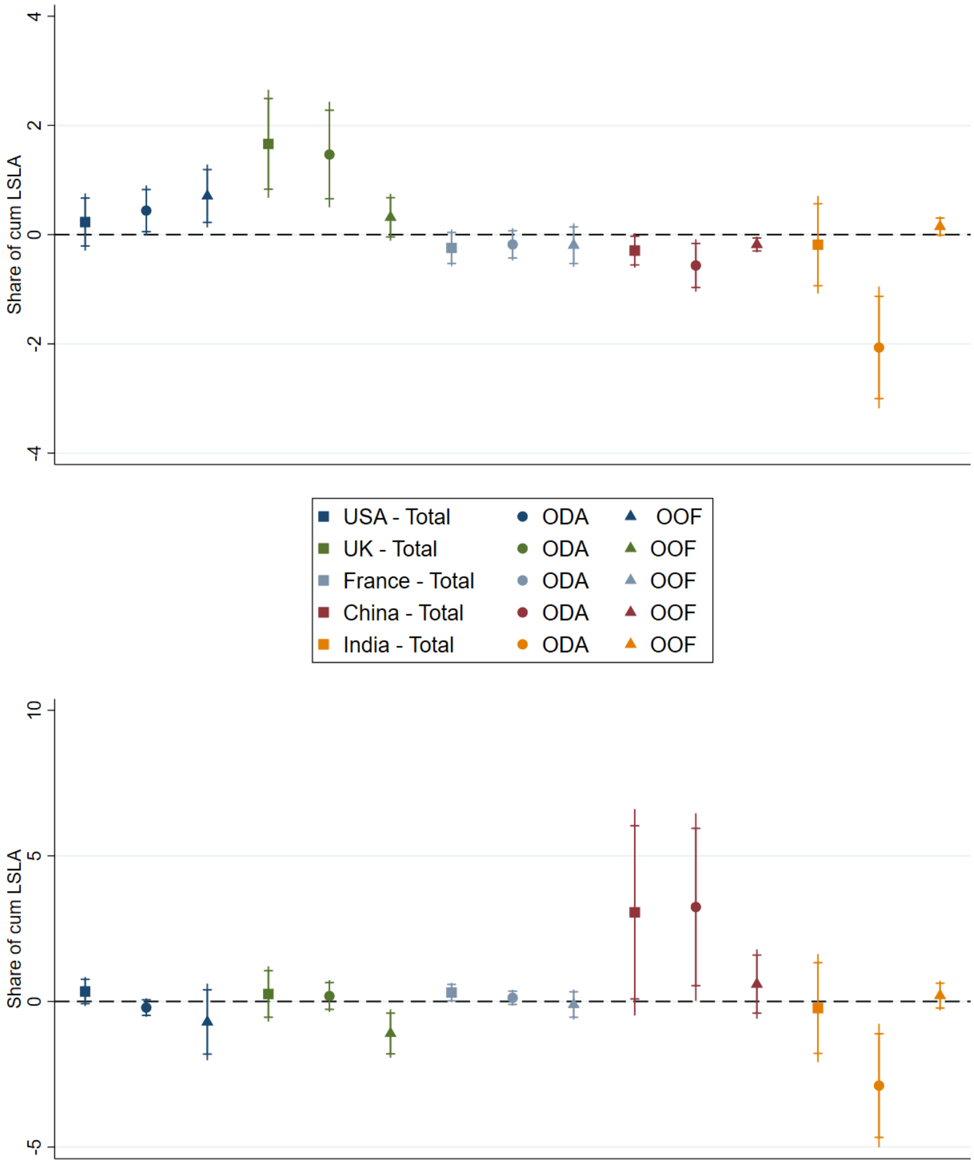
Notes: This table presents the results from regression 3.2 to test Hypothesis 2 for land deals. The main coefficient of interest is α_3 associated with $Sh(DonorCum.OF)_{t-1}$×Sh(CompetFlowType)$_{t-1}$. $\alpha_3 < 0$ notes a substitution effect and $\alpha_3 > 0$ marks a complementary effect. All cumulated total official finance flows (Cum. OF) and large-scale land acquisitions (LSLA) deals are at the recipient-year level. The cumulative land deals start in 2000 and stop in 2014. Controls include the log distance between recipient and donor countries, the existence of a colonial or dependency relationship, the GDP per capita and the log of the population at the recipient level during year t. Standard errors are clustered at the recipient-year level, $^{*}p < 0.1$,** $p < 0.05$,*** $p < 0.01$.

Figure 3.12: Hypothesis 2: Complementarity and substitution effects of each competing donor on all other donor countries' large-scale land acquisitions.



Notes: This graph displays the coefficients α_3 from equation 3.2 of the interaction between the share of each competing donor's official finance flow type (total, ODA or OOF) and the share of all other donors. $\alpha_3 > 0$ denotes a complementary effect and $\alpha_3 < 0$ a substitution effect. Each coefficient comes from a separate regression.

Figure 3.13: Hypothesis 2: Complementarity and substitution effects on large-scale land acquisitions of each competing donor on DAC (upper) and non-DAC donor countries (lower)



Notes: These graphs display the coefficients α_3 from equation 3.2 of the interaction between the share of each competing donor's official finance flow type (total, ODA or OOF) and the share of all other donors. $\alpha_3 > 0$ denotes a complementary effect and $\alpha_3 < 0$ a substitution effect. Each coefficient comes from a separate regression.

3.6 Heterogeneity analysis

This section aims at shedding light on how the complement/substitute effects differ across the institutional environment within recipient countries, and cannot claim to be a proof of mechanism. It brings suggestive evidence of the different strategies adopted by donors according to the level of regulation of property rights within recipient countries.

3.6.1 Heterogeneity across recipient countries' property right index

I choose the property rights index from the Mo Ibrahim Foundation because of its availability among all African countries, and more as the best proxy than the ideal index. Indeed, it is a composite index released at the country-year level built by the Foundation from secondary sources,[17] and only starts in 2010. This might create endogeneity issues as the index could be capturing the increase of land deals conducted by foreign investors. Ideally, an index that describes the situation before 2000 would better enable to split the samples[18] I calculate a dummy variable equal to one if a country was below the continental median in 2010 (out of 54 countries). Table C.3 in the Appendix lists all the countries below the median property right index.

The rationale behind this heterogeneity analysis is that donor countries may target different African countries where access to land is easier (low index) or more difficult (high index) and that they may use different official finance tools. Table 3.8 provides the results of the main competing non-DAC donors (China and India) when running equation 3.2 across the two samples of recipient countries, and Table 3.9 displays the results for the main competing DAC donors (the USA and the UK). Figures C.15, C.16 and C.17 ensure that the following results are not driven by a drastically different allocation of each donor country across recipients property right index and that there is no flagrant "specialization" of a donor country towards a particularly low or high index recipient country only.

Results in Table 3.8 show that the main effect of official flows' influence (α_1) is positive and significant for China only in recipient countries with low property

[17] The Foundation used information retrieved from Bertelsmann Stiftung (Bertelsmann Transformation Index) and the World Justice Project (Rule of Law Index).

[18] The CPIA index from the World bank covers a larger time window, yet is available only among 33 out of the 54 African countries.

rights index and that it is positive and significant for India in all recipient countries. Results suggest that the substitution effect (α_3) of Chinese total financial flows is only significant in African countries with lower property rights and that it is Chinese ODA that drives this substitution. In countries with higher property rights, it is Chinese OOF that plays a substitution effect. This hints towards a different effect of Chinese flows: ODA seems to be more efficient to evict other donors' land acquisitions in countries where property rights are less respected, while there seems to be a possibility to use more commercially oriented loans in settings where access to land is more difficult to gain. One possible interpretation could be that recipient countries with lower property rights could be more tempted to accept Chinese ODA in exchange for land, at the detriment of concluding a land deal with other donors, than countries with higher property rights. Distinctly, Indian ODA has a substitute effect on other donors in recipient countries with both high and low property rights indexes and seems to be more efficient among countries with a low index. Other Indian flows do not play such a role, and on the contrary, Indian OOF seems to complement other donors' activity in high property right index countries. One possible interpretation could be that India mainly uses its ODA to evict other donors but may use loans in better-managed countries to provide more public goods infrastructures that benefit other donors.

On the contrary, results in Table 3.9 show that both American and British official financial flows have positive and significant influence (α_1) on their land deals only in recipient countries with high property rights index. American flows, and especially OOF, complement ($\alpha_3 > 0$) other donors' land-related activity in recipient countries with low property rights index, while British flows complement other donors' activity regardless of their level of property regulation. I find no heterogeneity across recipients for French flows (see Table C.6 in Appendix).

This section has presented a simple heterogeneity analysis and has provided some evidence that the complement/substitute effects of non-DAC countries differ across the recipient country's level of property rights. Yet, further work will need to elaborate more on the proxy for institutions that regulate the use and management of land deals and natural resources in general. The next section studies the influence and eviction effects of DAC and non-DAC donors across two other types of natural resources: fisheries and mines.

Table 3.8: Hypothesis 2: Complementary and substitution effects of Chinese and Indian financial flows across recipient countries' property rights level

Outcome	Share (Donor's cumulated land deals)$_t$											
Competing donor country	China						India					
Flow type	Total		ODA		OOF		Total		ODA		OOF	
Recipient's property rights index	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Sh(DonorCum.OF)$_{t-1}$×Sh(CompetFlowType)$_{t-1}$	-0.591***	-0.181	-0.831***	-0.522	-0.175	-0.210**	-0.101	-0.235	-2.403***	-1.436**	0.112	0.229**
	[0.188]	[0.294]	[0.238]	[0.662]	[0.110]	[0.0827]	[0.467]	[0.703]	[0.546]	[0.722]	[0.106]	[0.108]
Sh(DonorCum.OF)$_{t-1}$	0.217***	0.0829	0.188***	0.0995**	0.218***	0.0953	0.0669*	0.0908**	0.0914**	0.103**	0.0630*	0.0762*
	[0.0641]	[0.0513]	[0.0648]	[0.0495]	[0.0593]	[0.0593]	[0.0344]	[0.0443]	[0.0368]	[0.0437]	[0.0332]	[0.0423]
Sh(CompetFlowType)$_{t-1}$	0.0117	0.00133	0.0287**	0.0441**	0.00800*	0.000125	-0.106**	0.0113	-0.0890	0.0216	-0.0186**	0.00128
	[0.00795]	[0.00926]	[0.0137]	[0.0219]	[0.00429]	[0.00364]	[0.0417]	[0.0373]	[0.0674]	[0.0537]	[0.00795]	[0.00526]
Constant	0.564***	-0.822***	0.566***	-0.865***	0.566**	-0.914***	0.600***	-1.002***	0.588**	-0.996***	0.565***	-0.892***
	[0.213]	[0.302]	[0.216]	[0.301]	[0.221]	[0.315]	[0.225]	[0.345]	[0.230]	[0.355]	[0.216]	[0.340]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Donor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Recipient FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.138	0.144	0.136	0.145	0.138	0.144	0.137	0.141	0.138	0.141	0.137	0.142
Outcome mean	0.0265	0.0258	0.0265	0.0258	0.0265	0.0258	0.0277	0.0272	0.0277	0.0272	0.0277	0.0272
N	5,716	5,435	5,716	5,435	5,716	5,435	5,716	5,433	5,716	5,433	5,716	5,433

Notes: This table presents the results from regression 3.2 to test Hypothesis 2 for land deals. The main coefficient of interest is α_3 associated with $Sh(DonorCum.OF)_{t-1}$×Sh(CompetFlowType)$_{t-1}$. $\alpha_3 < 0$ notes a substitution effect and $\alpha_3 > 0$ marks a complementary effect. All cumulated total official finance flows (Cum. OF) and large-scale land acquisitions (LSLA) deals are at the recipient-year level. The cumulative land deals start in 2000 and stop in 2014.Controls include the log distance between recipient and donor countries, the existence of a colonial or dependency relationship, the GDP per capita and the log of the population at the recipient level during year t. Standard errors are clustered at the recipient-year level, $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

Table 3.9: Hypothesis 2: Complementary and substitution effects of USA and UK financial flows across recipient countries' property rights level

Outcome	Share (Donor's cumulated land deals)$_t$											
Competing donor country	United States of America						United Kingdom					
Flow type	Total		ODA		OOF		Total		ODA		OOF	
Recipient's property rights index	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Sh(DonorCum.OF)$_{t-1}$×Sh(CompetFlowType)$_{t-1}$	0.646*	-0.0430	0.0330	-0.0117	0.981***	-0.212	2.041***	1.158*	1.807***	0.583	0.160	0.615
	[0.343]	[0.252]	[0.212]	[0.212]	[0.374]	[0.149]	[0.487]	[0.628]	[0.472]	[0.441]	[0.123]	[0.415]
Sh(DonorCum.OF)$_{t-1}$	0.0183	0.122*	0.0566	0.118**	0.0318	0.125**	-0.0352	0.0859**	-0.0449	0.101***	0.0315	0.123***
	[0.0385]	[0.0622]	[0.0479]	[0.0581]	[0.0333]	[0.0490]	[0.0294]	[0.0388]	[0.0313]	[0.0380]	[0.0312]	[0.0294]
Sh(CompetFlowType)$_{t-1}$	-0.0348	-0.00686	-0.0432*	-0.0183	-0.0206**	0.00651	-0.00832	0.0273**	-0.0436	0.0255	-0.00136	0.0132**
	[0.0216]	[0.0123]	[0.0230]	[0.0115]	[0.00810]	[0.00709]	[0.0379]	[0.0110]	[0.0419]	[0.0200]	[0.00815]	[0.00611]
Constant	0.444*	-1.108***	0.453**	-1.014***	0.321	-1.125***	0.620***	-0.957***	0.637***	-0.882***	0.629***	-0.997***
	[0.229]	[0.338]	[0.226]	[0.328]	[0.209]	[0.340]	[0.218]	[0.347]	[0.218]	[0.333]	[0.213]	[0.335]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Donor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Recipient FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.135	0.142	0.134	0.142	0.142	0.143	0.142	0.0801	0.141	0.0773	0.135	0.0792
Outcome mean	0.0268	0.0268	0.0268	0.0268	0.0268	0.0268	0.0264	0.0223	0.0264	0.0223	0.0264	0.0223
N	5,717	5,433	5,717	5,433	5,717	5,433	5,716	5,432	5,716	5,432	5,716	5,432

Notes: This table presents the results from regression 3.2 to test Hypothesis 2 for land deals. The main coefficient of interest is α_3 associated with $Sh(DonorCum.OF)_{t-1}$×Sh(CompetFlowType)$_{t-1}$. $\alpha_3 < 0$ notes a substitution effect and $\alpha_3 > 0$ marks a complementary effect. All cumulated total official finance flows (Cum. OF) and large-scale land acquisitions (LSLA) deals are at the recipient-year level. The cumulative land deals start in 2000 and stop in 2014.Controls include the log distance between recipient and donor countries, the existence of a colonial or dependency relationship, the GDP per capita and the log of the population at the recipient level during year t. Standard errors are clustered at the recipient-year level, $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

3.6.2 Comparison with the industrial exploitation of other natural resources

This section describes a replication exercise to capture the dynamics behind official finance flows and two other types of natural resources also extracted industrially: fishing and mining. As in the previous section that matched each land investor's country of origin with a donor country, I associate each vessel's flag that has been detected as in the maritime zone of a recipient country with the corresponding donor country. For industrial mining, I combine the country of registration of the company that owns the mining site with the corresponding donor country. A discussion will be provided on the relevance and the limits of such a combination. The analysis is similar to the previous section: it first looks at the influence of each donor's flow on its capacity to extract natural resources (equation 3.1) and then considers the complementarity or substitution effects of one specific competing donor on other donors (equation 3.2).

3.6.3 Industrial fishing

This analysis is led on the 20 countries both sending official finance flows and conducting industrial fishing between 2012-2014, and the 37 coastal African countries.

Influence. Table C.7 displays the result of the equation 3.1 when adding the controls step by step, in the same way as in the land deals analysis. I find a positive and significant effect, at the 10 percent level, of the share of cumulative official finance flows of donor countries on their industrial fishing activity within recipients' closest maritime zone (36 NM) but not within their Exclusive Economic Zone. An increase of 1 percent of a donor's share of cumulative official finance flows is associated with an increase of 0.159 percent (with 95% CI [-0.027; 0.344]) of the share of industrial fishing hours in the recipient country's 36 NM maritime zone. This result suggests that official finance flow positively influences the industrial fishing activity only near the coast where most of the fishing grounds are and where regulation is alledgedly stricter than in the EEZ. This results is in line with the previous analysis on land, yet caution has to be taken for the interpretation, as there might be a lack of statistical power. Indeed, only 3 years of observations are covered and there is a noticeable absence of flags registered in the USA and other non-DAC donors than China during this period, which reduces the number of involved donors. Out of the too few observations, the analysis across financial flow classes cannot be undertaken, and only the split across group of donors has been attempted (see Figure C.19 and its corresponding Tables C.8 and C.9 in the Appendix).

Complementarity and substitution effects. Figure C.20 lays out the coefficients α_3 of the interaction term in equation 3.2 for the main flags under which industrial fishing has been conducted between 2012 and 2014. There is a negative and significant interaction effect of official finance flows from Norway and Italy within the 36 NM maritime zone and from Italy and Japan in the EEZ of recipient countries. The substitution effect of these major actors of the global industrial fishing sector suggests that the official finance flows (nearly exclusively ODA) of these three countries manage to reduce the industrial fishing activity of other donor countries in the corresponding maritime zones. No tangible effect can so far be found among vessels registered under the flags of other countries than these donors, and it may well be a strong underestimation of the actual effect. Future research covering a longer time range will have to confirm these preliminary findings.

3.6.4 Industrial mining

This analysis is led on the 25 countries that are both sending official finance flows and that have opened an industrial mine between 2000-2014, and the 47 African countries with industrial mining activity. Contrary to the analysis on land deals and fishing, only the mining analysis enables us to take into account the past industrial mines that donors have opened within the recipient countries. Indeed, as the mining data starts covering mines that opened as early as the XIXth century, it is possible to measure the stock of mines that each donor had opened with a recipient country before the start of our analysis (i.e. before 2000). I, therefore, include in the following regressions, a control for the share represented by the donor's mines within the recipient country before 2000: $Sh(D.mines)_{b.2000}$.

Influence. Table C.10 displays the results of the equation 3.1 when adding the controls step by step, in the same way as in the land deals analysis. I find a negative and significant effect of the share of cumulative official finance flows of donor countries within the recipient country the previous year, on the share of the cumulative number of openings of mines currently owned by a company registered in the donor country (columns 1 to 5) and even when controlling for the share of the past mines (before 2000), that plays a significant and positive role on the share of future mine openings. An increase of 1 percent of a donor's share of cumulative official finance flows is associated with a decrease of 0.026 percent (95 % CI [-0.051;-0.001]) of the share of open mines in the recipient country. However, this result no longer holds when excluding the United Kingdom (columns 9-10) and put forwards the key role played by the country[19]. A possible explanation could be that industrial mining activity requires such high capital investments that they are more determined by private investments only and that the consideration of official flows from donor countries comes only second. Another possible explanation could be that most of the major global mining companies active in Africa are partly registered in the UK (Anglo American, BHP Billiton, Rio Tinto, ...), and that there is a strong over-representation of UK-registered industrial mine owners compared to the UK official finance flows, which may unbalance the game for other donor and investing countries and makes it hard to capture any influence of their official finance flows. Figure C.21 plots the coefficient associated with this influence, across group of DAC and non-DAC countries. The official finance flows from Belgium, France, Germany, Italy, and Portugal on the one side, and Japan and South Korea on the other side play a positive and significant influence on their countries' industrial mining companies. It is all the contrary for the group of the UK and the USA, as well as for Switzerland and Luxembourg.

Complementarity and substitution effects. Table C.11 focuses on the interaction effect of UK flows on other donors (α_3 of the interaction term in equation 3.2). If the previous paragraph recorded a negative and significant effect of donors' financial flows influence, columns 2 and 3 show that this relationship is altered when looking at DAC countries. Official flows from the UK stimulate only the mine opening of other DAC donors and make their influence become positive (α_3 = 1.036 is much higher in magnitude than α_2 = -0.041). Columns 4 and 5 show that the cooperative effect of the UK flows is merely driven by its ODA flows. These results bring suggestive evidence of the complementarity of UK flows with other DAC donors' industrial mining activity. Yet, this interpretation also needs to take into account that as major global mining companies have quite complex structures, they often have several countries of registration (for example UK-USA, UK-Australia, UK-Canada), and this may partially explain the current findings. Finally, additional caution needs to be taken as the owning company of an industrial mine may be different from the company who was granted the concessional lease of exploitation and different from the company which undertook the exploration and discovery. Moreover, most major mining companies are multinational firms with complex structures of different

[19] UK was the only donor country for which exclusion changed the significance of the results. The same test was run on recipient countries and the negative relationship remains significant. Yet please note that the hand work did not retrieve mine opening dates from South Africa and only used the dates initially available. It is likely that we underestimate the mine openings in South Africa.

entities, and this makes the link with the country of registration more questionable than for mining companies from a smaller scale.

The current analysis of mining has to be taken with caution and calls for future work on defining a better measure of industrial mining activity. Indeed, the long process of granting a lease concession for exploration, discovery, and for finally opening a mining site compared to the relatively potentially shorter temporality of land deals, will need to be taken into account. So far, the same temporality of official finance flows has been used (up to the previous year), but different lags and time windows will have to be tested for.

This section has provided an heterogeneity analysis of the raw materials diplomacy on land acquisitions and its complementary/substitute effects across the level of property rights of recipient countries. It has brought suggestive evidence that these effects are different across DAC and non-DAC donors: the influence is higher for DAC donors among recipient countries with high property rights index while it is higher for non-DAC donors among recipient countries with low property rights index. Chinese flows have a substitute effect on other donor's influence mostly in low property rights index countries, while Indian flows have a substitute effect in all recipient countries, no matter their property rights level. The flows from the USA have a complementary effect mostly in countries with low property rights levels, while it is the case across all recipient countries for the UK flows. This section also undertook a replication exercise on industrial fishing and industrial mining. The analysis so far find consistent findings for industrial fishing: official finance flows mostly have a positive effect on the capacity to conduct industrial fishing, in areas with more fishing regulations (close to the coast). Results on industrial mining have to be deepened. The next section provides a long discussion on the analysis and exhibits leads for further research.

3.7 Discussion

This paper empirically tested two hypotheses and provided the following results. In the first step, I found a positive and significant correlation between the share of cumulative official finance flows from donor countries within the recipient country the previous year, and the share of the cumulative number of land deals conducted by an investor from the donor country. I interpret this result as evidence of the relevance and the existence of Raw materials diplomacy. In particular, I highlight the still pertaining influence that former colonial powers have among their former colonies. I find that emerging donors mostly have a significant Raw materials diplomacy among recipient countries with low property rights index, while for the USA and the UK, it is mostly the case among countries with high property rights index. In the second step, I found a complement and substitute effect of a competing donor's finance flows on other donors' capacity to acquire land. Flows from the USA and the UK tend to complement DAC land investors, while Chinese and Indian flows tend to substitute them. Heterogeneity on the type of flows across donors is also provided: the substitute effect is especially high for Chinese and Indian ODA flows, compared to their OOF, and the UK has a significant substitute effect on non-DAC investors mostly through its OOF. I interpret these results to bring suggestive evidence of three different characteristics of donors' competition that would need to be tested more systematically to see if they hold in wider settings: (i) donors' official development flows influence other donors' natural resources extraction activities; (ii) DAC and Non-DAC donors crowd each other out on the natural resources market; (iii) Non-DAC donors need higher levels of concessionality (i.e. aid) to evict DAC donors while the latter manages the crowding-out by using less concessional and more commercially-oriented flows (i.e. credits).

The section now discusses the main limitations of the current results by examining the endogeneity issues and the measurement errors. It then proposes hints for further work.

The results presented so far only provide suggestive evidence of correlations between the outcome and explanatory variables, and not causal effects. The main challenge of this project is to find an exogenous source of variation for all donors that would influence official finance flows and not the industrial extraction of natural resources - except for official finance flows.

Further work will have to deal with reverse causality issues. Indeed, investing companies from donor countries may well better succeed in concluding land deals when its government has an increased influence in the recipient country, but the reverse could also hold: official development finance flowing to recipient countries where national companies have more activities or flow coming to support the construction of infrastructure such as roads, ports or communication to improve the returns of the investment. It can also be true that in exchange for a concluded deal, investing countries also order the construction of schools, health centers, or agricultural centers. Reverse causality has been tested through the Granger causality tests but the latter has so far been inconclusive due to the too-short period. Nevertheless, one should note that the reverse causality issue is less important for the results of complementarity and substitution effects.

The current paper does not yet deal with several time-varying unobservable variables that may bias the results. Further work will need to control for the intensity of diplomatic ties existing between each pair of recipient and donor countries, which could be proxied by the historical ties not captured by the colonial or dependency relationship, such as former communist countries, or by the political ties reflected in the alignment of votes at the UN General Assembly. Moreover, the importance of the first tie or link between countries will have to be included, as the context and timing are essential in the way the trajectory of the relationship is shaped afterward. For example, the year of the establishment of the first embassy could proxy its foundation. The current study does not encompass military aid or related exports, or any conflict-related variables that could bias our results. Indeed, military aid constitutes a foreign policy tool that could complement or substitute official finance flows (Kisangani and Pickering, 2015), and omitting this explanatory variable could lead to either an upward (if complement) or downward bias (if substitute). Moreover, increased military flows are likely associated with either existing conflicts or can trigger new conflicts that could ease the acquisitions of land, the exploitation of mines by foreign investors, or deter them by creating a too business-risky environment. It is an empirical question to determine which of these effects dominates. Other dimensions of the bilateral relationship between recipient and donor countries will also have to be controlled for, especially including Foreign Direct Investment Flows from DAC countries as the latter have a much smaller proportion of OOF than non-DAC countries. The evolving privileged relationship between recipient countries' elites and a donor country would also be important to take into account as the diplomatic activities of the ruling elites could also facilitate business transactions. If the ruling elite is well acquainted with a donor country's company, it may require less official finance flows for the company to conclude deals.

Sample bias will also have to be analyzed in more detail, as the results so far exclude countries without official finance flows, but that could be acquiring land, opening a mining site, or conducting industrial fishing. Their latter activity is taken into account in the shares of $CumActivity$ of each donor-recipient pair but we cannot make the distinction across these investing countries. Further work will also have to better take into account donors that are not conducting natural resources activity. One possibility could be to group them and they would represent an "external option" for recipient countries that would not need to exchange access to their natural resources for aid. We will have to find a way to test whether the absence of their extraction activities is true zeros or missing values that are endogenously correlated with other confounding factors (reporting bias in less regulated countries for example). It would then be interesting to study the influence of official finance flows on the extensive margin: and how it can prevent other donors to join the market of natural resources extraction.

Finer measurements of natural resources regulation will have to be integrated. Characteristics on the land tenure regime (i.e. proportion of land under communal or customary rights, state-owned land or private land, Global Index of the Governance for Land Tenure Security and the timing of land reforms (i.e. privatization waves or expropriations) could shed light on the increased possibility of transnational deals with the national land market and how exposed they are to the influence of official finance flows. Similarly, the stringency of fishing agreements, the proportion of maritime zone under protected areas or each country's number of boats dedictated to monitoring their maritime zone, could proxy the management of fisheries resources. In the mining sector, the signature of the Extractive Industries Transparency Initiative and its implementation status could grasp to what extent mining concessions are leased through transparent processes.

In the design of the future work to conduct, a heterogeneity analysis will be conducted to compare the pre and post-2008 global financial crisis to see how the influence of China and India has changed.

Finally, a last agenda for future research would be to analyze the complementarity and substitution effects of official flows on imports and exports of commodities such as agricultural products and minerals (FAO data), to look at whether donor countries manage to secure their supply of strategic goods. It would also be the opportunity to update the "aid and trade" relationship (Suwa-Eisenmann and Verdier, 2007) with these new databases.

3.8 Conclusion

This paper brings some new hindsight on the competition across traditional and emerging donors, and its effect on the market of natural resource extraction. Using recent panel data on official finance flows and industrial extraction of natural resources, this paper provides suggestive evidence of the existence of Raw materials diplomacy. Through an extended descriptive analysis, I find that official development flows from DAC and non-DAC countries are positively associated with their capacity to conclude large-scale land acquisitions in Africa, over the 2000-2014 period. An increase of 1 percent of a donor's share of cumulative official finance flows is associated with an increase of 0.067 p.p. (with 95% Confidence interval: [0.017; 0.118]) of the share of land deals in the recipient country. Moreover, a stronger association is found among OECD-DAC donors and former colonial countries even when introducing donor, recipient, and year-fixed effects, and controlling for many factors among which past colonial or dependency relationship. I find strong heterogeneity among DAC and non-DAC donors across recipient countries' property rights levels. This association is stronger among DAC donors in countries with high property rights index and on the contrary, is stronger among Non-DAC donors in countries with low property rights index. In the second step, the estimation shows that a donor's official development flows affect the influence of other donors on their capacity to conclude land deals. I find that financial flows from the USA and the UK complement the activity of other DAC land investors, while financial flows from China and India substitute DAC flows, and reduce the capacity for their investors to conclude land deals. This current work opens the way to further research to refine the replication analysis on industrial fishing and industrial mining and to bring more heterogeneity across the regulation stringency levels of the exploitation of natural resources.

Bibliography

AFDB (2019). *Feed Africa*. Tech. rep. African Development Bank Group.

Alesina, Alberto and David Dollar (2000). "Who Gives Foreign Aid to Whom and Why?" In: *Journal of Economic Growth*.

Altonji, Joseph G., Todd E. Elder, and Christopher R. Taber (2005). "Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools". In: *Journal of Political Economy* 113.1, pp. 151–184.

Arezki, Rabah, Klaus Deininger, and Harris Selod (2015). "What Drives the Global Land Rush?" In: *World Bank Economic Review* 29.2.

Asiedu, Elizabeth, Yi Jin, and Boaz Nandwa (2009). "Does foreign aid mitigate the adverse effect of expropriation risk on foreign direct investment?" In: *Journal of International Economics* 78.2, pp. 268–275.

Asmus, Gerda, Vera Eichenauer, et al. (2021). "Does India Use Development Finance to Compete With China? A Subnational Analysis". In: *Courant Research Centre 'Poverty, Equity and Growth in Developing and Transition Countries' Discussion Paper No. 281.*

Asmus, Gerda, Andreas Fuchs, and Angelika Müller (2020). "BRICS and Foreign Aid". In: *The Political Economy of the BRICS Countries*. Chap. CHAPTER 7, pp. 139–177.

Azam, Jean-Paul and Jean-Jacques Laffont (2003). "Contracting for aid". In: *Journal of Development Economics* 70.1, pp. 25–58.

Balestri, Sara and Mario A. Maggioni (2021). "This Land Is My Land! Large-Scale Land Acquisitions and Conflict Events in Sub-Saharan Africa". In: *Defence and Peace Economics* 32.4, pp. 427–450.

Ben-Artzi, Ruth (2017). "IOs and Peer Pressure: An Examination of the Development Assistance Committee (DAC)". In: *10th Annual Conference on the Political Economic of International Organization.*

Bermeo, Sarah Blodgett (2011). "Foreign Aid and Regime Change: A Role for Donor Intent". In: *World Development* 39.11, pp. 2021–2031.

Bourguignon, François and Jean-Philippe Platteau (2013). *Optimal Discipline in Donor-Recipient Relationships -Reframing the Aid Effectiveness Debate*. Tech. rep. HAL.

– (2015). "The Hard Challenge of Aid Coordination". In: *World Development* 69. Aid Policy and the Macroeconomic Management of Aid, pp. 86–97.

– (2017). "Does Aid Availability Affect Effectiveness in Reducing Poverty? A Review Article". In: *World Development* 90.C, pp. 6–16.

Brautigam, Deborah (2009). *The Dragon's GiftThe Real Story of China in Africa*. Oxford University Press.

Buckley, Peter J. et al. (2010). "What Can Emerging Markets Learn from the Outward Direct Investment Policies of Advanced Countries?" In: *Foreign Direct Investments from Emerging Markets: The Challenges Ahead*. New York: Palgrave Macmillan US.

Buur, Lars et al. (2020). "The politics of natural resource investments and rights in Africa: A theoretical approach". In: *The Extractive Industries and Society* 7.3, pp. 918–930.

Cabral, Reniel B et al. (2018). "Rapid and lasting gains from solving illegal fishing". In: *Nature Ecology and Evolution* (2), pp. 650–658.

Chaturvedi, Sachin (2008). *Emerging Patterns in Architecture for Management of Economic Assistance and Development Cooperation : Implications and Challenges for India*. Tech. rep. 22092. East Asian Bureau of Economic Research.

Chin, Gregory T (2012). "China as a net donor: tracking dollars and sense". In: *Cambridge Review of International Affairs* 25.4, pp. 579–603.

Chuhan-Pole, Punam, Andrew L. Dabalen, and Bryan Christopher Land (2017). "Mining in Africa : Are Local Communities Better Off?"

Colella, Fabrizio et al. (Feb. 28, 2020). "Inference with Arbitrary Clustering". In: *IZA Discussion Paper*.

Collier, Paul and Anke Hoeffler (2004). "Greed and Grievance in Civil War". In: *Oxford Economic Papers* 56.4, pp. 563–595.

Conigliani, Caterina, Nadia Cuffaro, and Giovanna D'Agostino (2018). "Large-scale land investments and forests in Africa". In: *Land Use Policy* 75, pp. 651–660.

Conte, Madalena, Pierre Cotterlas, and Thiery Mayer (June 28, 2021). *The CEPII Gravity Database*. Tech. rep. CEPII.

Cotula, Lorenzo (2013). "The Great African Land Grab? Agricultural investments and the global food system." In: *London and New York NY: Zed Books for the International African Institute*.

Custer, Sam et al. (2021). "Tracking Chinese Development Finance: An Application of AidData's TUFF 2.0 Methodology". In: *Williamsburg, VA: AidData at William and Mary.*

Davies, Ronald B. and Stephan Klasen (2019). "Darlings and Orphans: Interactions across Donors in International Aid". In: *The Scandinavian Journal of Economics* 121.1, pp. 243–277.

Deininger, Klaus et al. (2011). *Rising Global Interest in Farmland: Can it Yield Sustainable and Equitable Benefits?* The World Bank Group.

Djankov, Simeon, Jose G. Montalvo, and Marta Reynal-Querol (2008). "The curse of aid". In: *Journal of Economic Growth* 13.3, pp. 169–194.

Dreher, Axel, Andreas Fuchs, Roland Hodler, et al. (2021). "Is Favoritism a Threat to Chinese Aid Effectiveness? A Subnational Analysis of Chinese Development Projects". In: *World Development* 139.

Dreher, Axel, Andreas Fuchs, Bradley Parks, et al. (2022). *Banking on Beijing: The Aims and Impacts of China's Overseas Development Program.* Cambridge University Press.

Dreher, Axel, Peter Nunnenkamp, and Rainer Thiele (2011). "Are New Donors Different? Comparing the Allocation of Bilateral Aid Between nonDAC and DAC Donor Countries". In: *World Development* 39.11. Expanding Our Understanding of Aid with a New Generation in Development Finance Information.

Dudley, Leonard and Claude Montmarquette (1976). "A Model of the Supply of Bilateral Foreign Aid". In: *American Economic Review* 66.1, pp. 132–42.

Dunning, John H, Roger Van Hoesel, and Rajneesh Narula (1997). *Third world multinationals revisited: new developments and theoretical implications.* Vol. 227. University of Reading, Department of Economics.

Fraser, Alastair and Lindsay Whitfield (2008). "The politics of aid: African strategies for dealing with donors," in: *GEG Working Paper, No. 2008/42, University of Oxford,Global Economic Governance Programme (GEG), Oxford.*

Frot, Emmanuel and Javier Santiso (2011). "Herding in Aid Allocation". In: *Kyklos* 64.1, pp. 54–74.

Fuchs, Andreas, Axel Dreher, and Peter Nunnenkamp (2014). "Determinants of Donor Generosity: A Survey of the Aid Budget Literature". In: *World Development* 56, pp. 172–199.

Fuchs, Andreas and Krishna Chaitanya Vadlamannati (2013). "The Needy Donor: An Empirical Analysis of India's Aid Motives". In: *World Development* 44.C, pp. 110–128.

Garriga, Ana Carolina and Brian J. Phillips (2014). “Foreign Aid as a Signal to Investors: Predicting FDI in Post-conflict Countries”. In: *Journal of Conflict Resolution* 58.2, pp. 280–306.

Giovannetti, Giorgia and Elisa Ticci (2016). “Determinants of biofuel-oriented land acquisitions in Sub-Saharan Africa”. In: *Renewable and Sustainable Energy Reviews* 54, pp. 678–687.

Gittard, Melanie and Irene Hu (2022). “MiningLeaks: Water Pollution and Infant Mortality in Africa”. Thesis Chapter.

Humphrey, Chris and Katharina Michaelowa (2019). “China in Africa: Competition for traditional development finance institutions?” In: *World Development* 120, pp. 15–28.

Humphreys, Macartan, Martin E. Sandbu, and George Soros (2007). “The Political Economy of Natural Resource Funds”. In: *Escaping the Resource Curse*. Columbia University Press. (Visited on 07/28/2022).

Johnston, Lauren and Marina Rudyak (2017). “China’s Innovative and Pragmatic Foreign Aid: Shaped by and now Shaping Globalisation”. In: pp. 431–451.

Karleskint, Ga, Ra Turner, and Ja Small (2013). *Introduction to Marine Biology*. Belmont, CA.

Kilama, Eric Gabin (2016). “Evidences on Donors Competition in Africa: Traditional Donors versus China”. In: *Journal of International Development* 28.4, pp. 528–551.

Kilby, Christopher (2011). “Informal influence in the Asian Development Bank”. In: *The Review of International Organizations* 6.3, pp. 223–257.

Kisangani, Emizet F and Jeffrey Pickering (2015). “Soldiers and development aid: Military intervention and foreign aid flows”. In: *Journal of Peace Research* 52.2.

Kong, Bo and Kevin P. Gallagher (2017). “Globalizing Chinese Energy Finance: The Role of Policy Banks”. In: *Journal of Contemporary China* 26.108, pp. 834–851.

Kragelund, Peter (2011). “Back to BASICs? The Rejuvenation of Non-traditional Donors’ Development Cooperation with Africa”. In: *Development and Change* 42.2, pp. 585–607.

Kroodsma, David et al. (2018). “Tracking the global footprint of fisheries”. In: *Science* 359.6378, pp. 904–908.

Kuziemko, Ilyana and Eric Werker (2006). “How Much Is a Seat on the Security Council Worth? Foreign Aid and Bribery at the United Nations”. In: *Journal of Political Economy* 114.5, pp. 905–930. (Visited on 07/28/2022).

Lay, Jann et al. (2021). *Taking stock of the global land rush: Fewdevelopment benefits, many human and environmental risks. Analytical Report III.* Tech. rep. Bern, Montpellier, Hamburg, Pretoria: Centre for Development, Environment,University of Bern; Centre de coopération internationale en recherche agronomiquepour le développement; German Institute for Global, and Area Studies; University of Pretoria; Bern Open Publishing.

Leite, Carlos and Jens Weidmann (2002). "Does mother nature corrupt? : Natural resources, corruption, and economic growth". In: *Governance, corruption, and economic performance. - Washington, DC : International Monetary Fund.*

Li, Jing et al. (2013). "The Two-Tier Bargaining Model Revisited: Theory and Evidence from China's Natural Resource Investments in Africa". In: *Global Strategy Journal* 3.4.

Manzano, Osmel and Roberto Rigobon (2001). *Resource Curse or Debt Overhang?* Working Paper 8390. National Bureau of Economic Research.

Mascarenhas, Raechelle and Todd Sandler (2006). "Do donors cooperatively fund foreign aid?" In: *The Review of International Organizations* 1.4.

McKinley, Roger David and Robert Little (1979). "The US Aid relationship: a test of the recipient need and the donor itnerest models". In: *Political Studies* 27.2.

Mehmood, Sultan and Avner Seror (2019). *The Political Economy of Foreign Aid and Growth:Theory and Evidence.* Working Papers 19-10. Chapman University, Economic Science Institute.

Nunnenkamp, Peter, Hannes Ohler, and Rainer Thiele (2013). "Donor coordination and specialization: did the Paris Declaration make a difference?" In: *Review of World Economics (Weltwirtschaftliches Archiv)* 149.3, pp. 537–563.

Nunnenkamp, Peter, Albena Sotirova, and Rainer Thiele (2016). "Do Aid Donors Specialize and Coordinate within Recipient Countries? The case of Malawi". In: *Development Policy Review* 34.6, pp. 831–849.

Ramamurti, Ravi (2001). "The Obsolescing 'Bargaining Model'? MNC-Host Developing Country Relations Revisited". In: *Journal of International Business Studies* 32.1.

Ravetti, Chiara, Mare Sarr, and Tim Swanson (2018a). "Foreign aid and political instability in resource-rich countries". In: *Resources Policy* 58.C.

– (2018b). "Foreign aid and political instability in resource-rich countries". In: *Resources Policy* 58.

Robinson, James, Ragnar Torvik, and Thierry Verdier (2006). "Political foundations of the resource curse". In: *Journal of Development Economics* 79.2, pp. 447–468.

– (2017). "The political economy of public income volatility: With an application to the resource curse". In: *Journal of Public Economics* 145.C, pp. 243–252.

Robinson, James and Thierry Verdier (2013). "The Political Economy of Clientelism". In: *Scandinavian Journal of Economics* 115.2, pp. 260–291.

Ross, Michael L. (2001). "Does Oil Hinder Democracy?" In: *World Politics* 53.3, pp. 325–361.

Sachs, Jeffrey D. and Andrew Warner (2001). "The curse of natural resources". In: *European Economic Review* 45.4-6, pp. 827–838.

Steinwand, Martin and Bernhard Reinsberg (2020). "Multilateral aid to the rescue? Sectoral fragmentation of bilateral development aid and the role of the World Bank."

Suwa-Eisenmann, Akiko and Thierry Verdier (2007). "Aid and trade". In: *Oxford Review of Economic Policy* 23, pp. 481–507. (Visited on 01/06/2023).

Svensson, Jakob (2000). "When is foreign aid policy credible? Aid dependence and conditionality". In: *Journal of Development Economics* 61.1, pp. 61–84.

Swedlund, Haley (2017). "Is China eroding the bargaining power of traditional donors in Africa?" In: *International Affairs* 93.

Tierney, Michael J. et al. (2011). "More Dollars than Sense: Refining Our Knowledge of Development Finance Using AidData". In: *World Development* 39.11. Expanding Our Understanding of Aid with a New Generation in Development Finance Information, pp. 1891–1906.

Torsvik, Gaute (2005). "Foreign economic aid; should donors cooperate?" In: *Journal of Development Economics* 77.2, pp. 503–515.

Vadlamannati, Krishna Chaitanya et al. (2019). *Building Bridges or Breaking Bonds? The Belt and Road Initiative and Foreign Aid Competition.* Working Papers 201906. Geary Institute University College Dublin.

Vreeland, James and Axel Dreher (2014). *The Political Economy of the United Nations Security Council: Money and Influence.*

Watkins, Mitchell (2021). "Undermining conditionality? The effect of Chinese development assistance on compliance with World Bank project agreements". In: *The Review of International Organizations.*

WorldBank (2011). *The Changing Wealth of Nations : Measuring Sustainable Development in the New Millennium.* Tech. rep. World Bank.

Yuhui, Zhang (2011). "Chinese Foreign Aid, 1950-2010". In: *Jiuzhou Press.*

General conclusion

The three chapters of this dissertation shed some new light on the natural resource curse. The first two chapters focused on the effects of industrial fishing on migration and the detrimental effect of industrial mining on child mortality, through the channel of water pollution. The last chapter builds the ground for future research on the competition among donors at play to secure access to natural resources in Africa. These three empirical studies are all led at the scale of the African continent and aim at grasping some common patterns. Yet, further work will need to focus on the country level to provide case studies and include more contextual details among the diversity of situations, institutions, and populations. More heterogeneity across investors will also be crucial to assess, between public and private companies, joint-ventures or stock-exchange multinational firms, and historical or new companies that may have different business practices. The current dissertation did not introduce the distinction between the legal or illegal nature of these extractive activities, mostly out of data availability issues, but this characteristic is of the utmost importance for improving the regulation of natural resources.This dissertation should be complemented with fieldwork investigation and in other disciplines such as anthropology or political science, especially to better capture the interplay between small-scale and artisanal activities with the industrial ones.

Appendix A

Appendix to Chapter 1: Man Overboard! Industrial Mining as a Driver of Migration out of Africa

A.1 Data and Descriptive statistics

Table A.1: 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 A.2: 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 A.3: 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

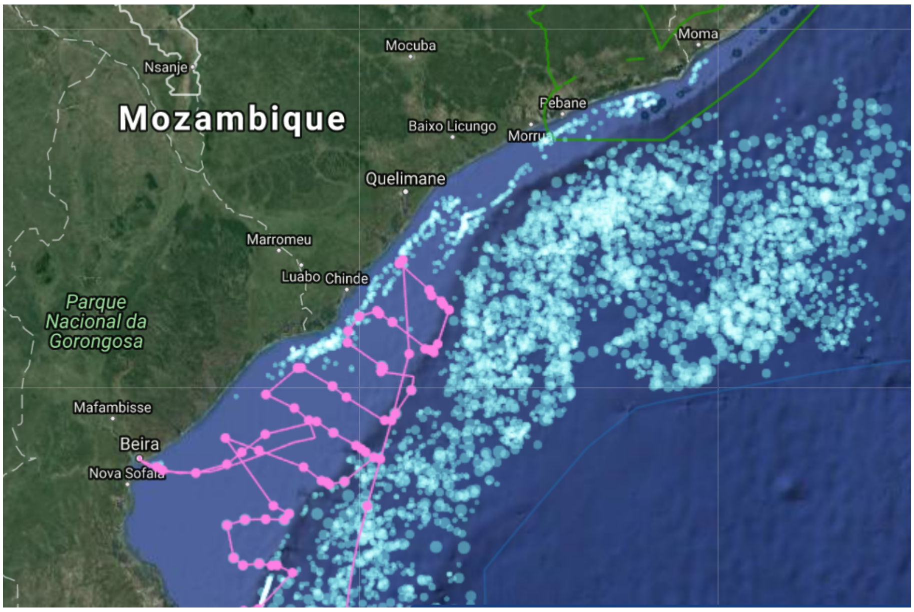
Notes: This table gives the summary statistics of our micro analysis. The hub coast is the closest access to the sea of each DHS cluster. We run buffers of three different distances around each hub and sum up the industrial fishing efforts detected as well as the fishing conditions.

Table A.4: 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 A.1: Exemple of vessel tracking in July-December 2014 by the coast of Mozambique, Global Fishing Watch platform



Source: Global Fishing Watch, accessible at `https://globalfishingwatch.org/map`.

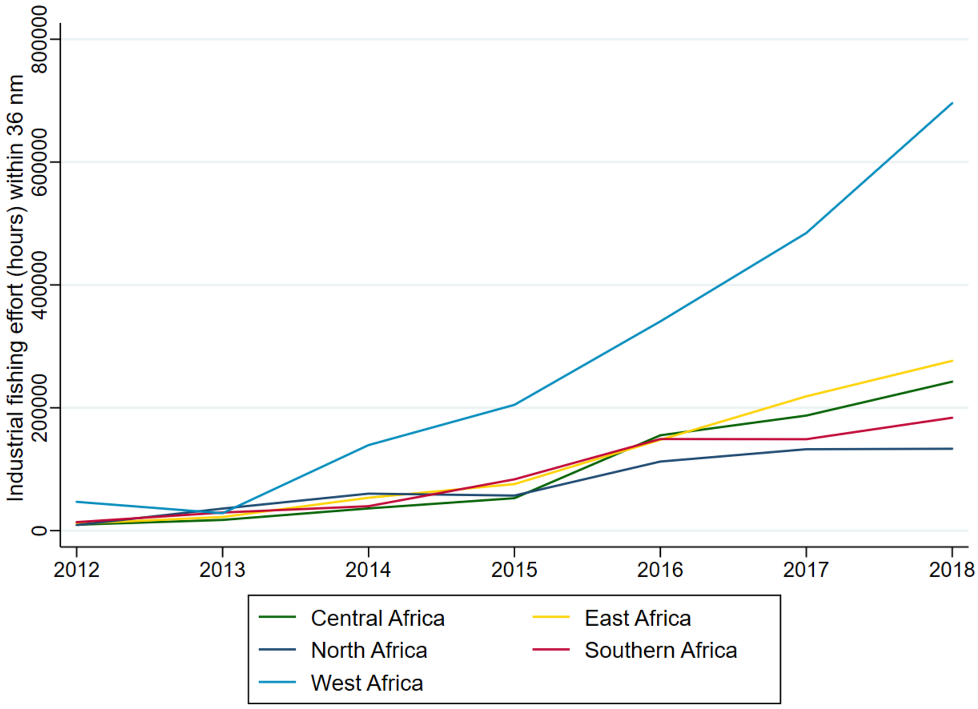
A.1.1 Industrial fishing data

A.1.2 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[1], 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., 2018). 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.

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

Figure A.2: Industrial fishing activity (in hours) detected within 36 NM



Source: Authors' elaboration using Global Fishing Watch data.

The sea surface temperature (SST) data were accessed through the Giovanni online data platform[2], 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.

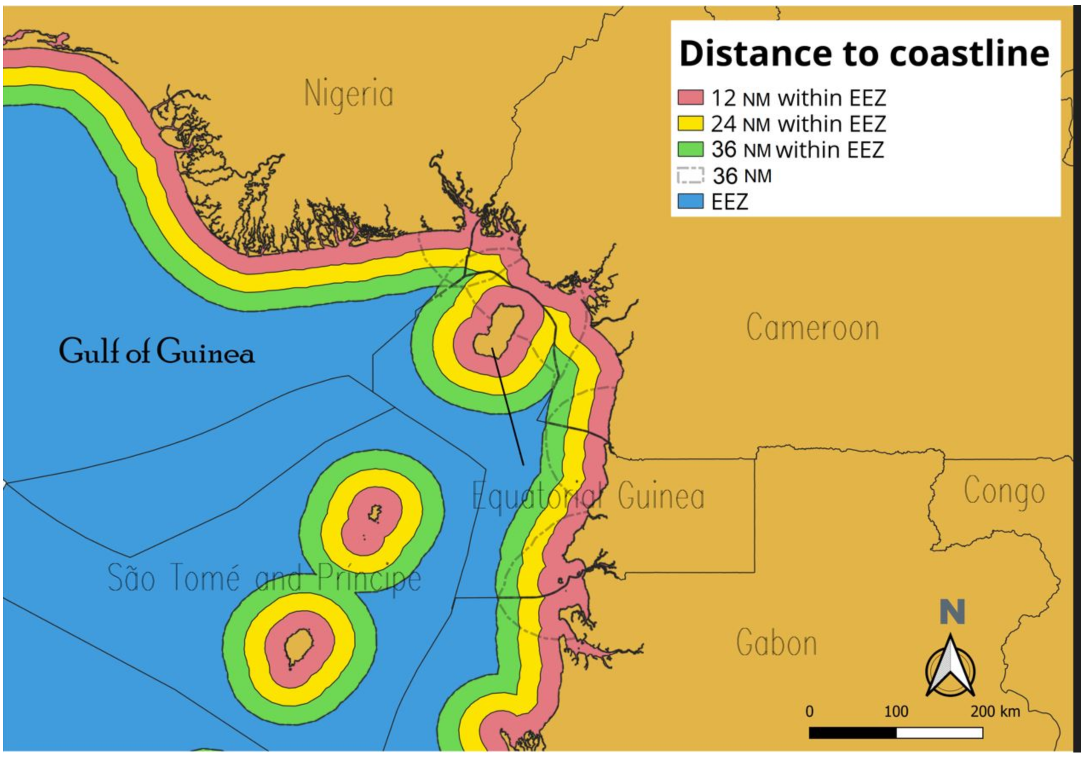
[2]https://cmr.earthdata.nasa.gov/search/concepts/C1615905770-OB_DAAC#Collection_Information

Table A.5: 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, $^{*}p < 0.1$,$^{**}\ p < 0.05$,$^{***}\ p < 0.01$.

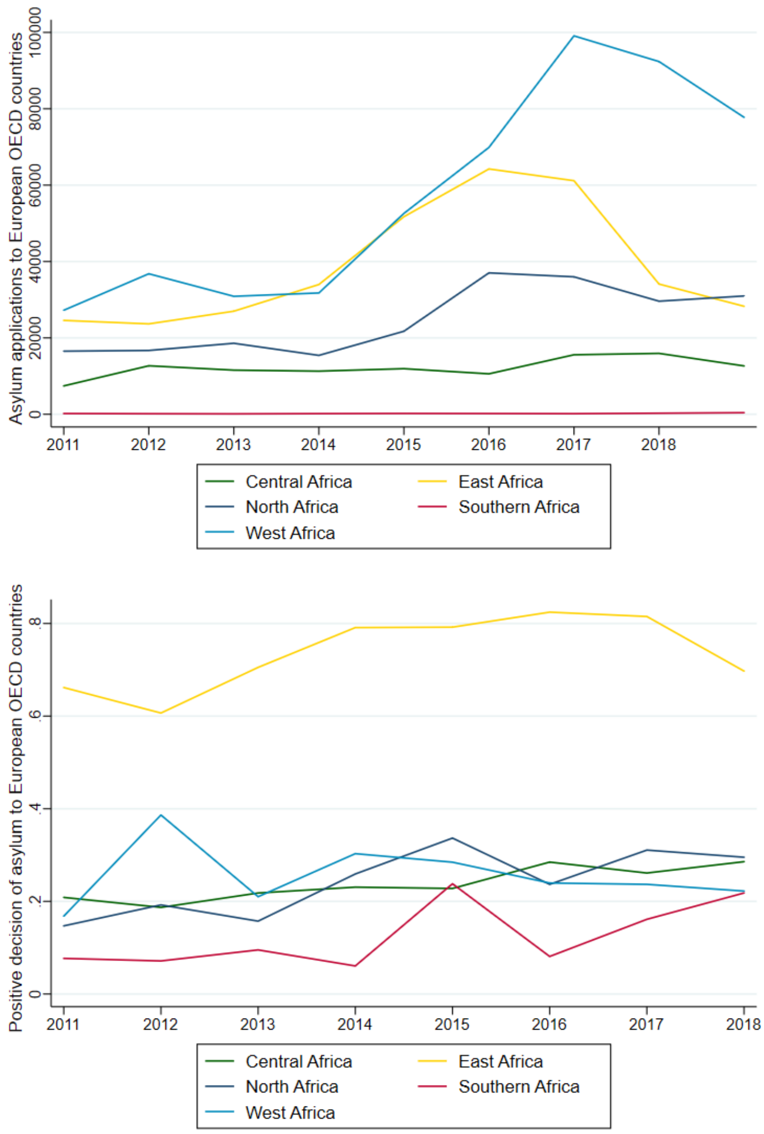
Figure A.3: Aggregation at different distances from the shore



Source: Authors' elaboration.

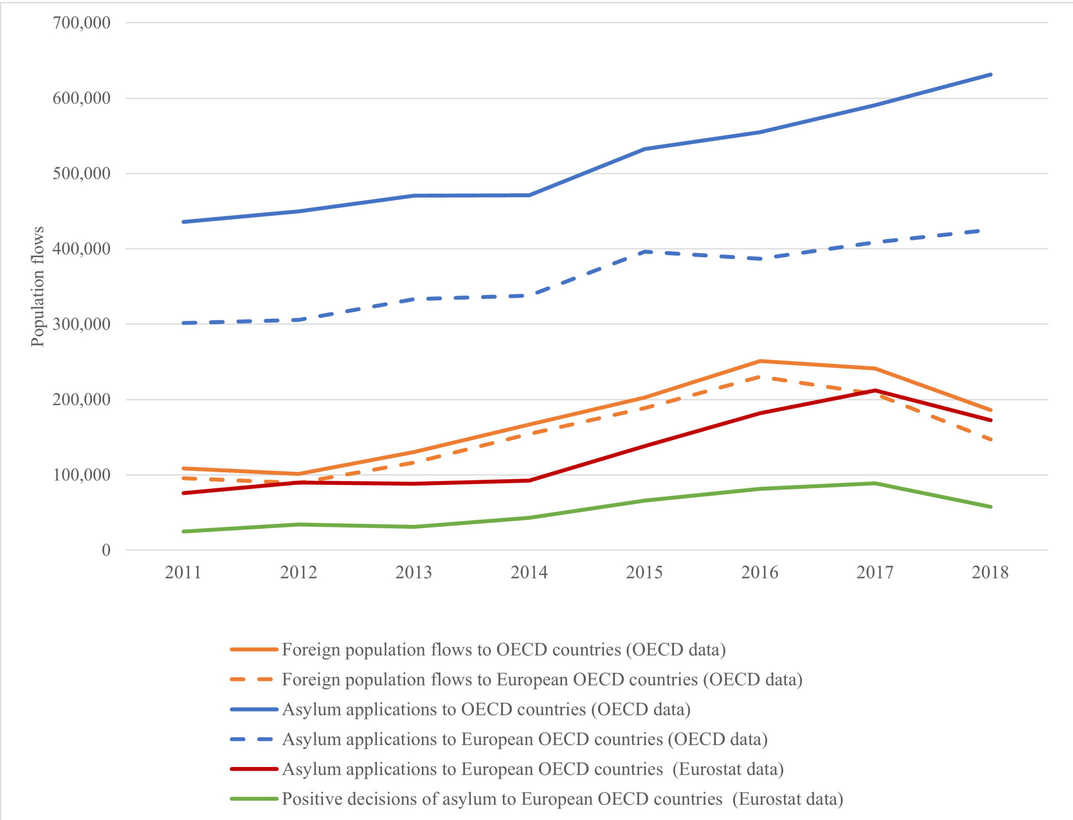
A.1.3 Migration and asylum applications data

Figure A.4: Bilateral flows of asylum application and positive decisions rates



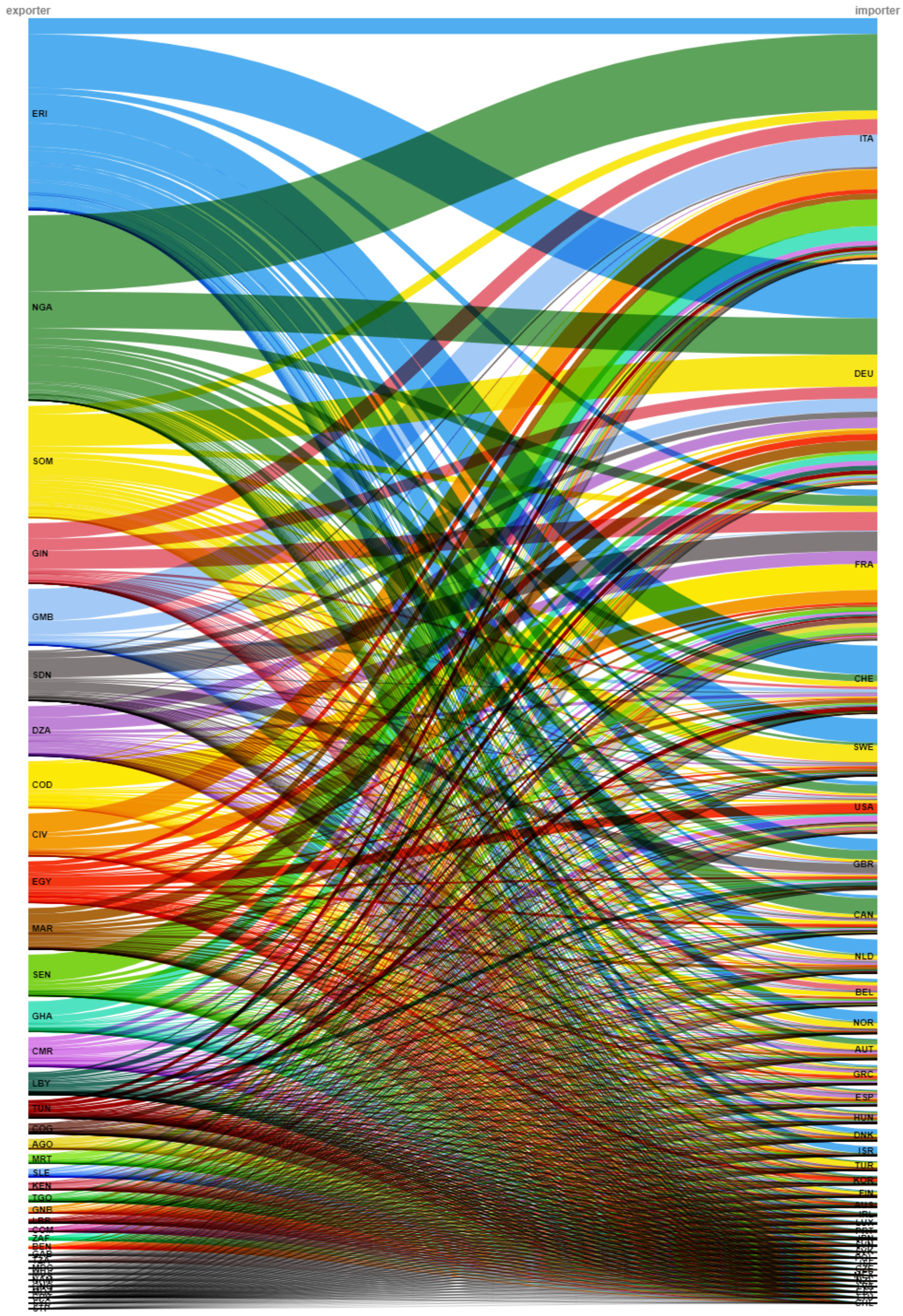
Source: Authors' computation using Eurostat data.

Figure A.5: Comparison of population flows between OECD and Eurostat data



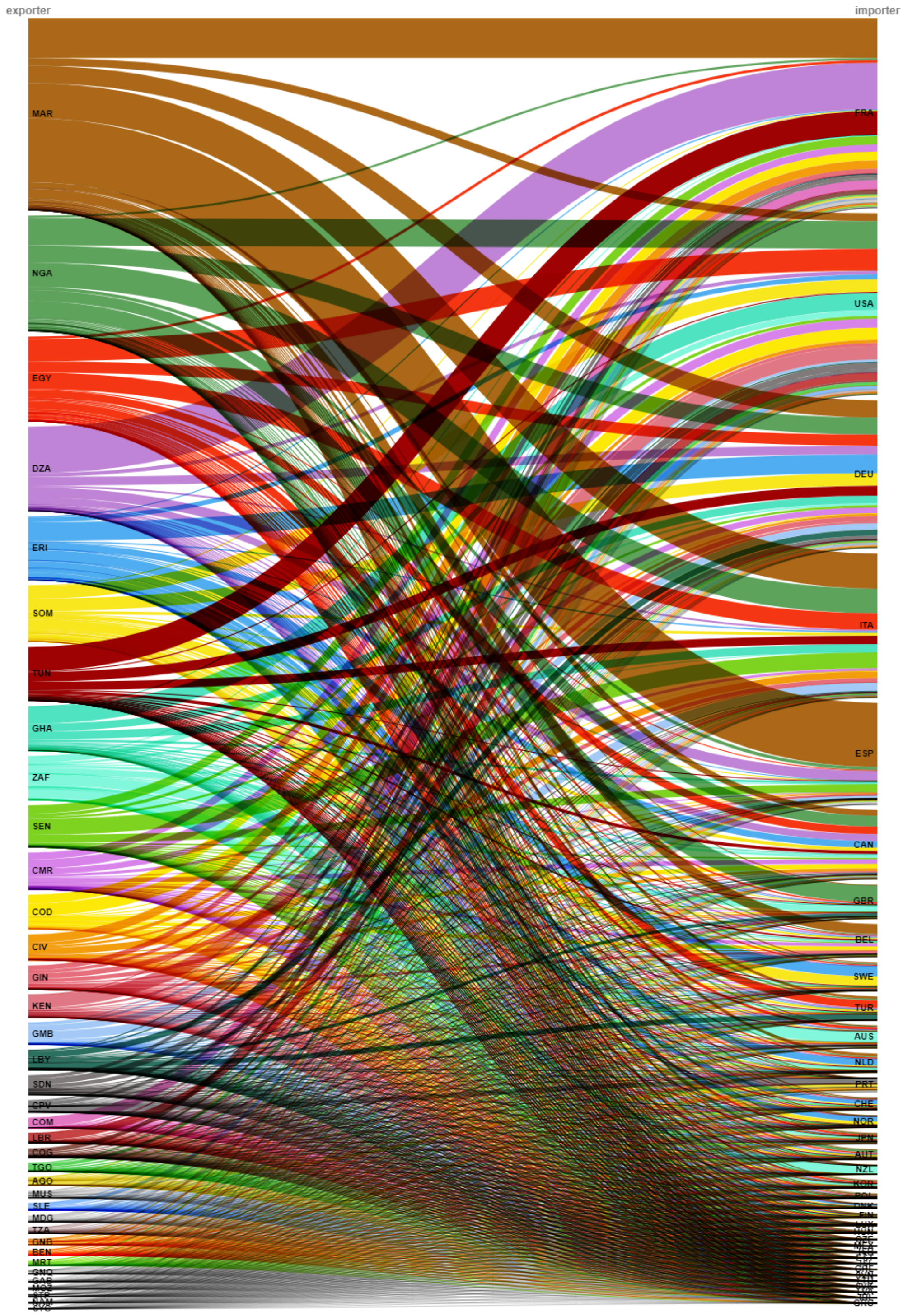
Source: Authors' computation using OECD and Eurostat data.

Figure A.6: Bilateral foreign population flows over 2012-2018 (OECD data)



Source: Authors' computation using OECD data.

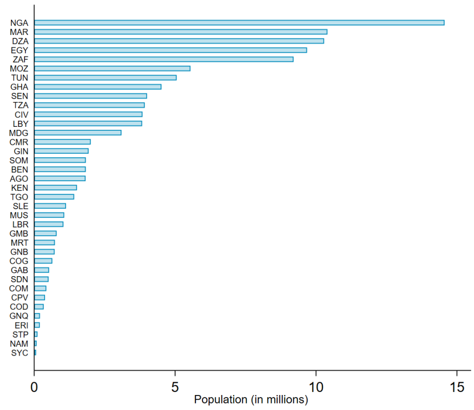
Figure A.7: Bilateral flows of asylum applications over 2012-2018 (OECD data)



Source: Authors' computation using OECD data.

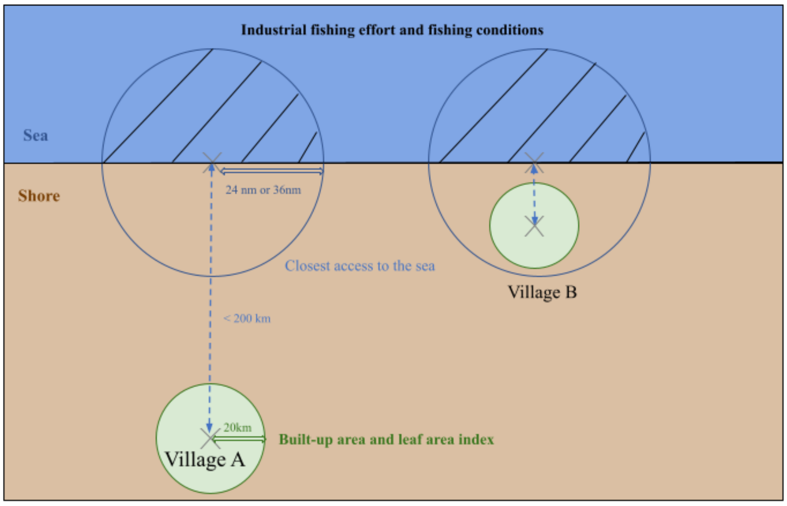
A.1.4 Population data

Figure A.8: Coastal population and urban population rates in Africa



Source: Authors' elaboration using WorldPop count and World Bank data.

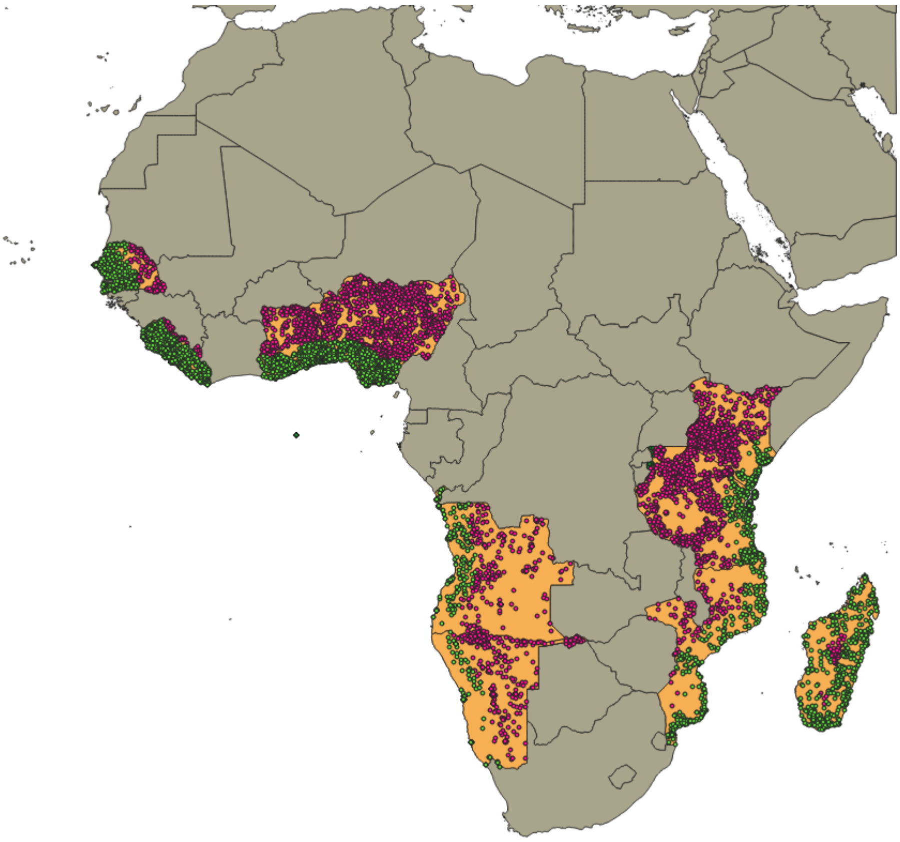
Figure A.9: Difference-in-difference for the micro-level analysis



Source: Authors' elaboration.

A.2 Empirical strategy

Figure A.10: DHS countries and clusters included in our micro study



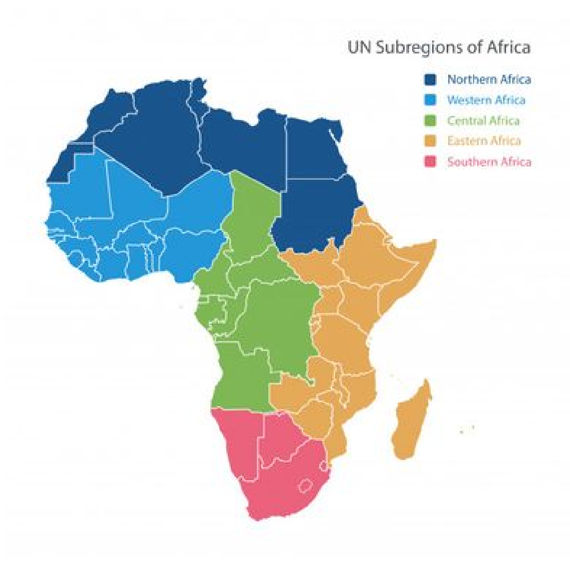
Source: Authors' elaboration using DHS data.

Figure A.11: 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 A.12: African sub-regions as defined by the United Nations



A.3 Results

Table A.6: 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 1.2 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, $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

Appendix B

Appendix to Chapter 2: MiningLeaks : Water Pollution and Child Mortality in Africa

B.1 Descriptive Statistics

B.1.1 Data

Table B.1 displays for each country the number and years of DHS waves, and the total number of DHS clusters and children under 5 years old. Overall, DHS sample gathers 36 countries overall Africa, from 1986 to 2018. In our main empirical analysis, we decided to only keep DHS countries that had at least two survey rounds, in order to have comparable temporal variation across countries. Our final sample accounts for the following countries (cf. Table B.2): Tanzania, Burkina-Faso, Ghana, Zimbabwe, Mali, Democratic Republic of Congo, Guinea, Namibia, Madagascar, Cote d'Ivoire, Sierra Leone, Liberia, Nigeria, Senegal, Ethiopia, Uganda, Botswana, Malawi, Cameroon, Morocco, Niger, Kenya, Mauritania, Rwanda, Burundi, Lesotho, Togo, Eswatini, Algeria, Benin, Eritrea, Republic of the Congo, Guinea-Bissau, Somalia, Sudan, Tunisia, Djibouti, Equatorial Guinea (by order of importance in terms of mining activity according to Figure B.4).

Table B.1: DHS surveys overall across countries

Countries	Survey Years	Number of clusters	Number of children under 5
AO	2015	625	14,177
BF	1993, 1999, 2003, 2010	1,413	36,744
BJ	1996, 2001, 2012, 2017	1,752	31,884
BU	2010, 2016	930	20,824
CD	2007, 2013	836	27,307
CF	1994	230	2,639
CI	1994, 1998, 2012	674	12,227
CM	1991, 2004, 2011, 2018	1,619	31,279
EG	1992, 1995, 2000, 2003, 2005, 2008, 2014	7,741	75,394
ET	2000, 2005, 2010, 2016	2,313	42,173
GA	2012	334	5,911
GH	1993, 1998, 2003, 2008, 2014	2,037	17,931
GN	1999, 2005, 2012, 2018	1,289	26,588
KE	2003, 2008, 2014	2,391	32,235
KM	2012	252	3,134
LB	1986, 2007, 2013	776	16,224
LS	2004, 2009, 2014	1,199	10,269
MA	2003	480	6,030
MD	1997, 2008	860	15,932
ML	1996, 2001, 2006, 2012, 2018	1,867	52,996
MW	2000, 2004, 2010, 2015	2,655	56,688
MZ	2011	610	10,950
NG	1990, 2003, 2008, 2013, 2018	3,830	106,848
NI	1992, 1998	503	11,332
NM	2000, 2006, 2013	1,290	13,630
RW	2005, 2008, 2010, 2014	1176	21,927
SL	2008, 2013	787	17,483
SN	1993, 1997, 2005, 2010, 2012, 2014, 2015, 2016, 2017	2,572	73,084
SZ	2006	274	2,706
TD	2014	624	18,441
TG	1988, 1998, 2013	768	13,869
TZ	1999, 2010, 2015	1,259	20,520
UG	2000, 2006, 2011, 2016	1,765	37,603
ZA	2017	671	3,397
ZM	2007, 2013, 2018	1,585	29,105
ZW	1999, 2005, 2010, 2015	1,431	19,847

Notes: This table gives the sample size of children under five years old overall DHS surveys.

Table B.2: DHS surveys in regression sample across countries

Countries	Survey Years	Number of clusters	Number of children under 5
BF	1993, 1999, 2003, 2010	694	23,846
BJ	2001, 2012, 2017	62	1,911
BU	2010, 2016	317	8,280
CD	2007, 2013	82	5,092
CI	1994, 1998, 2012	196	4,838
CM	1991, 2004, 2011, 2018	90	2,513
ET	2000, 2005, 2010, 2016	100	2,956
GH	1993, 1998, 2003, 2008, 2014	1,217	12,074
GN	1999, 2005, 2012, 2018	360	11,775
KE	2003, 2008, 2014	233	4,130
LB	1986, 2007, 2013	190	7,537
LS	2004, 2009, 2014	336	2,810
MD	1997, 2008	131	3,301
ML	1996, 2001, 2006, 2012, 2018	570	19,147
MW	2000, 2004, 2010, 2015	207	6,651
NG	1990, 2003, 2008, 2013, 2018	105	3,993
NI	1992, 1998	40	1,105
NM	2000, 2006, 2013	138	2,175
RW	2005, 2008, 2010, 2014	713	14,615
SL	2008, 2013	377	13,717
SN	1993, 1997, 2005, 2010, 2012, 2014, 2015, 2016, 2017	363	10,111
TG	1988, 1998, 2013	104	2,187
TZ	1999, 2010, 2015	325	6,866
UG	2000, 2006, 2011, 2016	305	9,031
ZM	2007, 2013, 2018	364	10,966
ZW	1999, 2005, 2010, 2015	468	8,307

Notes: This table gives the sample size of children under five years old that are in our main analysis, meaning within 100 km of an industrial mine.

Tables B.3, B.4, and B.5 display the descriptive statistics of all our outcome and control variables for the sample of all individuals living within 45 km of an industrial mine, regardless of their topographic position, in the 26 countries of Sub-Saharan Africa with at least 2 waves of DHS and for heavy metals and coal mines. These descriptive figures are important to show that our analysis does not suffer from selection biases across the samples we use for our different regressions.

Table B.3: Descriptive statistics of children's outcomes

	Mean	SD	Med	Min	Max	N
Mortality rates						
12-month mortality	0.064	.244	0	0	1	189,181
24-month mortality	0.083	.275	0	0	1	139,683
Control variables						
Birth order number	3.655	2.421	3	1	18	240,431
Male	0.508	0.500	1	0	1	240,431
Anthropometric measures						
Stunting	0.319	0.466	0	0	1	137,834
Underweight	0.234	0.423	0	0	1	136,043
Wasting	0.077	0.267	0	0	1	138,222
Weight and size at birth						
Less than 2.5 kg	0.164	0.370	0	0	1	117,651
Small or very small size	0.161	0.367	0	0	1	226,796
Measured anemia level						
Any anemia	0.633	0.482	1	0	1	67,567
Illness in the last 2 weeks						
Diarrhea	0.168	0.374	0	0	1	216,097
Cough	0.260	0.439	0	0	1	214,940
Fever	0.265	0.441	0	0	1	214,913
Nutrition						
Given plain water	0.187	0.390	0	0	1	122,915
Ever breastfed	0.980	0.140	1	0	1	223,039
Months breastfed	14.788	8.917	15	0	59	156,011
Health access						
No prenatal care	0.101	0.301	0	0	1	169,268
Ever vaccinated	0.788	0.409	1	0	1	82,082
Characteristic of paired mine						
Domestic mine	0.177	0.381	0	0	1	240,431
Open-pit mine	0.676	0.468	1	0	1	103,667

Notes: We present the mortality rates at n months, conditionnally on having reached n months, for the whole sample of children living within 45 km of an industrial mine and regardless of their topographic position. The sample is restricted to the 26 Sub-Saharan countries with at least two waves of DHS and to heavy metals and coal mines.

Table B.4: Descriptive statistics of mothers' outcomes

	Mean	SD	Med	Min	Max	N
Mother's characteristics						
Mother's age	28.918	6.979	28	15	49	240,431
Years of education	3.985	4.226	3	0	22	240,332
Urban	0.287	0.452	0	0	1	236,966
Migrant	0.594	0.491	1	0	1	161,292
Access to sanitation and health facilities						
Piped water as main drinking water source	0.261	0.439	0	0	1	240,431
Has flushed toilet	0.086	0.280	0	0	1	239,773
Has electricity	0.218	0.413	0	0	1	236,692
Visited health facility in the last 12 months	0.623	0.485	1	0	1	218,053

Notes: The sample is restricted to all mothers of 0-5 years old children living within 45 km of an industrial mine in the 26 Sub-Saharan countries with at least two waves of DHS and to heavy metals and coal mines.

Table B.5: Descriptive statistics of women's outcomes

	Mean	SD	Med	Min	Max	N
Fertility behavior and health						
Ever had a child	0.736	0.441	1	0	1	330,889
Total lifetime fertility	2.890	2.785	2	0	18	330,889
Currently pregnant	0.091	0.288	0	0	1	330,744
Ever had a miscarriage	0.127	0.333	0	0	1	296,235
Any anemia	0.378	0.485	0	0	1	115,481
Placebo disease						
Any STD	0.049	0.216	0	0	1	276,924
Heard of tuberculosis	0.935	0.246	1	0	1	88,438

Notes: The sample is restricted to all women aged 15-49 living within 45 km of an industrial mine in the 26 Sub-Saharan countries with at least two waves of DHS and to heavy metals and coal mines.

B.1.2 Handwork

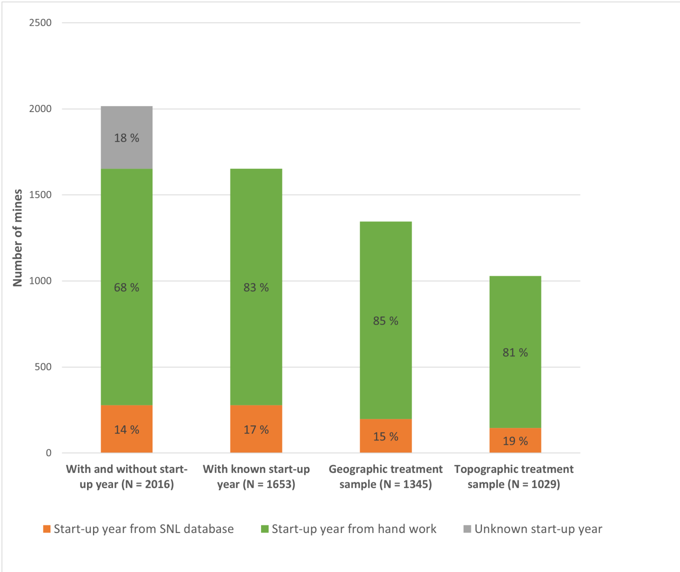
Out of the 3815 industrial mines recorded by the SNL database in Africa, 2016 were located within 100 km of a DHS cluster (with at least 2 waves of DHS). 278 had information on the opening and closing years within the database, and for the 1738 remaining mines, we searched for their years of opening [1]. The handwork consisted in reading the reports (comments and work history) available in the database and browsing through the aerial images available on the SNL platform which provided the exact GPS coordinates and main location labels. This information was corroborated with online research (press releases, mining companies' websites, specialized websites on global mining activities, etc.) as well as Google maps and Google timelapse satellite imagery. A mine opening corresponds to the beginning of the production.

The exact startup year could not be determined for 18 % of our sample (Figure B.1 Bar (1)), and these mines are dropped in our regressions. In total we hand-checked 83% of the mines located within 100 km of a DHS cluster, and for which we know their year of opening (Figure B.1 Bar (2)). Among the sample of mines with startup year, 83.2 % opened after 1981 (first year of birth within the DHS child surveys). For each of the following graphs, we study the whole sample of 2016 mines and plot the percentage of mines that were hand-checked and the percentage of mines that ends up having a startup year and are thus included in our study. We conduct this analysis on all the available mines within 100 km of a DHS cluster to be transparent on the creation of our sample compared to the original one.

The distribution across each mining site's primary commodity of production can be found in Figure B.3. Half of our sample consists of gold mining sites. Figure B.4 represents the distribution across country of location. Ownership information is available for 65 percent of our sample and the main owners are from the USA, UK, Canada, Australia, and China (Figure B.6).

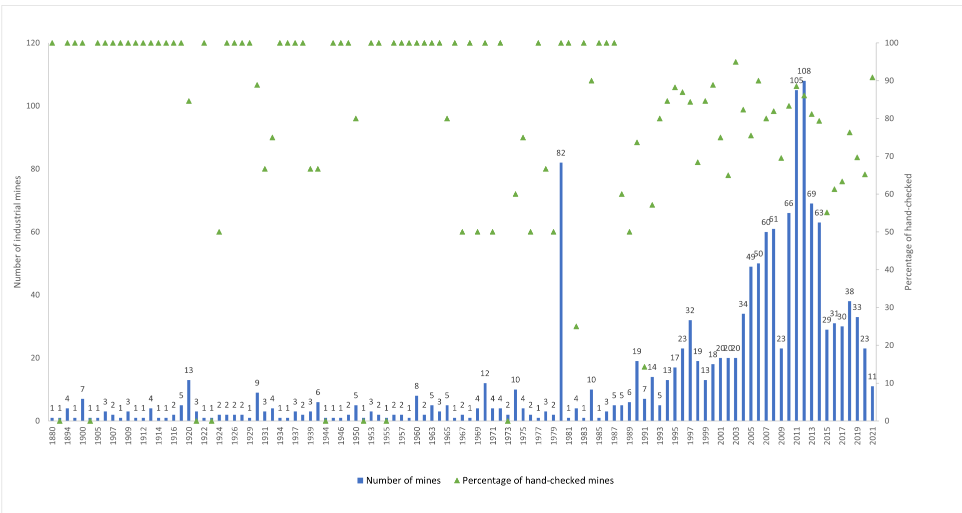
[1] We also looked at their closure date as well as their current activity status, i.e. whether the mining site looked active or inactive. However, this was an information harder to retrieve and finally we focused on the date of opening.

Figure B.1: Description of hand work and industrial mines samples



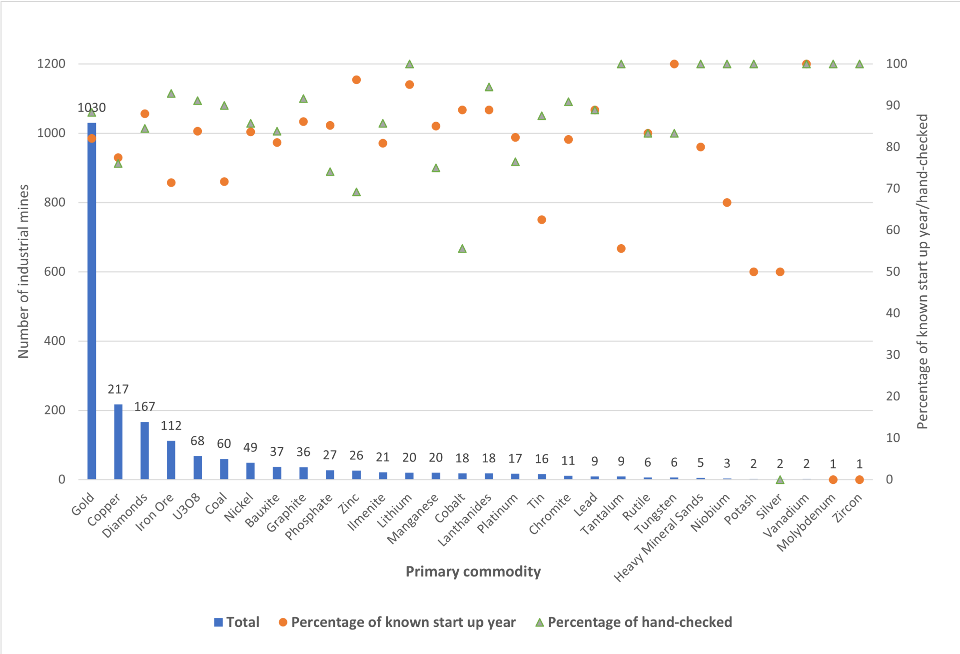
Notes: This Figure gives the number and percentage of mines for which we have retrieved the year of opening by hand. Bars (1) and (2) gives it for all the mines located within 100 km of a DHS cluster, Bar (3) for the sample associated to the replication of Benshaul-Tolonen, 2018 Section B.6. Bar (4) corresponds to the main analysis, i.e to mines that have at least one DHS cluster upstream within 100km, and one DHS cluster downstream within the three closest sub-basins (cf pairing strategy Section2.4.1.1) .
Sources: Authors' elaboration on DHS and SNL data.

Figure B.2: Mines and percentage of hand-checked across start-up years



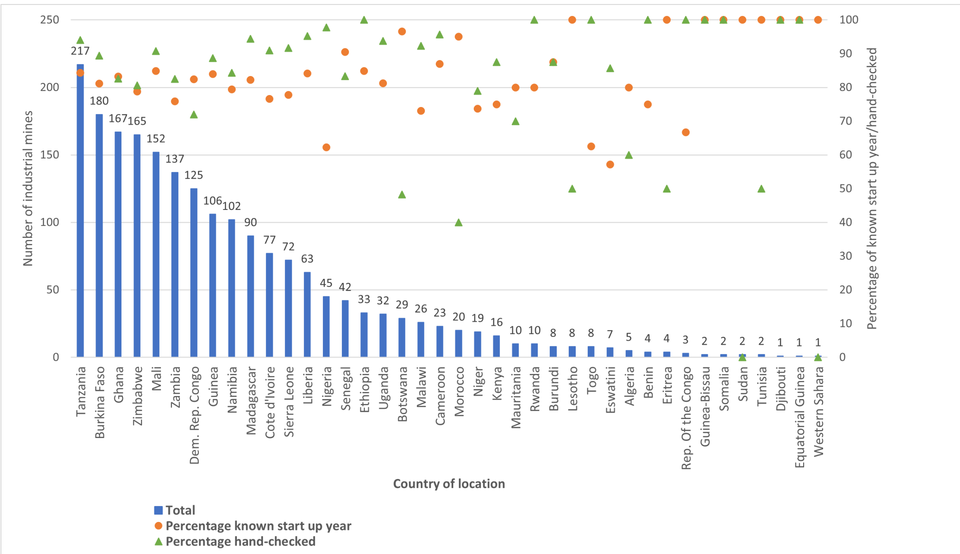
Notes: This graph displays the number of mines that opened during a specific year and the percentage of hand checked for the 2016 mines located within 100km of a DHS cluster.

Figure B.3: Mines and percentage of hand-checked across primary commodities



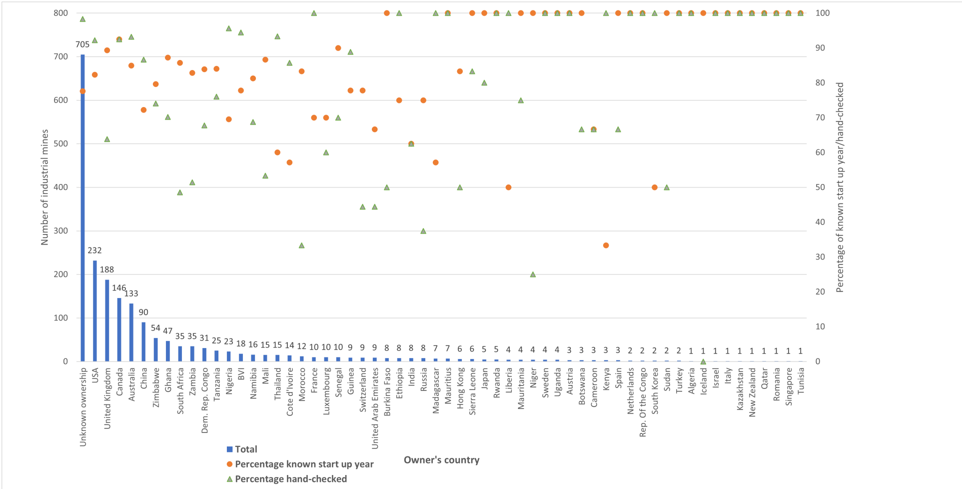
Notes: This graph gives the number of mines for each primary commodity, and the percentage of hand-checked, for the 2016 mines located wihin 100 km of a DHS cluster.

Figure B.4: Mines and percentage of hand-checked across country of location



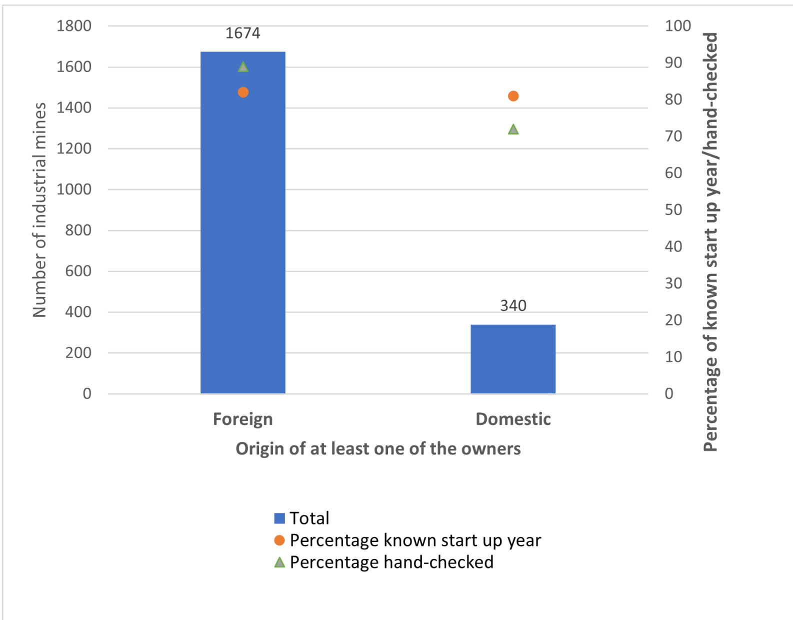
Notes: This graph gives the number of mines for each country of location, and the percentage of hand-checked, for the 2016 mines located wihin 100 km of a DHS cluster.

Figure B.5: Mines and percentage of hand-checked across owner's country



Notes: This graph gives the number of mines by owning company's registration country, and the percentage of hand-checked, for the 2016 mines located wihin 100 km of a DHS cluster.

Figure B.6: Mines across foreign and domestic ownership

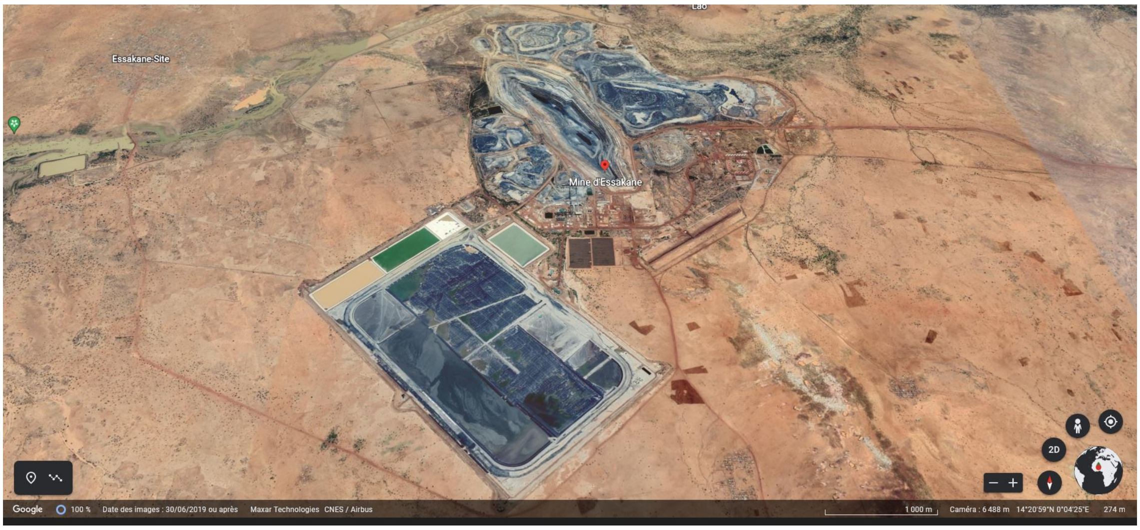


Notes: This graph gives the number of mines across domestic and foreign ownership, and the percentage of hand-checked, for the 2016 mines located wihin 100 km of a DHS cluster.

B.2 Context

B.2.1 Case study: the Essakane mine

Figure B.7: Satellite image of Essakane Mine in 2019



*Notes:*Satellite image of the Essakane Mine in 2019. Retention dams can be seen.
Sources: Google Earth.

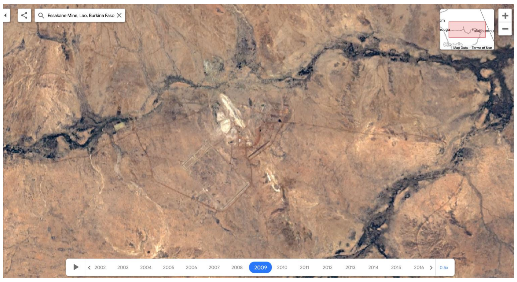
Figure B.7 shows the satellite image of a mine from our sample, the Essakane mine in 2019, and Figure B.8 shows the different stages of expansion and construction of the mine. Essakane is the most productive gold mine and the second largest in Burkina-Faso, still in activity. It is an open-pit gold mine that extends over a 100 km^2 area. It is located in the North-East of Burkina-Faso in the Oudalan province, near the Nigerian and Malian borders, and is hydrologically found in the sub-basin of Gorouol and Feildegasse rivers. It is exploited by the Burkinabé society Iamgold Essakane and belongs to the Canadian investor IamgoldInc (International African Mining Gold Corporation), who obtained the project in 2007. The installation in 2009 of the mine has forcibly displaced five villages, and 16,000 people with no choice, and the promised compensation to the communities for the displacement cost, loss of pastures and common forests have not been fulfilled (Atlas des Conflits pour la Justice Environnementale, 2022). Mining at Essakane has been shown to have negative impacts on the environment and the health of the local population, both indirectly and accidentally.

In November 2015 Drechsel, Engels, and Schäfer, 2018 has run qualitative interviews among the inhabitants of local communities of six active mining zones in Burkina-

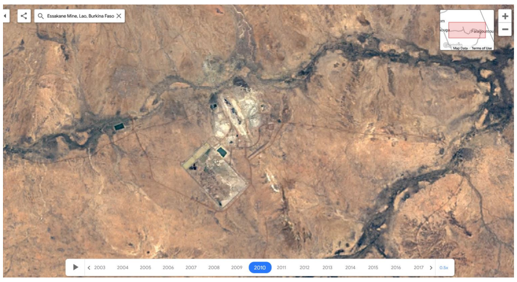
Faso, including the Essakane zone. If the local population admits the benefits of the construction of a primary school and educational establishment, of a health center, of roads and electricity, the interviewed people do not find it sufficient to outweigh the negative aspects. The mine does not display formal employment to the local population, not educated enough to undertake the required skilled-work. On the contrary, due to the loss of agricultural land and the prohibition to practice gold panning, the local population fell into unemployment and poverty, as a farmer from the Essakane area explains: *"Before the mine arrival, we had better lives, we had animals, we were rich"* (Drechsel, Engels, and Schäfer, 2018). In 2010, the tailing storage facility of the mine collapsed, which caused the death of the surrounding livestock poisoned by chemicals used in the mine, and created tensions between the local population and the operator. In 2011 a truck carrying two containers of cyanide fell into the water source of Djibo's dam and led to the death of all the fish in the dam. Tensions regarding water scarcity exist as well, the mine being water-consuming and reinforcing the vulnerability of the local population to droughts. Even if the regional government had prohibited the mine to use the village water, the national government overruled the decision, and the operator directly uses the water originally intended for the village. This led to the protestation of the local population around the mine in 2011, with no success. Finally, miners had major impacts on soil degradation, due to the construction of mining infrastructures, the multiplication of satellite pits and abandoned sterile holes devoid of gold (Porgo and Gokyay, 2016).

Environmental pollution has also degraded living conditions around the Essakane mine. Porgo and Gokyay, 2016 use water sampling and digital calipers to capture water pollution and particle measurement in the Essakane zone and survey the surrounding population to understand the related health conditions. They find high levels of particles at the Essakane site center due to transportation and mining activity, such as the work of perforation, blasting, loading, transportation of ore, crushing, grinding, and energy production based on hydrocarbons. This air pollution mainly concerns mine workers, who develop acute respiratory infections (ARI), uncurable lung diseases caused by prolonged and severe inhalation of fine particles. The drilled well water samples display abnormally high concentrations of arsenic (higher than the WHO standard), which comes from the intensive use of acids (low pH) and the liberation of trace metals. The surrounding population presents diarrhea (13%) and affections of the skin and wounds (11%), reported to be caused by lack of hygiene, and use of drugs and chemicals. The main important health impact associated with the mine is the increase of malaria (20%), as stagnant water from mining dams attracts infected mosquitoes.

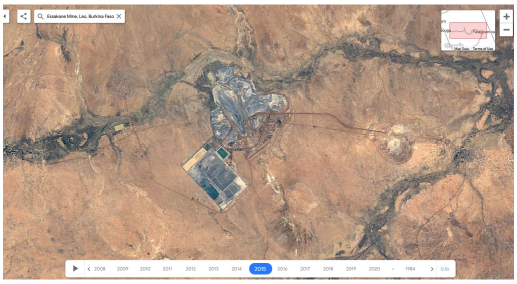
Figure B.8: Expansion of the Essakane Mine, 2005-2019.



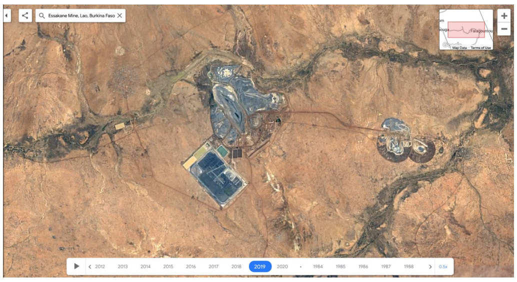
(a) 2009



(b) 2010



(c) 2015



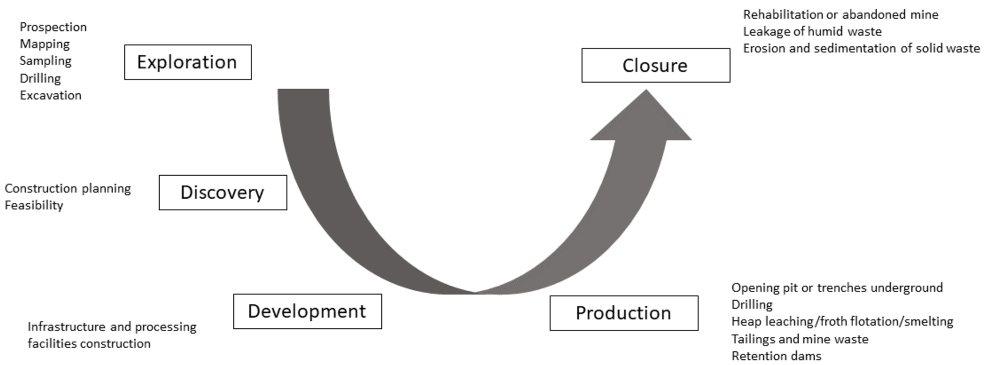
(d) 2019

Notes: The six satellite images represent the expansion of the Essakane plant, in Burkina Faso. Retention dams can be seen.
Sources: Google Earth engine Timelapse.

B.2.2 Mine life cycles and types

Figure B.9 gives the main stages of an industrial mining project, from the exploration phase to the start of the production and the closure of the mine. If it is hard to give the average length of each phase, yet the average mine lifetime is 16 years from the start of production to its closure (Figure 2.11). Figure B.10 gives the time evolution of international prices for all commodities used in our main sample.

Figure B.9: Industrial mine's life cycle



Notes: The figure schematizes the main stages of an industrial mining project .
Sources: Authors' elaboration, largely inspired by Coelho, Teixeira and Goncalves (2011)

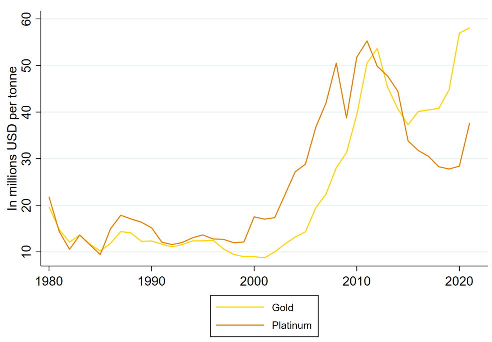
Table B.6 gives the chemical properties of each metal, including their main chemical compounds (Column 1), their density (Column 2), and displays their share in the main estimation sample (in terms of the number of mines Column (3) and Total Individual Sample (Column (4)). Heavy metals are defined according to their density as being greater than $5gcm^{-3}$ (Briffa, Sinagra, and R, 2020). If small amounts of heavy metals can be mandatory, a high and abnormal concentration of heavy metals may cause health issues due to chronic toxicity. Heavy metals released in mining activity are toxic elements that degrade the environment and human biology. This is the case as well for heavy metals released during the mining and burning of coal, which is linked to toxic heavy metals such as lead, mercury, arsenic, and nickel (Global Energy Monitor Wiki, 2021). This is the reason why the main regression analysis includes heavy metals and coal mines, to capture the negative externalities linked to the most toxic mines.

Table B.6: Metals, chemical properties and sample distribution

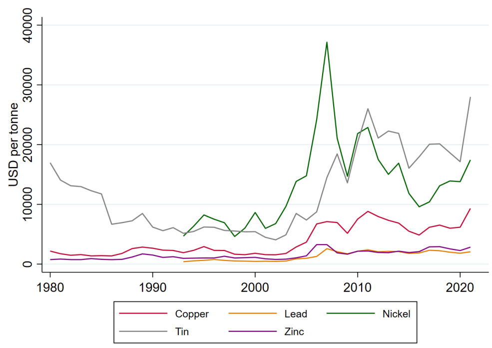
Metals	Main chemical coumpounds (1)	density (gcm^{-3}) (2)	Nb. Mines (3)	Total Individual Sample (%) (4)
Heavy Metals				
Gold	Gold	19.3	581	41.88
Copper	Copper	8.96	89	5.03
Iron ore	Iron	7.87	54	8.72
U308	Uranium	8.39	36	1.60
Nickel	Nickel	8.9	25	5.06
Platinum	Platinum	21.45	21	0.43
Zinc	Zinc	7.14	19	2.46
Chromite	Iron Chromium	[4.5,5.09]	16	0.57
Ilmenite	titanium	4.6	14	3.67
Lanthanides	Lanthane(57) Lutecium(71)	[6.1,9.8]	13	1.95
Manganese	Manganese	7.21	12	0.62
Tin	Tin	[5.7;7.26]	10	4.87
Cobalt	Cobalt	8.9	7	0.56
Tungsten	Tugsten	19.25	6	1.06
Tantalum	Tantalum	16.69	5	0.15
Vanadium	Vanadium	6.12	4	0.04
Niobium	Niobium	8.57	3	0.39
Heavy Mineral Sands	Zirconium Titanium Tungsten Thorum	[4.5,17.6]	3	0.16
Silver	Silver	10.49	1	0.00
Lead	Lead	11.29	1	0.06
Non-Heavy Metals				
Diamonds	Carbon	3.5	115	11.73
Coal	Carbon Mercury? Arsenic?	1.35	55	2.19
Bauxite	Aluminium	2.79	23	1.94
Graphite	Carbon	2.26	21	0.82
Phosphate	Phosphate	1.83	14	2.78
Lithium	Lithium	0.53	14	0.80
Rutile	titanium	4.23	2	0.29
Potash(Salt)	Potassium	0.89	1	0.17

Notes: This table gives for each metals the main chemical coumpounds (Column (1)) and their density (Column (2)). Columns (3) gives the number of mines within 100 km of a DHS cluster for which the metal is the main primary commodity, and Column (4) the percentage of children under 5 associated to these mines.

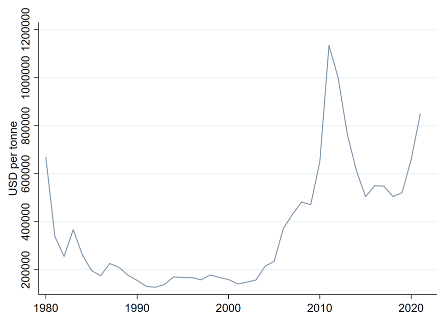
Figure B.10: Time evolution of international commodity prices



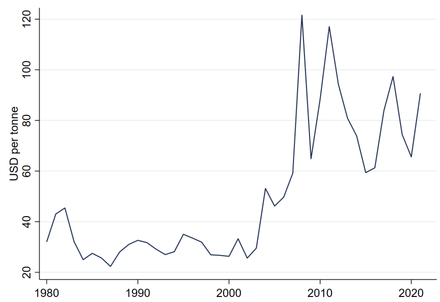
(a) Gold and Platinum



(b) Other metals



(c) Silver



(d) Coal

Notes: These Figures plot the evolution of metal prices from 1980 to 2020.
Sources: Author's elaboration from SNL data and World Bank pink sheet data.

B.3 Empirical Strategy - Descriptive statistics

Table B.7 gives the balance table for some household and mother characteristics. This is a descriptive table that accounts neither for controls nor fixed effects. Table B.8 gives the effect of being downstream of a mine for the same variables. We observe no statistical difference in terms of access to piped water, and electricity, the age, and years of education of the mother. However, Table B.8 shows that the proportion of urban households increases by 13 p.p once a mine has opened in downstrea areas, compared to upstream areas. The proportion of mothers that are migrants also increases by 8 p.p.. These results suggest that the in-migrants coming after the mine opening, seeking jobs, for instance, settle down in downstream areas that become more urban. It suggests that the miner villages are located downstream of the mine. This gives the necessity to control for migration and verify that this is not driving our results (cf Section 2.6.2).

We plot in Figure B.11 the distribution of mines opened within 100 km upstream or within the 3 closest sub-basins downstream during a child's birthyear, so as to see which countries gather the highest number of industrial mining activity in the vicinity of surveyed households over 1986-2018. Ghana, Zimbabwe, Tanzania, Zambia, Guinea and Sierra Leone have the highest density of open mines nearby DHS clusters, while Benin, Burundi, Cameroon, Lesotho and Niger have the lowest number of open mining sites. This figure also represents the variation in the number of mines that opened between the first and last year of surveys for each country. We can thus grasp the context of change in industrial mining activity over our period of interest. Ghana, Tanzania, Guinea, Mali, and Burkina-Faso witnessed the highest number of mine openings between 1986 and 2018.

Figures B.12, B.13 and B.14 give the spatial variation of the infant mortality outcomes and the mine openings for the sample restricted to our main analysis.

Table B.7: Balance Table - Double Difference with Topographic Treatment - Descriptive Statistics

	Before Mine Opening					After Mine Opening					Within Up.	Within Dwn.	Within
	Upstream		Downstream		Diff	Upstream		Downstream.		Diff			
	N	Mean /(SD)	N	Mean /(SD)	(4-2) /(p.v)	N	Mean /(SD)	N	Mean /(SD)	(9-7) /(p.v)	(7-2) /(p.v)	(9-4) /(p.v)	(12-11) /(p.v)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Household Charateristics													
% Urban Household													
All	29,399	0.33	9,835	0.175	-0.155	16,285	0.385	6,174	0.291	-0.094	0.055	0.116	0.061
		(0.47)		(0.38)	(0)		(0.487)		(0.454)	(0)	(0)	(0)	(0)
Mines	244		237			190		193					
Has piped water													
All	29,399	0.307	9,835	0.193	-0.115	16,285	0.365	6,174	0.27	-0.095	0.057	0.077	0.019
		(0.461)		(0.395)	(0)		(0.481)		(0.444)	(0)	(0)	(0)	(0.002)
Has electricity													
All	29,399	0.211	9,835	0.14	-0.071	16,285	0.356	6,174	0.226	-0.13	0.145	0.086	-0.059
		(0.408)		(0.347)	(0)		(0.479)		(0.418)	(0)	(0)	(0)	(0)
Mother Charateristics													
Age													
All	29,399	29.106	9,835	29.187	0.081	16,285	28.779	6,174	28.818	0.039	-0.328	-0.369	-0.042
		(7.065)		(7.039)	(0.325)		(6.847)		(6.986)	(0.707)	(0)	(0.001)	(0.764)
Years of Education													
All	29,399	2.406	9,835	2.91	0.504	16,285	4.297	6,174	4.851	0.554	1.891	1.941	0.05
		(3.6)		(3.741)	(0)		(4.417)		(4.2)	(0)	(0)	(0)	(0.001)
% Migrant													
All	18,509	0.615	6,593	0.578	-0.037	9,773	0.597	3,962	0.589	-0.007	-0.019	0.011	0.029
		(0.487)		(0.494)	(0)		(0.491)		(0.492)	(0.421)	(0.002)	(0.278)	(0.094)

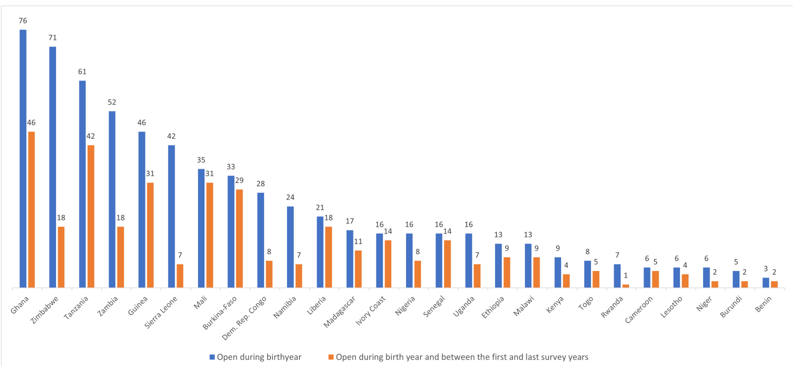
Notes: Standard errors and p-values in parentheses.

Table B.8: Average effects of mine opening on control variables

	Household's characteristics			Mother characteristics		
	% urban households	Has piped water	Has electricity	Age	Yers of education	% migrant
	(1)	(2)	(3)	(4)	(5)	(6)
Downstream×Open	0.131***	0.0205	-0.00100	0.0426	-0.0121	0.0881***
	[0.0422]	[0.0277]	[0.0200]	[0.162]	[0.144]	[0.0314]
Downstream	-0.0142	-0.0411*	0.00433	-0.0835	-0.119	-0.0327
	[0.0307]	[0.0239]	[0.0143]	[0.132]	[0.108]	[0.0272]
Open	-0.0455	-0.00637	-0.0104	-0.136	-0.126	-0.0432*
	[0.0293]	[0.0209]	[0.0181]	[0.136]	[0.112]	[0.0233]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Nb open mines	Yes	Yes	Yes	Yes	Yes	Yes
Birthmonth FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-birthyear FE	Yes	Yes	Yes	Yes	Yes	Yes
Mine SB FE	Yes	Yes	Yes	Yes	Yes	Yes
Mine SB-birthyear trend	Yes	Yes	Yes	Yes	Yes	Yes
Commodity FE	Yes	Yes	Yes	Yes	Yes	Yes
N	61690	61690	61179	61690	61690	38834
R2	0.608	0.489	0.547	0.681	0.463	0.185

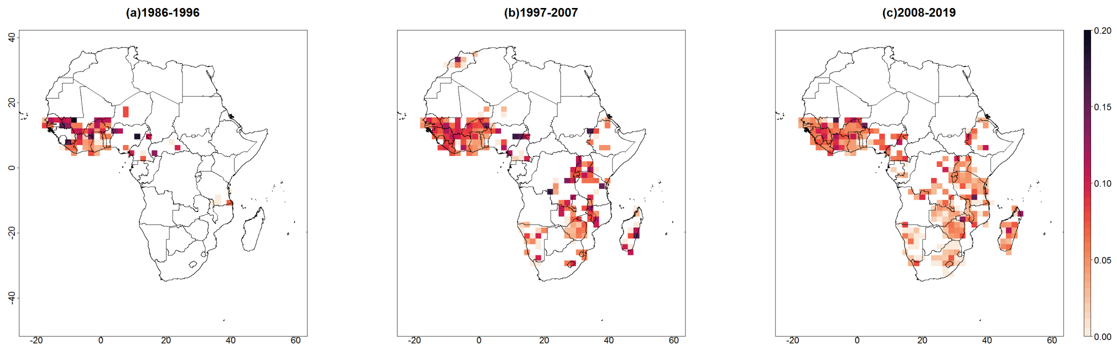
Notes: Standard errors clustered at the DHS village level, $^{*}p < 0.1$,** $p < 0.05$,*** $p < 0.01$. The variables Downstream and Opened are dummies which indicate whether the individual lives in a village downstream of at least one mining site, and whether the site opened before the birth year of the child. Each village DHS is paired to only one mining site, so that each individual appears only once in the regression. Other variables are control variables. The sample focuses on heavy metal mines.

Figure B.11: Number of open mines during the birth year and between first and last wave



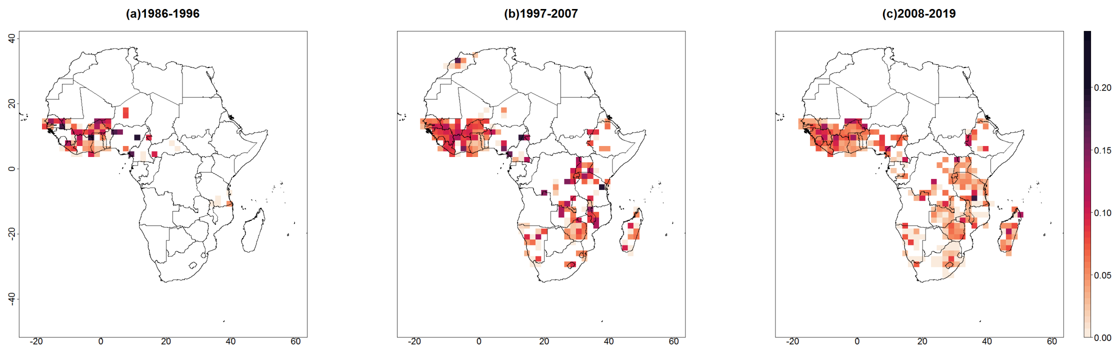
Notes: The figure represents the number of mines that were opened during the birth year of children located within our topographic treatment sample by country, and the number of mines that were opened during the birth year of children located within our topographic treatment sample and which opened between the first and last year of survey for each country.
Sources: Authors' elaboration on SNL and DHS data.

Figure B.12: Spatial variation of 12-month mortality rates per period - Restricted Sample



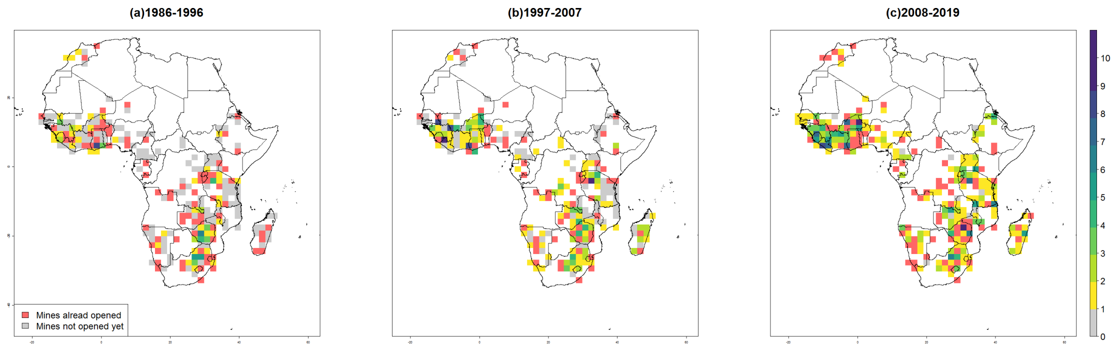
Notes : The figures represent the means of 12-month mortality rates averaged at the grid level over (a) 1986-1996, (b) 1997-2008, and (c) 2008-2019, for the sample of the main analysis. The mortality rates are estimated without the children that did not reach 12 months at the time of the survey.
Sources: Authors' elaboration on DHS data.

Figure B.13: Spatial variation of 24 months mortality rates per period - Restricted Sample



Notes: The figures represent the means of 24-month mortality rates averaged at the grid level over (a) 1986-1996, (b) 1997-2008, and (c) 2008-2019, for the sample from the main analysis. The mortality rates are estimated without the children that did not reach 24 months at the time of the survey.
Sources: Authors' elaboration on DHS data.

Figure B.14: Spatial variation of mine opening per period - Restricted Sample



Notes: The figures represent the number of mines that opened during the periods over the grid area (160 km on average). A red grid cell represents an area where no mine opened over the period, but where at least one mine has opened before the period. A grey cell represents an area where no mine opened over the period, but where at least one mine will open in the future.
Sources: Authors' elaboration on SNL data.

B.4 Heterogeneity

Table B.9: Effects of industrial mining activity, across sub-regions

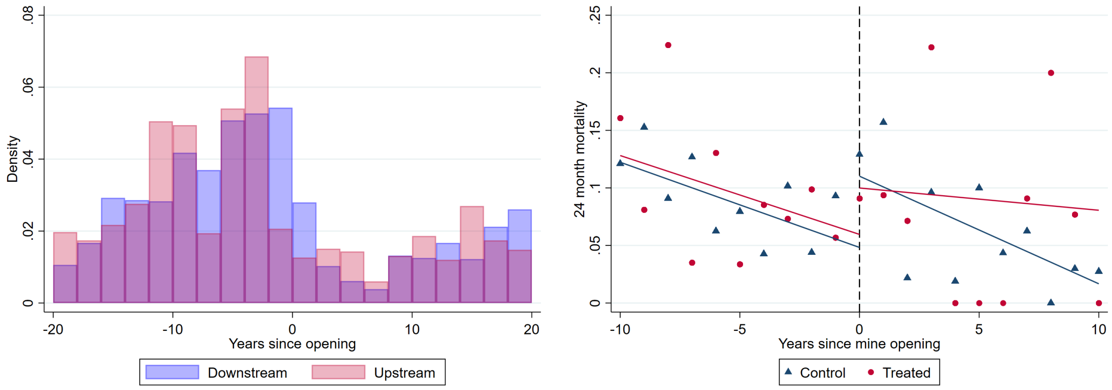
	Mortality under 24 months		
	Western Africa	Eastern Africa	Central and Southern Africa
	(1)	(2)	(3)
Downstream×Open	0.0443**	0.0292*	-0.0304
	[0.0176]	[0.0154]	[0.0225]
Downstream	-0.0153	-0.0369***	0.0538**
	[0.00946]	[0.0116]	[0.0227]
Open	0.00523	-0.0137	0.0120
	[0.0133]	[0.0157]	[0.00857]
Controls	Yes	Yes	Yes
Birthmonth FE	Yes	Yes	Yes
Country-birthyear FE	Yes	Yes	Yes
Mine SB FE	Yes	Yes	Yes
Mine SB-birthyear trend	Yes	Yes	Yes
Commodity FE	Yes	Yes	Yes
N	21,006	13,484	20,014
R2	0.0521	0.0457	0.0238
Outcome Mean	0.0981	0.0712	0.0836

Notes: Standard errors clustered at the DHS village level, $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

B.5 Dynamic effects - pre trends and event study

In this section, we display the appendix figures associated with Section 2.8. It gives the same analysis as in the main Section restricted to the balanced sample. Figure B.15 plots the parallel trends, while Figure B.16 plots the event study for the balanced sample.

Figure B.15: Linear trends of 24 month mortality - Balanced Sample

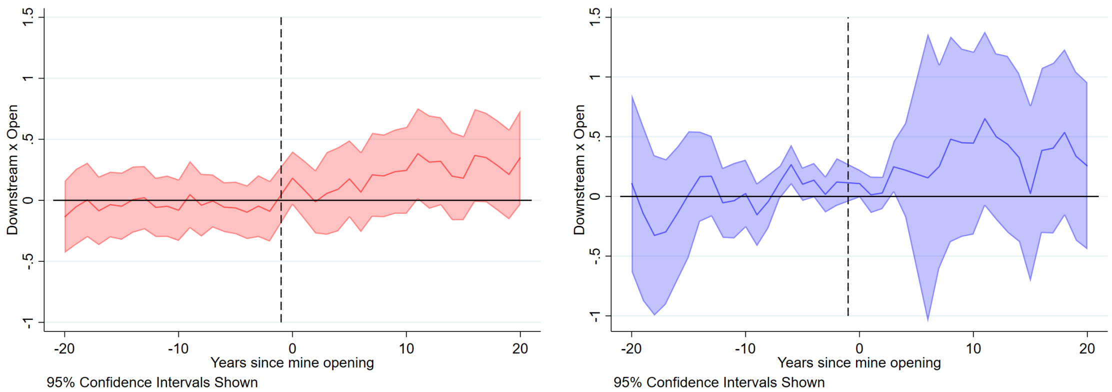


(a) Balanced sample

(b) Balanced sample

Notes: Figure (a) gives the distribution of the number of observations per opening year. Figure (b) plots the trends of the 24-month mortality rates according to the year of opening. The figures are made for the balanced sample and include neither control variables nor fixed effects.

Figure B.16: Event study - dynamic effect of mine opening on under 24 months mortality - Balanced Sample



(a) Balanced sample - upstream

(b) Balanced sample - downstream

Notes: Figure (a) plots the event study for the upstream villages, while Figure (b) plots the event study for the downstream villages for the balanced sample. Controls and fixed effects are the same as in the main analysis (column (4) Table 2.2)

B.5.1 Sensitivity analysis

Table B.10 shows that our result is stable when controlling for a dummy indicating whether the mine opening year has been found by hand or was given directly in the SNL database (column (2)).

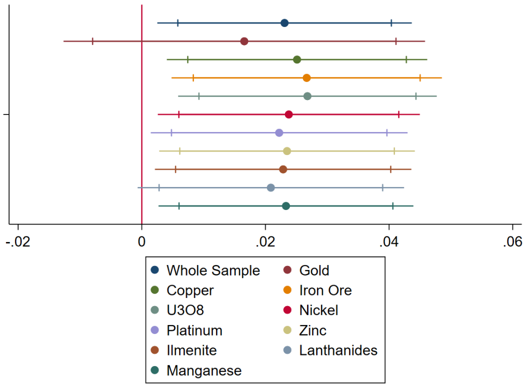
Table B.10: Effects of industrial mining opening, controlling for handwork.

Outcome	Mortality under 24 months			
Specification	Main result (1)	Adding control (2)	SNL database (3)	Handwork (4)
Downstream × Open	0.0218**	0.0218**	0.0222	0.0344**
	[0.0108]	[0.0108]	[0.0351]	[0.0138]
Dummy handwork		0.0254		
		[0.0335]		
Downstream	-0.0211***	-0.0212***	-0.0167	-0.0316***
	[0.00739]	[0.00739]	[0.0246]	[0.00844]
Open	-0.00496	-0.00489	-0.0194	-0.00973
	[0.0101]	[0.0101]	[0.0476]	[0.0126]
Controls	Yes	Yes	Yes	Yes
Birthmonth FE	Yes	Yes	Yes	Yes
Country-birthyear FE	Yes	Yes	Yes	Yes
Mine SB FE	Yes	Yes	Yes	Yes
Mine SB-birthyear trend	Yes	Yes	Yes	Yes
Commodity FE	Yes	Yes	Yes	Yes
N	35,638	35,638	6,702	22,017
R2	0.0511	0.0511	0.0615	0.0641
Outcome mean	0.0873	0.0873	0.0727	0.0954

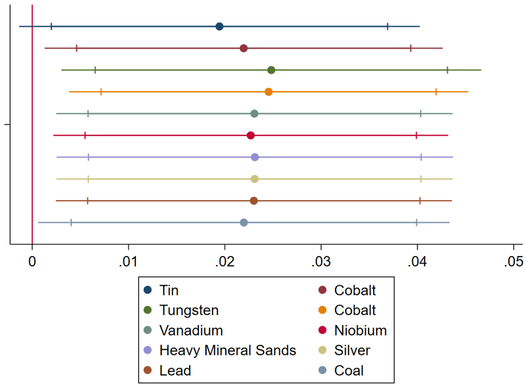
Notes: Standard errors clustered at the DHS village level, $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$. Columns (1) and (2) rely on the same sample and controls as Table 2.2 Column 2. Column (2) controls for the hand-work, while Columns (3) and (4) split the samples.

Figure B.17 displays the DiD estimators for different regression with restricted samples, meaning while dropping each metal one by one, using the sample for the 24-month mortality rates, and the heavy metals and coal mine sample. This suggests that our main results are not driven by a specific metal. Accordingly, Figure B.18, plots the DiD estimators while dropping countries one by one and show that our analysis is not driven by a particular country.

Figure B.17: Regression results when dropping commodities one by one

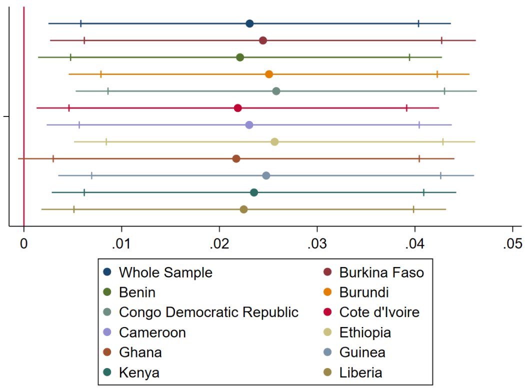


(a)

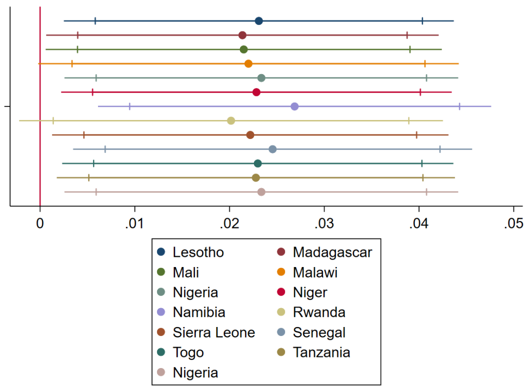


(b)

Figure B.18: Regression results when dropping countries one by one



(a)



(b)

Sources: Authors' elaboration on DHS and SNL data.

B.6 Geographic Treatment

In this section, we propose to replicate the empirical strategy of Benshaul-Tolonen, 2018, who finds that a mine opening is associated with a 5.5 p.p decrease in the 12-month mortality. The identification strategy relies on a treatment based on proximity, comparing individuals living nearby to those living further from an industrial mine. In this estimation, geographical proximity is used as a proxy exposure to industrial mining activity, including both positive and negative externalities, such as exposure to mining pollution.

The identification strategy relies on a DiD strategy.It compares within each district, the infant mortality in areas within 10 km of a mine deposit (treatment group) to infant mortality in DHS clusters further away from a mine deposit (10-100km, control group), before and after the opening of the mine deposit. As the strategy is a two-way fixed-effects, including a district-fixed effect, the comparison is made within each district. The identification can be formally written as:

$$\begin{aligned} Death_{i,v,c,m,SB} =& \alpha_0 + \alpha_1 Opened_{birthyear,i,v} + \alpha_2 MineDeposit_{[0;10km]v} \\ & + \alpha_3 Opened_{birthyear,i,v} \times MineDeposit_{[0;10km]v} + \alpha_4 X_i \\ & \gamma_d + \gamma_{d-bthtrend} + \gamma_{c,birthyear} + \epsilon_v \end{aligned} \tag{B.1}$$

With $Death_{i,v,c,district}$ a dummy equals to one if child i from DHS village v (within district d) of country c, has reached the n^{th} month and has died (n being 12 for the 12-month mortality, 24 and so on). $Opened_{birthyear,i,v}$ is a dummy equal to 1 if at least one mine located within 10 km for the treatment group, or within 100 km for the control group, has opened before child i's year of birth (this cohort comparison can be considered here as a source of tripe difference).$MineDeposit_{[0;10km]v}$ is a dummy of proximity (1 if village DHS v is within 10 km of a mine deposit, 0 if it is within 10-100km), X_i a vector of child/mother level controls (mother's age and age square, years of education, urban status). Finally, γ_d is a district fixed effect, $\gamma_{d-bthtrend}$ a district birthyear linear trend, and $\gamma_{c,birthyear}$ a country-birthyear fixed effect. Please note that the matching of DHS clusters to mines relies on the same strategy as in Benshaul-Tolonen, 2018, and assigns a DHS cluster to the closest mine (without consideration of its opening status). Thanks to this pairing, if a DHS cluster is both in the treatment and control groups of two different mines (i.e within 10km of mine A and within 10-100km from Mine B), we assign it mechanically to the treatment group (so linked to mine A). This creates bias explained in Section 2.2.3, which explains the choice for a district fixed effects and reduces the noise linked to DHS random displacements.

Firstly, we give our estimators from the exact replication of Benshaul-Tolonen, 2018 results, using our own calculation, and find similar impacts (Tables B.11 and B.12). Second, we propose the replication of the results using our extended sample, including more countries, DHS waves, types of mines, and mines hand-checked, and show the results from Benshaul-Tolonen, 2018 are mainly determined by the choice of countries.

B.6.1 Exact replication of Benshaul-Tolonen, 2018

The geographic treatment proxies exposure to mining activity using the distance to the site and follows partly the analysis from Benshaul-Tolonen, 2018, and finds contradictory impacts on infant mortality. To understand better how our results can be compared to the literature, we propose in this section a replication exercise of the main result from Benshaul-Tolonen, 2018[2].

For this replication analysis, we used the same mines and DHS survey rounds as Benshaul-Tolonen, 2018. Please note that we have few differences in terms of the whole sample, as Benshaul-Tolonen, 2018 counts 37,365 children *vs* 41,902 for us, that might be explained by the way we calculated the 100km buffer distance [4]. A main difference between our paper and Benshaul-Tolonen, 2018 is the independent variable, as we use as a shock the opening of the industrial mine whereas Benshaul-Tolonen, 2018 uses the activity status based on production data given by the SNL product. This accounts for interim years, between the opening and final closing of the mine, where the production has been on hold. In this section, we replicate this exact same variable.

Table B.11 displays the replication of the main results from Benshaul-Tolonen, 2018 Table 2. We find that a mine opening within 10 kilometers is associated with a 4.7

[2]Please note that a first difference between the two analyses is the sample, as Benshaul-Tolonen, 2018 uses 43 gold mines that match with 31 DHS surveys from nine countries (Burkina Faso, Cote D'Ivoire, Ethiopia, Ghana, Guinea, Mali, Senegal, Tanzania, and DRC [3]). However, when pairing the DHS cluster to the same industrial mining sites from Benshaul-Tolonen, 2018, no DHS from DRC remained. In the end, the analysis is only on the 8 first countries, in accordance with Figure A6 from Appendix of Benshaul-Tolonen, 2018), for a whole sample of 1-year-old children of 48,151.

[4]In the replication codes of Benshaul-Tolonen, 2018, one can observe that the distance has been determined using the Stata command *nearstat* [...] dband(0,25) which relies on different projections (not specified) as ours from *R* libraries, explaining the small sample differences

Table B.11: Replication Benshaul-Tolonen, 2018 Main Results

Dependent variable	Infant mortality first 12 months			
Sample :	Children (1)	Children drop spillover (2)	Boys (3)	Girls (4)
Industrial × mine deposit (at birth)	-0.0472**	-0.0474*	-0.0289	-0.0781***
	[0.0230]	[0.0260]	[0.0320]	[0.0301]
Mine deposit [0;10km]	0.0392**	0.0546***	0.0517**	0.0561**
	[0.0169]	[0.0195]	[0.0229]	[0.0231]
Mother's age	-0.0145***	-0.0154***	-0.0155***	-0.0152***
	[0.00190]	[0.00210]	[0.00274]	[0.00297]
Mothers's age × Mother's age	0.000222***	0.000236***	0.000223***	0.000245***
	[0.0000302]	[0.0000335]	[0.0000435]	[0.0000475]
Years edu.	-0.00214***	-0.00230***	-0.00272***	-0.00184**
	[0.000489]	[0.000547]	[0.000827]	[0.000760]
Urban$_h h$	-0.0125***	-0.0120**	-0.00710	-0.0183***
	[0.00428]	[0.00480]	[0.00687]	[0.00659]
Birth-month FE	Yes	Yes	Yes	Yes
Country birth year FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
District BirthYear trend	Yes	Yes	Yes	Yes
Drop10-30 km away	No	Yes	Yes	Yes
Drop investment phase	No	Yes	Yes	Yes
Mean of outcome	0.102	0.104	0.110	0.099
Mean(treatment, pre-treatment)	0.154	0.163	0.173	0.153
Observations	41902	34228	17534	16694

Notes: $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$. Standard errors clustered a DHS cluster level. The variables Mine deposit [0;10km] and Industrial × mine deposit (at birth) are a replication from Benshaul-Tolonen, 2018 and indicate whether the child is born within 10km of at least one industrial mining site and whether this site was active at the time of the birth. All regressions control for mother's age, age square, mother's education and whether the household is urban, for district, birth month and country-birth year. The main outcome is infant mortality in the 12 months since birth. Columns 2-5 drop the two years preceding th opening year, defined as investment phase in Benshaul-Tolonen, 2018 and the individuals living within 10-30km of the closest industrial mine. Mean (treatment, pre-treatment) is the sample for the treatment group before the mine were active.
dummies which indicate whether the individual lives in a village within at least one mining site, and whether the site opened before the birth year of the child. Each village DHS is paired to the closest opened mining site, so that each individual appears only once in the regression. Other variables are control variables.

percentage point decrease in infant mortality rates, while Benshaul-Tolonen, 2018 found 5.5 p.p. Our results is slightly less significant than from Benshaul-Tolonen, 2018, and we identify a different impact according to gender, with a significant reduction of girl mortality rates of 7 p.p *vs* a non-significant reduction for boys, which differs from the previous study. To follow Benshaul-Tolonen, 2018 example, we excluded in Columns 2-5 from Table B.11 individuals born within 10-30 kilometers of the closest industrial mining site and those born the two years before the opening of a mine, which is a proxy for the investment phase according to Benshaul-Tolonen, 2018.

Please note that in accordance with the descriptive statistics from Benshaul-Tolonen, 2018 we have in the sample a very high mean of 12-month mortality rates (from 10 to 17 % according to the groups). These are relatively high numbers, that do not match with World Bank data. This is because Benshaul-Tolonen, 2018 drops all the individuals that are still alive but did not reach the age of 12 months yet to measure the mortality, in order to avoid growing mechanically the mortality rates of these cohorts [5]. For replication purposes, we propose to keep this variable and correct this in Table B.12, where we observe average mortality rates around 7%. Figure B.19 replicates the Figure A6 from Benshaul-Tolonen, 2018, which shows the coefficient estimates of the main regression for *industrial* $\times$ *mine deposit* on infant mortality, each regression excluding the sample from one country as indicated by the country name. The Figure B.19 shows that results are highly sensitive to the presence of Mali, Senegal, and Ghana in the sample (whereas they do not consist for the majority of the sample (5847, 1098 and 5595 respectively).

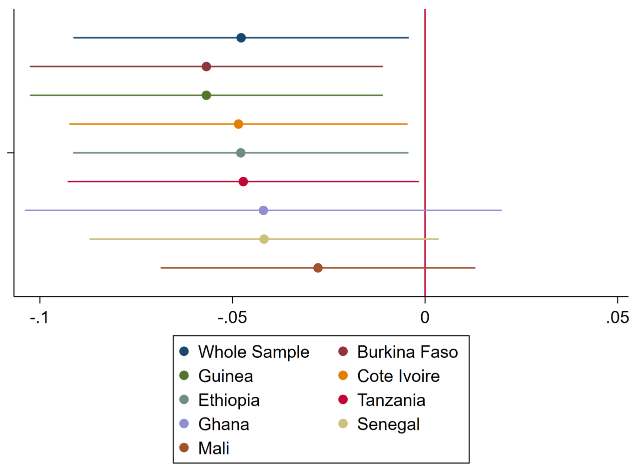
[5] We can read in the codes that if the living individuals were dropped, the children that died before their 12 months from these specific cohorts were not dropped: mechanically, the mortality rates for all the years preceding the survey rounds are 100 %, which explain the high mean of outcomes.

Table B.12: Replication Benshaul-Tolonen, 2018 Main Results

Dependent variable	Infant mortality first 12 months corrected			
Sample :	Children (1)	Children drop spillover (2)	Boys (3)	Girls (4)
Industrial × mine deposit (at birth)	-0.0494**	-0.0471*	-0.0439	-0.0631**
	[0.0229]	[0.0244]	[0.0317]	[0.0298]
Mine deposit [0;10km]	0.0394**	0.0587***	0.0682***	0.0513**
	[0.0179]	[0.0198]	[0.0255]	[0.0235]
Mother's age	-0.0118***	-0.0123***	-0.0120***	-0.0124***
	[0.00175]	[0.00196]	[0.00256]	[0.00283]
Mothers's age × Mother's age	0.000182***	0.000189***	0.000172***	0.000203***
	[0.0000279]	[0.0000312]	[0.0000405]	[0.0000452]
Years edu.	-0.00143***	-0.00152***	-0.00204***	-0.000803
	[0.000455]	[0.000510]	[0.000772]	[0.000715]
$\text{Urban}_h h$	-0.0106***	-0.0113***	-0.00501	-0.0196***
	[0.00384]	[0.00436]	[0.00661]	[0.00600]
Birth-month FE	Yes	Yes	Yes	Yes
Country birth year FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
District BirthYear trend	Yes	Yes	Yes	Yes
Drop10-30 km away	No	Yes	Yes	Yes
Drop investment phase	No	Yes	Yes	Yes
Mean of outcome	0.079	0.080	0.083	0.077
Mean(treatment, pre-treatment)	0.109	0.118	0.120	0.115
Observations	40386	32873	16823	16050

Notes: $^*p < 0.1,^{**} p < 0.05,^{***} p < 0.01$. Standard errors clustered a DHS cluster level. The variables Mine deposit [0;10km] and Industrial × mine deposit (at birth) are a replication from Benshaul-Tolonen, 2018 and indicate whether the child is born within 10km of at least one industrial mining site and whether this site was active at the time of the birth. All regressions control for mother's age, age square, mother's education and whether the household is urban, for district, birth month and country-birth year. The main outcome is infant mortality in the 12 months since birth. Columns 2-5 drop the two years preceding th opening year, defined as investment phase in Benshaul-Tolonen, 2018 and the individuals living within 10-30km of the closest industrial mine. Mean (treatment, pre-treatment) is the sample for the treatment group before the mine were active.
dummies which indicate whether the individual lives in a village within at least one mining site, and whether the site opened before the birth year of the child. Each village DHS is paired to the closest opened mining site, so that each individual appears only once in the regression. Other variables are control variables.

Figure B.19: Regression results when dropping one country at a time



Sources: Authors' elaboration on DHS and SNL data.

B.6.1.1 Replication using an extended sample

Table B.13 and Table B.14 display the results, replicating Benshaul-Tolonen, 2018 estimation strategy, with our overall sample of mines and DHS surveys. Table B.13 focuses on the 12-month mortality rates and shows that we find a significant reduction of infant mortality by 0.8 p.p only when controlling for migrants (column (2)). Columns (1) and (2) display the results for the whole sample, while columns (3) and (4) while dropping the spillovers effects (areas between [10-30]km and the two years before the mine opening, which represents the investment phase in Benshaul-Tolonen, 2018). Columns (5) and (6) replicate the analysis for the male sample while columns (7) and (8) for the girls.

Table B.14 displays the result for the 12-month mortality rates (Columns (1)-(4)) and 24 months mortality rates (Columns (5)-(8)) and compares the estimators when not including the migrant control variable (Columns (1), (3) (5) and (7)), and when including it (Columns ((2),(4),(6) and (8)). We also display the estimators for the restricted sample of rural areas (Columns (3),(4), (7), and (8)). Again, we observe a significant reduction of 12 months mortality rates in Column (2), i.e for the overall sample while controlling for migrants, and find no results otherwise. This absence of results suggests that using proximity as a proxy for exposure to mining activity averages contradictory effects, including both positive and negative externalities, and shows the importance of our main estimation strategy which relies on topographic position.

Figure B.20 plots the linear trends of the 12 and 24 months mortality rates for the geographic treatment, including our overall mine and DHS sample. We see that the linear trends assumption seems to be validated for the 24-month mortality, but not for the 12-month mortality rates.

Table B.13: Geographic Treatment

	Infant mortality first 12 months							
	All		Drop spillover		Boys		Girls	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Indus. × deposit	-0.00259	-0.00823**	-0.00189	-0.00575	0.00250	-0.00302	-0.00513	-0.00807
	[0.00329]	[0.00418]	[0.00407]	[0.00537]	[0.00570]	[0.00764]	[0.00522]	[0.00674]
Deposit	0.00130	0.00374	0.00103	-0.000128	0.00632	0.0113	-0.00366	-0.0109*
	[0.00252]	[0.00317]	[0.00392]	[0.00500]	[0.00546]	[0.00708]	[0.00513]	[0.00628]
Birth order	0.00389***	0.00315***	0.00360***	0.00320***	0.00349***	0.00304***	0.00382***	0.00356***
	[0.000345]	[0.000428]	[0.000423]	[0.000518]	[0.000606]	[0.000742]	[0.000549]	[0.000671]
Mother's age	-0.0105***	-0.0107***	-0.0102***	-0.0110***	-0.0116***	-0.0128***	-0.00884***	-0.00924***
	[0.000541]	[0.000668]	[0.000669]	[0.000824]	[0.000953]	[0.00119]	[0.000903]	[0.00111]
agesquare	0.000147***	0.000151***	0.000142***	0.000156***	0.000163***	0.000183***	0.000121***	0.000127***
	[0.00000853]	[0.0000106]	[0.0000106]	[0.0000131]	[0.0000150]	[0.0000187]	[0.0000142]	[0.0000175]
Years edu.	-0.000877***	-0.00103***	-0.000874***	-0.00101***	-0.000881***	-0.00103***	-0.000873***	-0.000968***
	[0.000135]	[0.000167]	[0.000164]	[0.000200]	[0.000238]	[0.000290]	[0.000216]	[0.000265]
Urban	-0.00610***	-0.00725***	-0.00708***	-0.00906***	-0.00825***	-0.0111***	-0.00563**	-0.00622**
	[0.00135]	[0.00172]	[0.00169]	[0.00214]	[0.00235]	[0.00297]	[0.00227]	[0.00289]
migrant		0.00543***		0.00509***		0.00255		0.00754***
		[0.00120]		[0.00145]		[0.00208]		[0.00196]
Constant	0.229***	0.232***	0.226***	0.240***	0.251***	0.273***	0.201***	0.206***
	[0.00826]	[0.0101]	[0.0103]	[0.0126]	[0.0146]	[0.0181]	[0.0138]	[0.0169]
Birth-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ctry-bthyr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dist-bthyr trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Drop10-30 km	No	No	Yes	Yes	No	No	No	No
Drop t-2	No	No	Yes	Yes	No	No	No	No
N	359219	243645	236573	165202	119860	83570	116696	81601

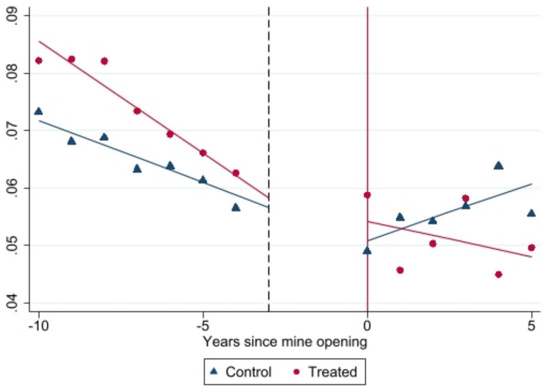
Notes: $^{*}p < 0.1,^{**}\ p < 0.05,^{***}\ p < 0.01$. Standard errors clustered a DHS cluster level. The variables Mine deposit [0;10km] and Industrial × mine deposit (at birth) are a replication from Benshaul-Tolonen, 2018 and indicate whether the child is born within 10km of at least one industrial mining site and whether this site was active at the time of the birth. All regressions control for mother's age, age square, mother's education and whether the household is urban, for district, birth month and country-birth year. The main outcome is infant mortality in the 12 months since birth.
dummies which indicate whether the individual lives in a village within at least one mining site, and whether the site opened before the birth year of the child. Each village DHS is paired to the closest opened mining site, so that each individual appears only once in the regression. Other variables are control variables.

Table B.14: Effects of industrial mining activity on under 12, 24 mortality - Geographic Treatment - All Households

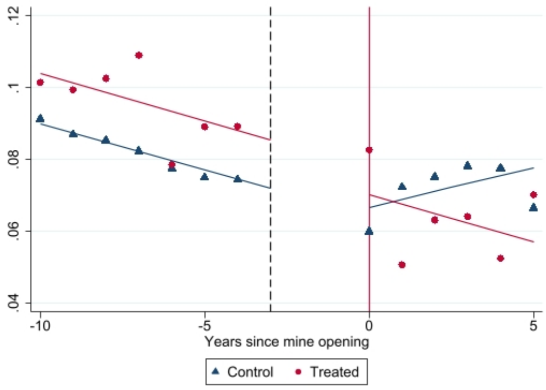
	Death <12m				Death < 24m			
	All	All	Rural	Rural	All	All	Rural	Rural
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
indus.×deposit	-0.00259	-0.00823**	-0.00259	-0.00627	0.000248	-0.00264	0.000248	-0.00248
	[0.00329]	[0.00418]	[0.00329]	[0.00509]	[0.00431]	[0.00535]	[0.00431]	[0.00657]
Deposit	0.00130	0.00374	0.00130	0.00313	0.000627	0.00121	0.000627	0.000859
	[0.00252]	[0.00317]	[0.00252]	[0.00368]	[0.00321]	[0.00411]	[0.00321]	[0.00477]
Indus.	0.00131	0.00222	0.00131	0.00340	0.00116	0.00122	0.00116	0.00190
	[0.00155]	[0.00200]	[0.00155]	[0.00230]	[0.00201]	[0.00259]	[0.00201]	[0.00297]
Birth order	0.00389***	0.00315***	0.00389***	0.00353***	0.00512***	0.00401***	0.00512***	0.00447***
	[0.000345]	[0.000428]	[0.000345]	[0.000500]	[0.000440]	[0.000549]	[0.000440]	[0.000642]
Mother's age	-0.0105***	-0.0107***	-0.0105***	-0.0116***	-0.0115***	-0.0124***	-0.0115***	-0.0140***
	[0.000541]	[0.000668]	[0.000541]	[0.000787]	[0.000704]	[0.000873]	[0.000704]	[0.00103]
Age square	0.000147***	0.000151***	0.000147***	0.000161***	0.000151***	0.000167***	0.000151***	0.000187***
	[0.00000853]	[0.0000106]	[0.00000853]	[0.0000122]	[0.0000110]	[0.0000136]	[0.0000110]	[0.0000159]
Years edu.	-0.000877***	-0.00103***	-0.000877***	-0.000792***	-0.00145***	-0.00157***	-0.00145***	-0.00132***
	[0.000135]	[0.000167]	[0.000135]	[0.000219]	[0.000173]	[0.000215]	[0.000173]	[0.000283]
Urban	-0.00610***	-0.00725***	-0.00610***		-0.00940***	-0.00995***	-0.00940***	
	[0.00135]	[0.00172]	[0.00135]		[0.00175]	[0.00222]	[0.00175]	
migrant		0.00543***		0.00514***		0.00727***		0.00630***
		[0.00120]		[0.00144]		[0.00155]		[0.00186]
Constant	0.229***	0.232***	0.229***	0.247***	0.273***	0.286***	0.273***	0.315***
	[0.00826]	[0.0101]	[0.00826]	[0.0120]	[0.0109]	[0.0134]	[0.0109]	[0.0159]
Birthmonth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cty-Bthyr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mine FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mine Bthyr trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Commodity FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	359,219	243,645	359,219	179,155	265,735	179,729	265,735	132,398
R2	0.0195	0.0235	0.0195	0.0281	0.0289	0.0337	0.0289	0.0393
Mean	0.0630	0.0653	0.0630	0.0688	0.0816	0.0851	0.0816	0.0903

Notes: Standard errors clustered at the village level, $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$. The variables Proximity and Opened are dummies which indicate whether the individual lives in a DHS village within 10 km of at least one mining site, and whether the site opened before the birth year of the child. Each village DHS is paired to only one mining site, so that each individual appears only once in the regression. Other variables are control variables. The sample focuses on heavy metal mines.

Figure B.20: Linear Trends dropping investment phase - Geographic Treatment



(a) Infant mortality Rate 12 months



(b) Infant mortality Rate 24 months

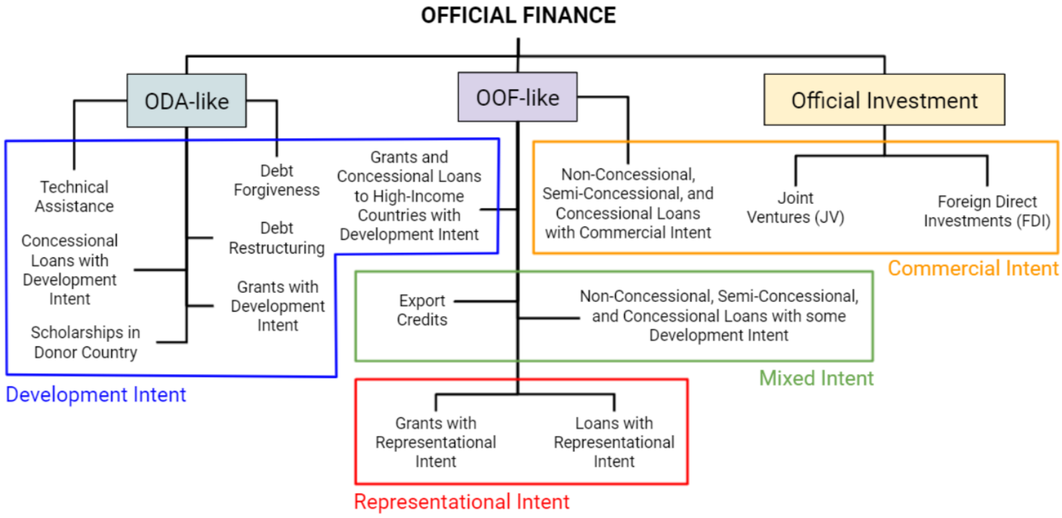
Sources: Authors' elaboration on DHS and SNL data.

Appendix C

Appendix to Chapter 3: Raw Materials Diplomacy, Official Development Finance and the Industrial Exploitation of Natural Resources in Africa

C.1 Official Finance Flows

Figure C.1: Classification of Official Finance in the Aiddata Global Development Finance Dataset



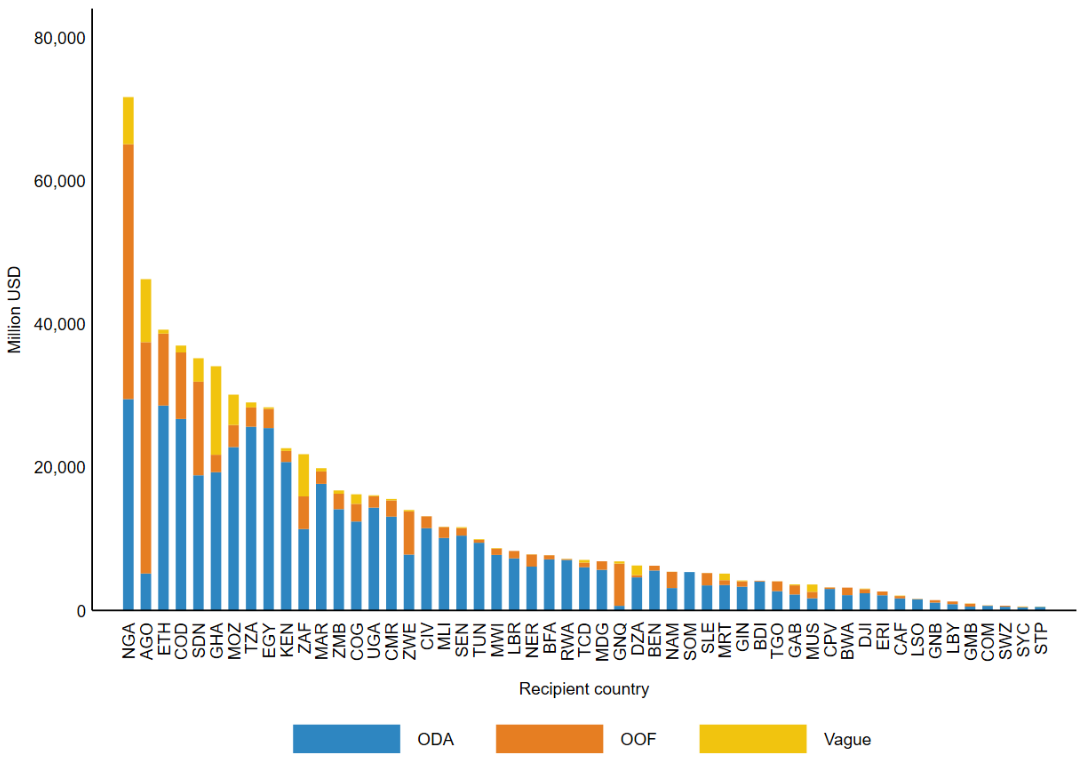
Notes: This figure represents the official financial flow class and flow types in the Aiddata Global Chinese Development Finance Dataset and is comparable to the Core OECD and India data. **Source:** Figure taken from Custer et al., 2021.

C.2 Recipients' side

C.3 Industrial fishing data

Kroodsma et al., 2018 provide daily fishing effort (in hours) at the 0.01-degree resolution. To build their databasem they used the information generated by automatic identification systems of boats (AIS). These positioning devices have to be on board of ships for maritime safety. They are needed to broadcast location, navigate, and avoid collisions. 2 billion global AIS positions from 2012-2016 (20 million messages added per day on average) were processed and machine learning tools were used to identify vessel characteristics and to detect AIS positions indicative of fishing activity. Their dataset contains labeled tracks of more than 70,000 identified fishing vessels that are 6 to 146 m 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 Global Fishing Watch's research team.

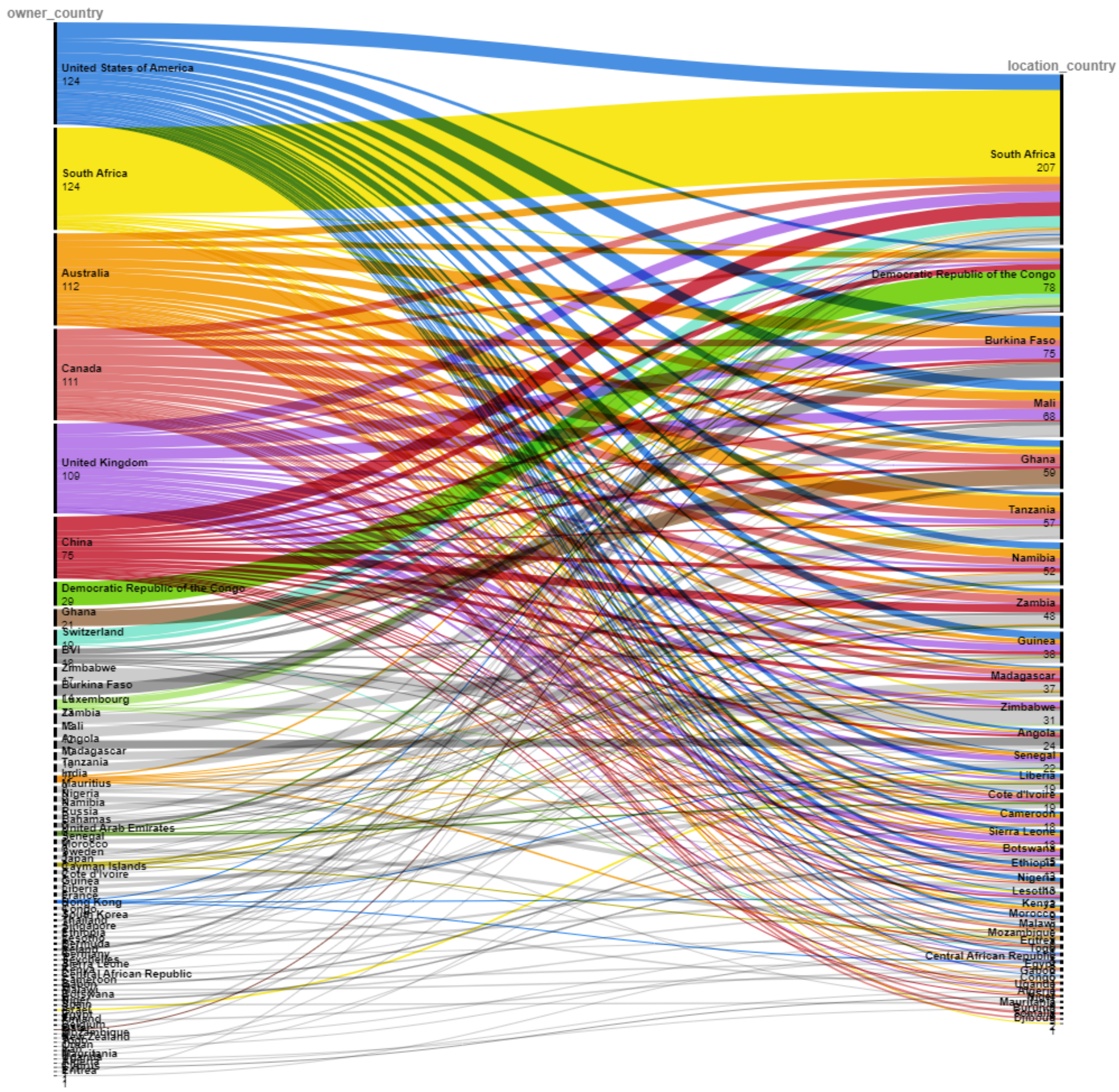
Figure C.2: Class decomposition of received financial flows (2000-2013)



Notes: This graph represents the official finance flows received by each African country over the 2000-2013 period. It makes the distinction between flow classes: Official Development Assistance (ODA), Other Official Finance (OOF), and Vague flows.
Source: Own elaboration using Core, China, and India Aiddata.

C.4 Industrial mining and industrial fishing alluvial plots

Figure C.3: Bilateral industrial mine openings in Africa (2000-2014)



Notes: This graph represents the total number of industrial mines owned by companies registered in a country (left nodes) and opening in an African country (right nodes) over the 2000-2014 period. If an industrial site was owned by several companies registered in different countries than each country had an opening counted.
Sources: Own elaboration using SNL Mining and Metals.

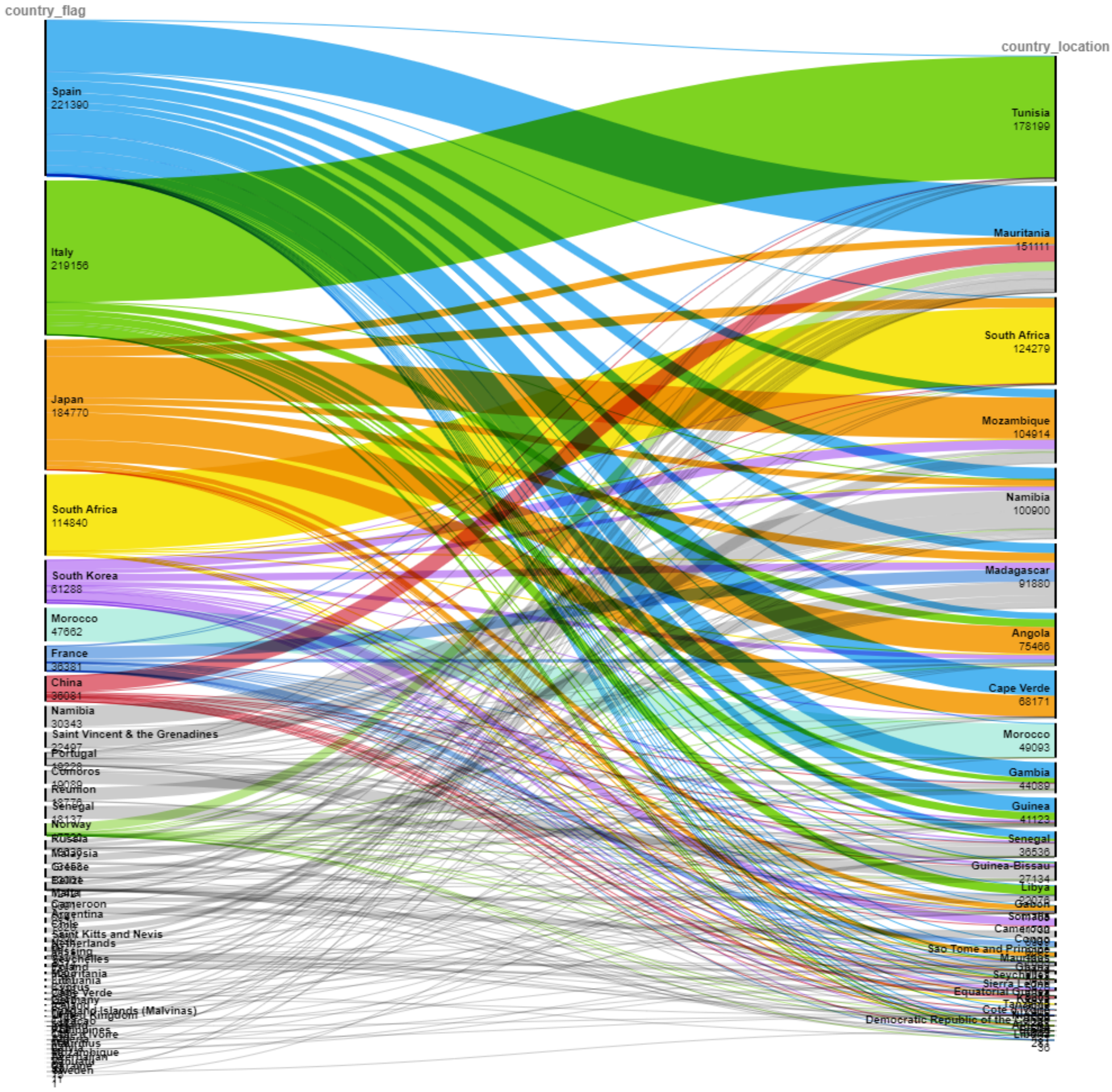
C.5 Sample of recipient and donor countries

Table C.1: Data sources and detail of bilateral observations

Variable	Data source			Time span
Official Finance flows	Aiddata			
	Core	57 recipients	81 multilateral and bilateral donors	1950-2017
	China	53 recipients	1 donor	2000-2017
	India	54 recipients	1 donor	2007-2014
Land acquisitions	Land matrix	45 countries	72 investors	2000-2017
Industrial mining	SNL Mining and Metals	47 countries	89 investors	19th Century-2022
Industrial fishing	Global Fishing Watch	37 countries	86 flags	2012-2018

Note: This table represents the original number of countries available in the raw datasets, and their respective time span, before the merging of the datasets to constitute the final sample.

Figure C.4: Bilateral industrial fishing hours within EEZ across vessels flag (2012-2014)



Notes: This graph represents the total number of fishing hours conducted by industrial vessels sailing under a specific flag (left nodes) within the EEZ of an African country (right nodes) over the 2012-2014 period.
Sources: Own elaboration using Global Fishing Watch data.

Table C.2: Donor countries activity across natural resources type

Donor country	Code	Official Finance Flows	With LSLA	With ind. mining	With ind. fishing	Total natural resource type
Australia*	AUS	1	1	1	1	3
Austria*	AUT	1	1	1	0	2
Belgium*	BEL	1	1	1	0	2
Brazil	BRA	1	1	0	0	1
Canada*	CAN	1	1	1	0	2
Chile	CHL	1	0	0	0	0
China	CHN	1	1	1	1	3
Colombia	COL	1	0	0	0	0
Cyprus	CYP	1	0	0	0	0
Czech Republic*	CZE	1	0	0	0	0
Denmark*	DNK	1	1	0	1	2
Estonia	EST	1	0	0	0	0
Finland*	FIN	1	0	1	1	2
France*	FRA	1	1	1	1	3
Germany*	DEU	1	1	1	1	3
Greece*	GRC	1	0	0	1	1
Hungary*	HUN	1	1	0	0	1
Iceland*	ISL	1	0	1	1	2
India	IND	1	1	1	0	2
Ireland*	IRL	1	1	1	1	3
Italy*	ITA	1	1	1	1	3
Japan*	JAP	1	1	1	1	3
Korea*	KOR	1	1	1	1	3
Kuwait	KWT	1	1	0	0	1
Liechtenstein	LIE	1	0	0	0	0
Lithuania*	LTU	1	0	0	0	0
Luxembourg*	LUX	1	1	1	0	2
Monaco	MCO	1	0	0	0	0
The Netherlands*	NLD	1	1	1	1	3
New Zealand*	NZL	1	0	1	0	1
Norway*	NOR	1	1	1	1	3
Poland*	POL	1	1	0	1	2
Portugal*	PRT	1	1	0	1	2
Saudi Arabia	SAU	1	1	0	0	1
Slovakia*	SVK	1	0	0	0	0
Slovenia*	SVN	1	0	0	0	0
South Africa	ZAF	1	1	1	0	2
Spain*	ESP	1	1	1	1	3
Sweden*	SWE	1	1	1	1	3
Switzerland*	CHE	1	1	1	0	2
Taiwan	TWN	1	0	0	0	0
Thailand	THA	1	0	0	0	0
United Arab Emirates	ARE	1	1	1	0	2
United Kingdom*	UK	1	1	1	1	3
United States of America*	USA	1	1	1	1	3
Total		45	29	25	20	

Notes: This table indicates the list of donors for which Official Finance Flow is available from Aiddata. We then indicate whether each donor has concluded large-scale land acquisitions (LSLA) deals in Africa between 2000-2014, if it has opened an industrial mine between 2000-2014 and if a flag for its country has been conducting industrial fishing within an African country's Exclusive Economic Zone between 2012-2014. The last column sums up the total number of types of natural resource extraction activity the donor country have been doing in Africa over 2000-2014. The * indicates whether a country is a DAC member.

Table C.3: Recipient countries across natural resources type

Recipient country	Code	Official Finance Flows	With Ind. mining	With LSLA	With ind. fishing	Total natural resource type
Algeria	DZA	1	1	1	1	3
Angola*	AGO	1	1	1	1	3
Benin	BEN	1	1	1	1	3
Botswana	BWA	1	1	1	0	2
Burkina Faso	BFA	1	1	1	0	2
Burundi	BDI	1	1	0	0	1
Cameroon*	CMR	1	1	1	1	3
Cape Verde	CPV	1	0	0	1	1
Central African Republic*	CAF	1	1	1	0	2
Chad	TCD	1	1	1	0	2
Comoros	COM	1	0	0	1	1
Congo*	COG	1	1	1	1	3
Cote d'Ivoire	CIV	1	1	1	1	3
Dem. Republic of the Congo*	COD	1	1	1	1	3
Djibouti	DJI	1	1	0	0	1
Egypt	EGY	1	1	1	1	3
Equatorial Guinea	GNQ	1	1	0	1	2
Eritrea*	ERI	1	1	1	1	3
Ethiopia*	ETH	1	1	1	0	2
Gabon*	GAB	1	1	1	1	3
Gambia	GMB	1	0	0	1	1
Ghana	GHA	1	1	1	1	3
Guinea*	GIN	1	1	1	1	3
Guinea-Bissau*	GNB	1	1	1	1	3
Kenya*	KEN	1	1	1	1	3
Lesotho	LSO	1	1	1	0	2
Liberia	LBR	1	1	1	1	3
Libya*	LBY	1	1	1	1	3
Madagascar	MDG	1	1	1	1	3
Malawi	MWI	1	1	1	0	2
Mali	MLI	1	1	1	0	2
Mauritania*	MRT	1	1	1	1	3
Mauritius	MUS	1	0	0	1	1
Morocco	MAR	1	1	1	1	3
Mozambique*	MOZ	1	1	1	1	3
Namibia	NAM	1	1	1	1	3
Niger*	NER	1	1	1	0	2
Nigeria	NGA	1	1	1	1	3
Rwanda	RWA	1	1	1	0	2
Sao Tome and Principe	STP	1	0	1	1	2
Senegal	SEN	1	1	1	1	3
Seychelles	SYC	1	0	0	1	1
Sierra Leone*	SLE	1	1	1	1	3
Somalia	SOM	1	1	0	1	2
South Africa	ZAF	1	1	1	1	3
South Sudan	SSD	1	0	0	0	0
Sudan*	SDN	0	1	1	1	3
Swaziland *	SWZ	1	1	1	0	2
Tanzania*	TZA	1	1	1	1	3
Togo	TGO	1	1	0	1	2
Tunisia	TUN	1	1	0	1	2
Uganda	UGA	1	1	1	0	2
Zambia*	ZMB	1	1	1	0	2
Zimbabwe*	ZWE	1	1	1	0	2
Total		53	47	42	37	

Notes: This table indicates the list of African countries for which Official Finance Flow is available from Aiddata. We then indicate whether each recipient has concluded large-scale land acquisitions (LSLA) deals in Africa between 2000-2014, if a foreign industrial mine has opened between 2000-2014 and if a foreign flag has been conducting industrial fishing within its Exclusive Economic Zone between 2012-2014. The last column sums up the total number of types of natural resource extraction activity the recipient country have been subject to between 2000-2014. The * indicates whether a country is below the median of property rights index in 2010.

C.6 Descriptive statistics

Table C.4: Summary statistics

Variable	Mean	Std. Dev.	Med.	Min	Max	Obs.
Nb. of LSLA deals	.03	.25	0	0	10	18,270
Cum. nb of deals by inv. rec. year	.21	.95	0	0	20	18,270
Sum deals in rec. by year	1.43	3.01	0	0	27	18,270
Cum. nb. deals in rec.	8.83	16.42	2	0	119	18,270
Share of investor's cum. nb. deals	.02	.1	0	0	1	12,528
Nb. of mines open before 2000	14.57	30.79	4	0	192	17,625
Nb. of mines by investor in rec.	.16	.61	0	0	12	4,410
Cum. mines by investor in rec.	.23	1.95	0	0	98	17,625
Cum. mines by rec.	9.23	20.82	1	0	195	17,625
Share of investor's cum. mines in rec.	.02	.08	0	0	1	17,625
Cum. hours within rec.'s EEZ	24,137	35,428	8,884	1.85	178,199	1,840
Cum. hours by flag within rec.'s EEZ	778	5,672	0	0	172,510	1,840
Share of activity within rec.'s EEZ by flag	.03	.13	0	0	1	1,840
Cum. hours within rec.'s 36 NM	8,992	15,333	2,614	0	93,008	1,840
Cum. hours by flag within rec.'s 36 NM	251.16	2,216	0	0	64,862	1,840
Share of activity within rec.'s 36 NM by flag	.02	.12	0	0	1	1,840
Share donor's cum. ODA (in %)	1.46	5.70	0	0	82.5	50,820
Share donor's cum. OOF (in %)	1.43	9.29	0	0	57.3	46,100
Share donor's cum. Total (in %)	1.46	5.78	0	0	90.7	50,820
Log(Dist)	8.48	.73	8.58	2.35	9.85	50,820
Colonial or dependency relationship ever	.02	.13	0	0	1	50,820
Log(GDPcap) rec	.77	.63	.51	.1	3.2	49,505
Below median Property rights level index (in 2010)	.50	.50	1	0	1	21,924

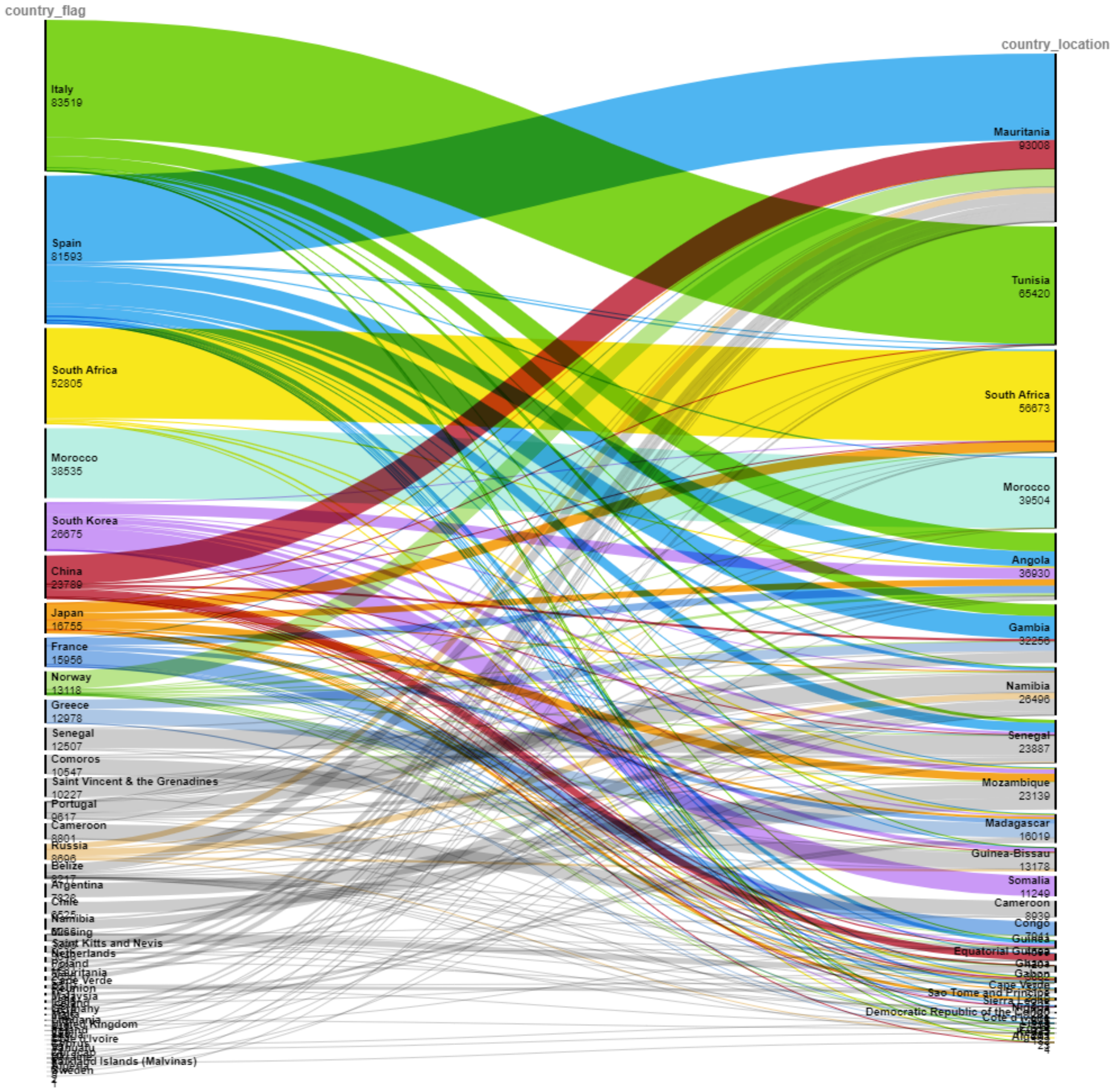
Note: This table summarizes the main dependent and independent variables included in our study before the restriction to each type of natural resource actors (donors and recipients) It describes the number of large-scale land acquisitions (LSLA) between 2000-2014, the number of industrial mines that have opened between 2000-2014 and the number of industrial fishing hours detected between 2012-2014. "Rec." is the abbreviation for "recipient". "Cum." is the abbreviation for "cumulative". ODA = Official Development Assistance. OOF = Other Official Flow.

Table C.5: Summary statistics of non-zero shares

	N	Mean	SD	Min	Max
Share(Donor's cum LSLA) : prop of zeros		0.848			
Share(Donor's cum LSLA) : if ¿ 0	1,821	0.162	0.200	0.008	1
Share (Donor's cum open mines) : prop of zeros		0.927			
Share (Donor's cum open mines) : if ¿ 0	1,234	0.189	0.219	0.005	1
Share (Donor's cum ind. fish hours EEZ) : prop of zeros		0.825			
Share (Donor's cum ind. fish hours EEZ) : if ¿ 0	311	0.173	0.2663	3.35e-06	1
Share (Donor's cum ind. fish hours 36 NM) : prop of zeros		0.879			
Share (Donor's cum ind. fish hours 36 NM) : if ¿ 0	214	0.195	.299	9.72e-05	1
Share(Donor's cum. OF within recipient-year)					
LSLA sample : prop of zeros		0.228			
LSLA sample : if ¿ 0	9,218	0.044	0.086485	9.78e-08	0.858
Mining sample : prop of zeros		0.1938			
Mining sample : if ¿ 0	12,555	0.047	0.094	1.48e-07	0.944
Industrial fishing sample (EEZ) : prop of zeros		0.102			
Industrial fishing sample (EEZ) : if ¿ 0	1,598	0.047	0.103	1.40e-07	0.936
Industrial fishing sample (36 NM) : prop of zeros		0.102			
Industrial fishing sample (36 NM) : if ¿ 0	1,598	0.047	0.103	1.40e-07	0.936

Note: This table represents the summary statistics of the non-zeros shares of the main outcome and independent variables for each of the samples used for estimating regression 3.1.

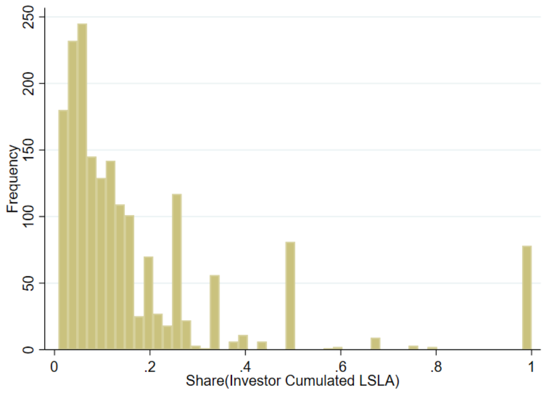
Figure C.5: Distribution of industrial fishing hours within 36 NM across vessels flag (2012-2014)



Notes: This graph represents the total number of fishing hours conducted by industrial vessels sailing under a specific flag (left nodes) within 36 NM of an African country (right nodes) over the 2012-2014 period.

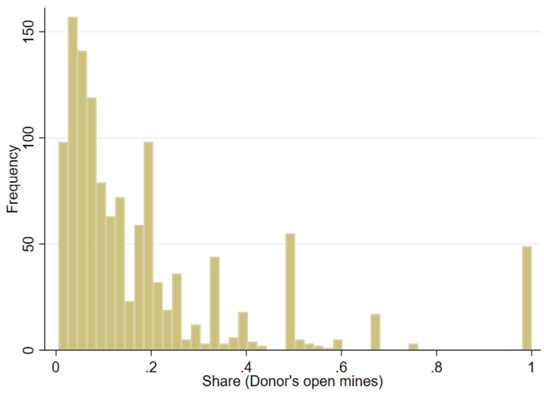
Sources: Own elaboration using Global Fishing Watch data.

Figure C.6: Distribution of non-zero shares of donors' cumulative land deals among recipient countries (2000-2014) in the final sample



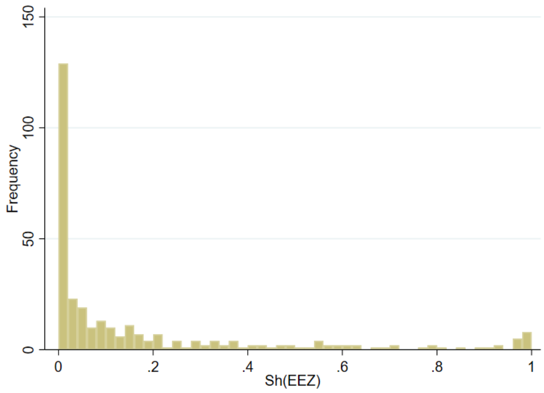
Note: Zero shares of cumulative land deals among recipient countries represent 84.8% of the final sample used for the analysis.
Source: Own elaboration using Landmatrix data.

Figure C.7: Distribution of non-zero shares of donors' cumulative open mines among recipient countries (2000-2014) in the final sample



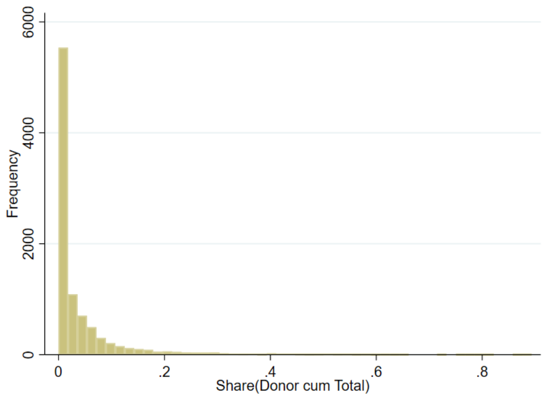
Note: Zero shares of the cumulative number of mines since 2000 among recipient countries represent 92.7% of the final sample used for the analysis.
Source: Own elaboration using SNL Mining and Metals data.

Figure C.8: Distribution of non-zero shares of donors' cumulative industrial fishing hours among recipient countries' EEZ (2012-2014) in the final sample



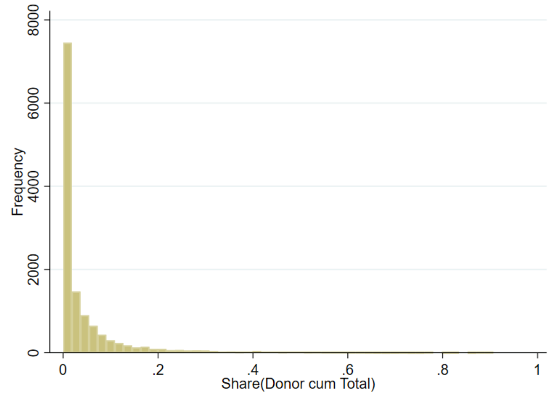
Note: Zero shares of cumulative industrial fishing efforts since 2012 among recipient countries' EEZ represent 82.5% of the final sample used for the analysis.
Source: Own elaboration using Global Fishing Watch data.

Figure C.9: Distribution of non-zero shares of donors' cumulative official finance among recipient countries with LSLA deals (2000-2013) in the final sample



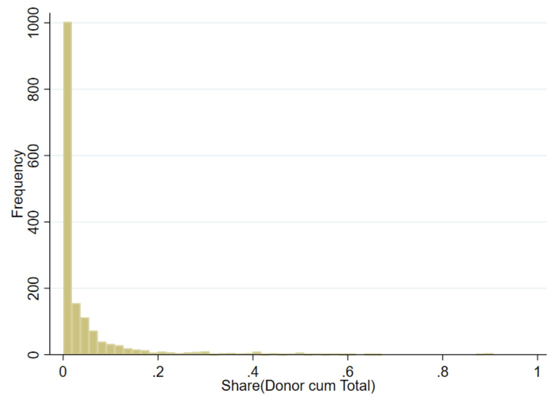
Note: Zero shares of cumulative official finance among recipient countries with LSLA deals represent 22.8% of the final sample used for the analysis.
Source: Own elaboration using Aiddata.

Figure C.10: Distribution of non-zero shares of donors' cumulative official finance among recipient countries with mine openings (2000-2013) in the final sample



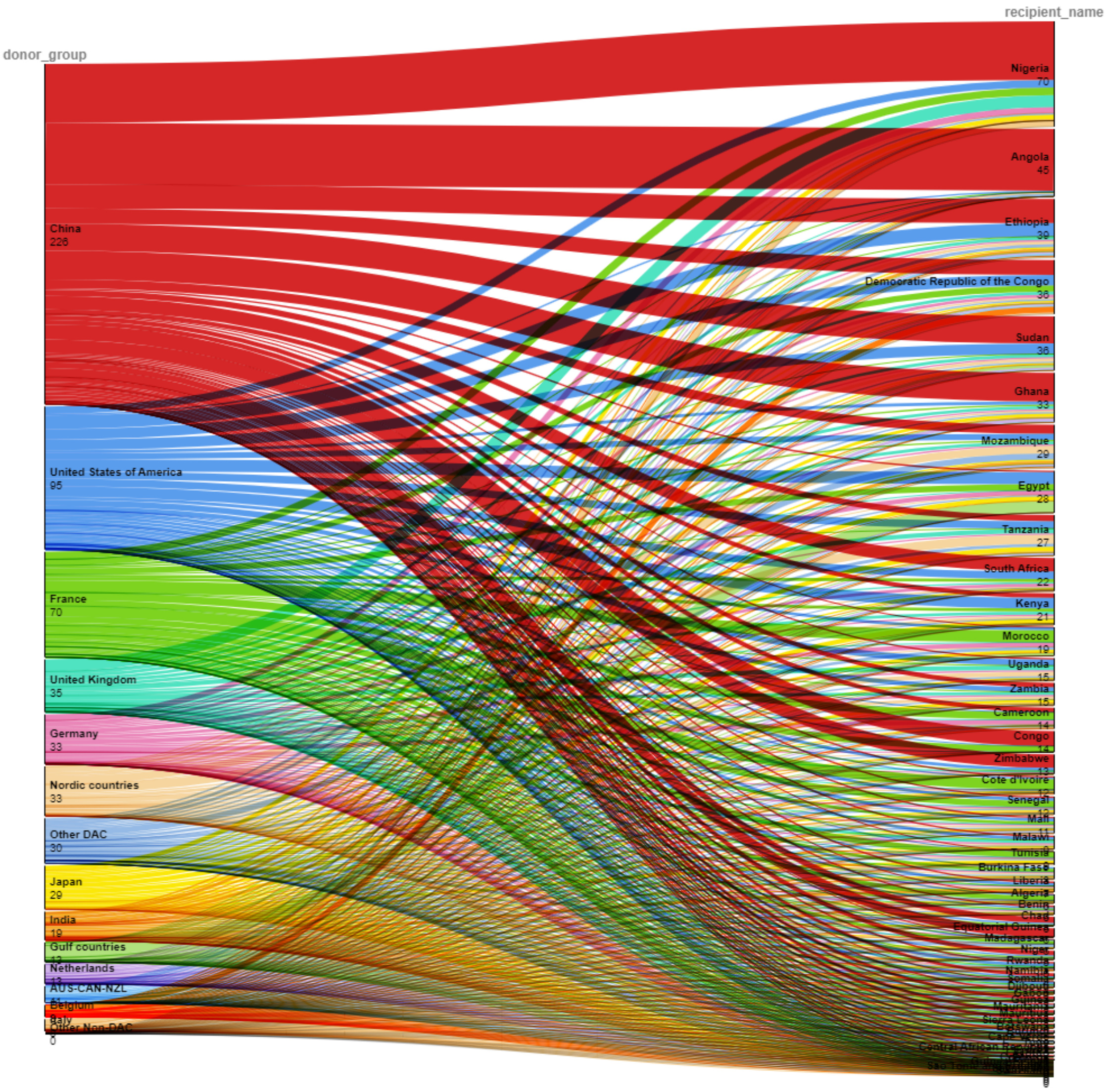
Note: Zero shares of cumulative official finance among recipient countries with mine openings represent 19.4% of the final sample used for the analysis.
Source: Own elaboration using Aiddata.

Figure C.11: Distribution of non-zero shares of donors' cumulative official finance among recipient countries with industrial fishing activity within their EEZ (2012-2014) in the final sample



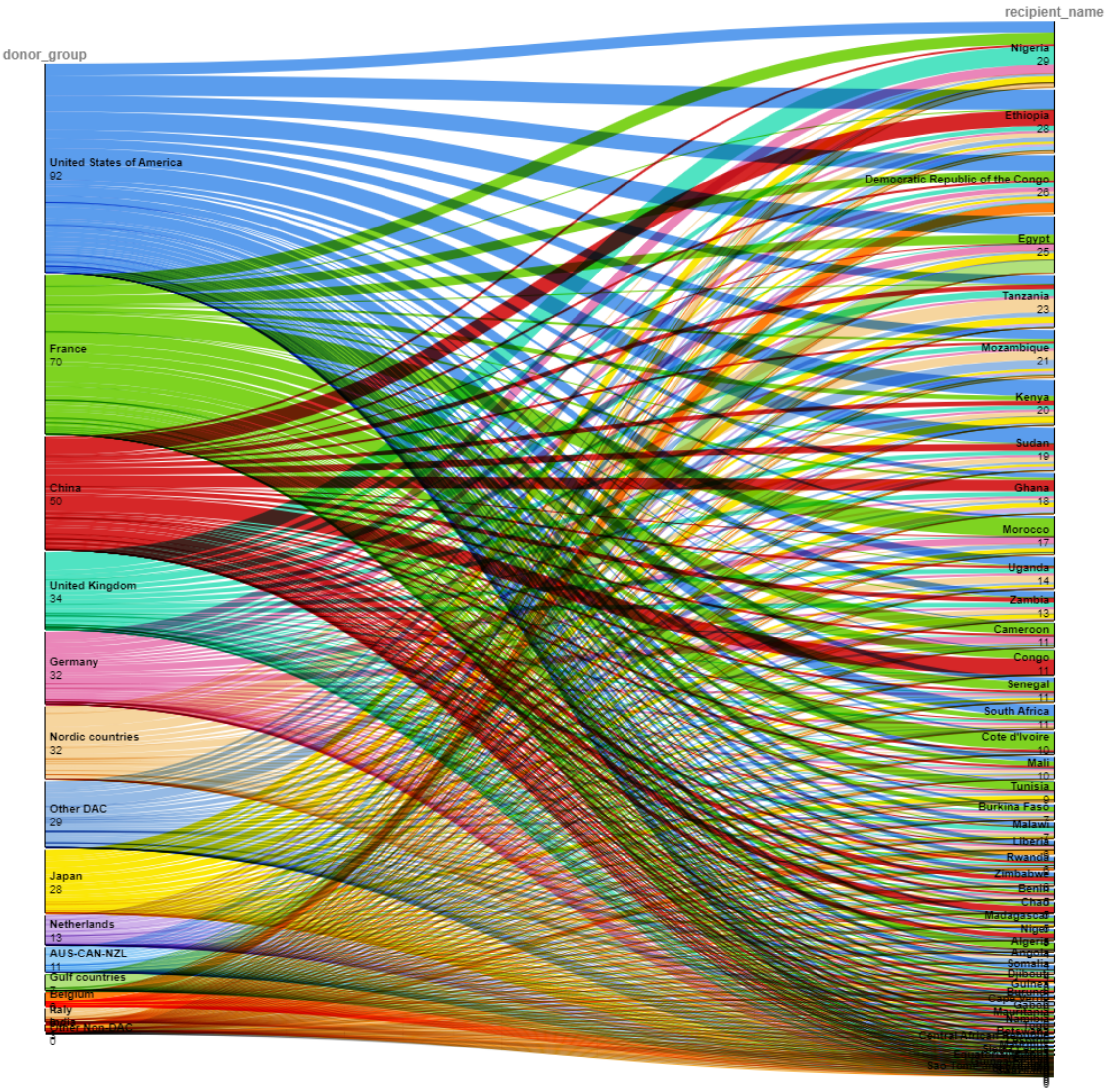
Note: Zero shares of cumulative official finance among recipient countries with industrial fishing activity within their EEZ represent 10.2% of the final sample used for the analysis.
Source: Own elaboration using Aiddata.

Figure C.12: Bilateral official finance flows to Africa, over 2000-2013



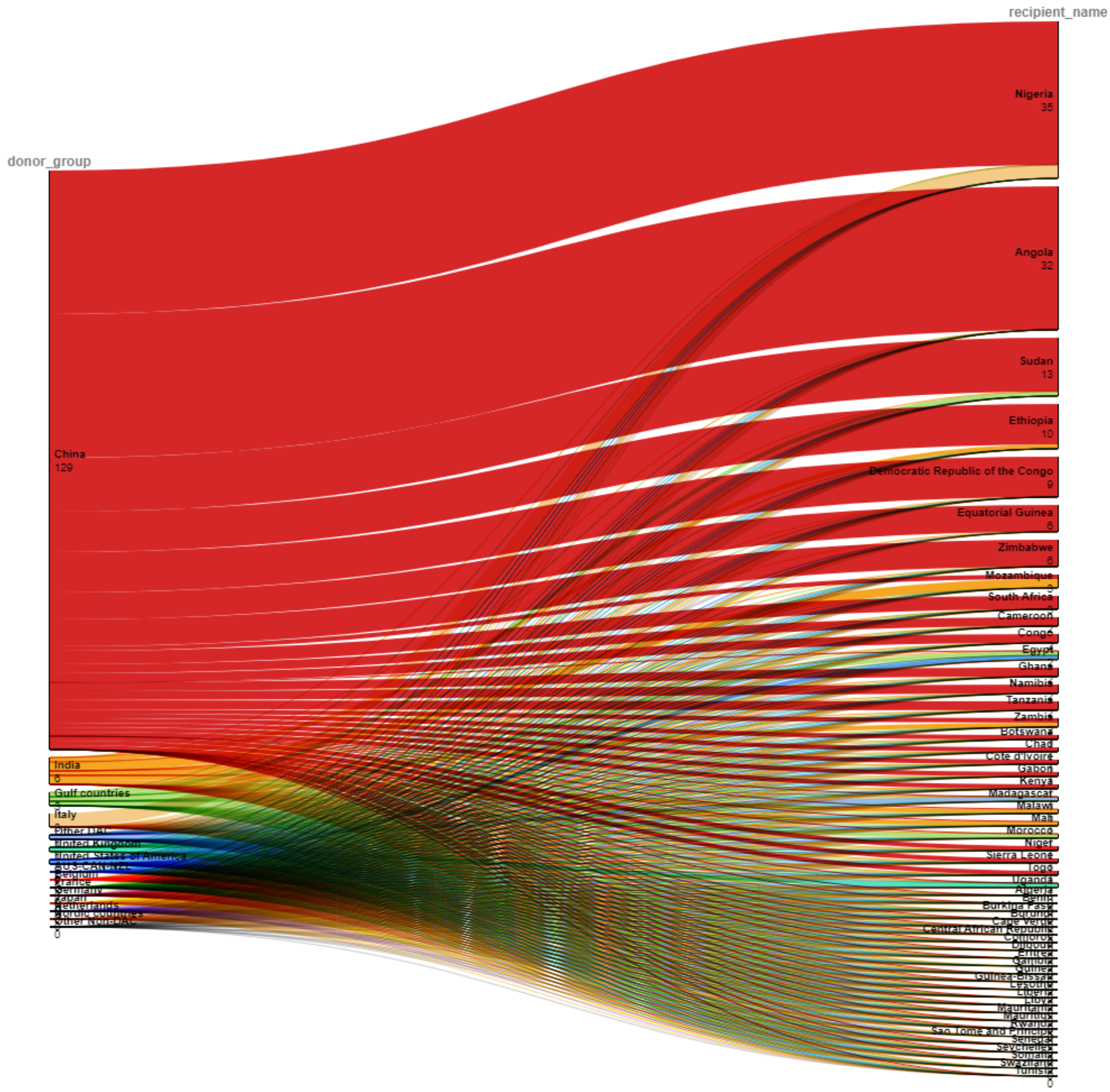
Notes: This alluvial chart represents the total bilateral official finance flows from each donor country (left nodes) to each African recipient country (right nodes) between 2000-2013.
Source: Own computation using Aiddata.

Figure C.13: Bilateral ODA flows to Africa, over 2000-2013



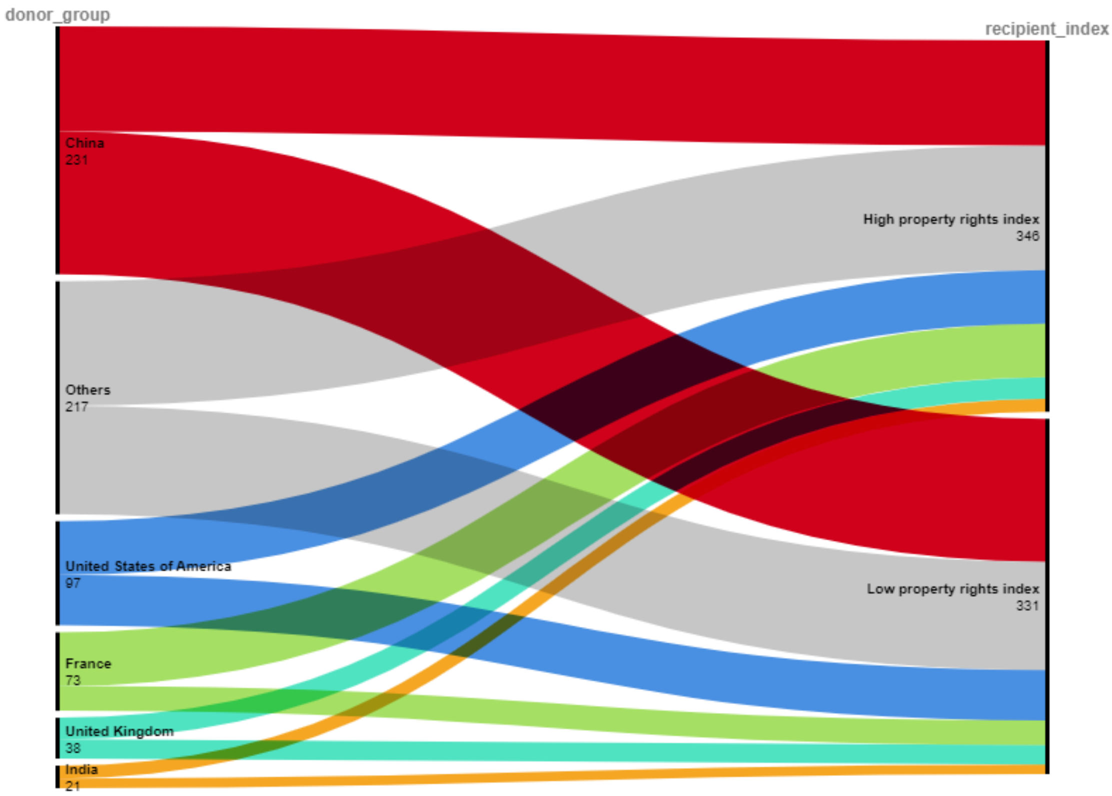
Notes: This alluvial chart represents the Official Development Assistant flows from each donor country (left nodes) to each African recipient country (right nodes) between 2000-2013.
Source: Own computation using Aiddata.

Figure C.14: Bilateral other official finance (OOF) flows to Africa, over 2000-2013



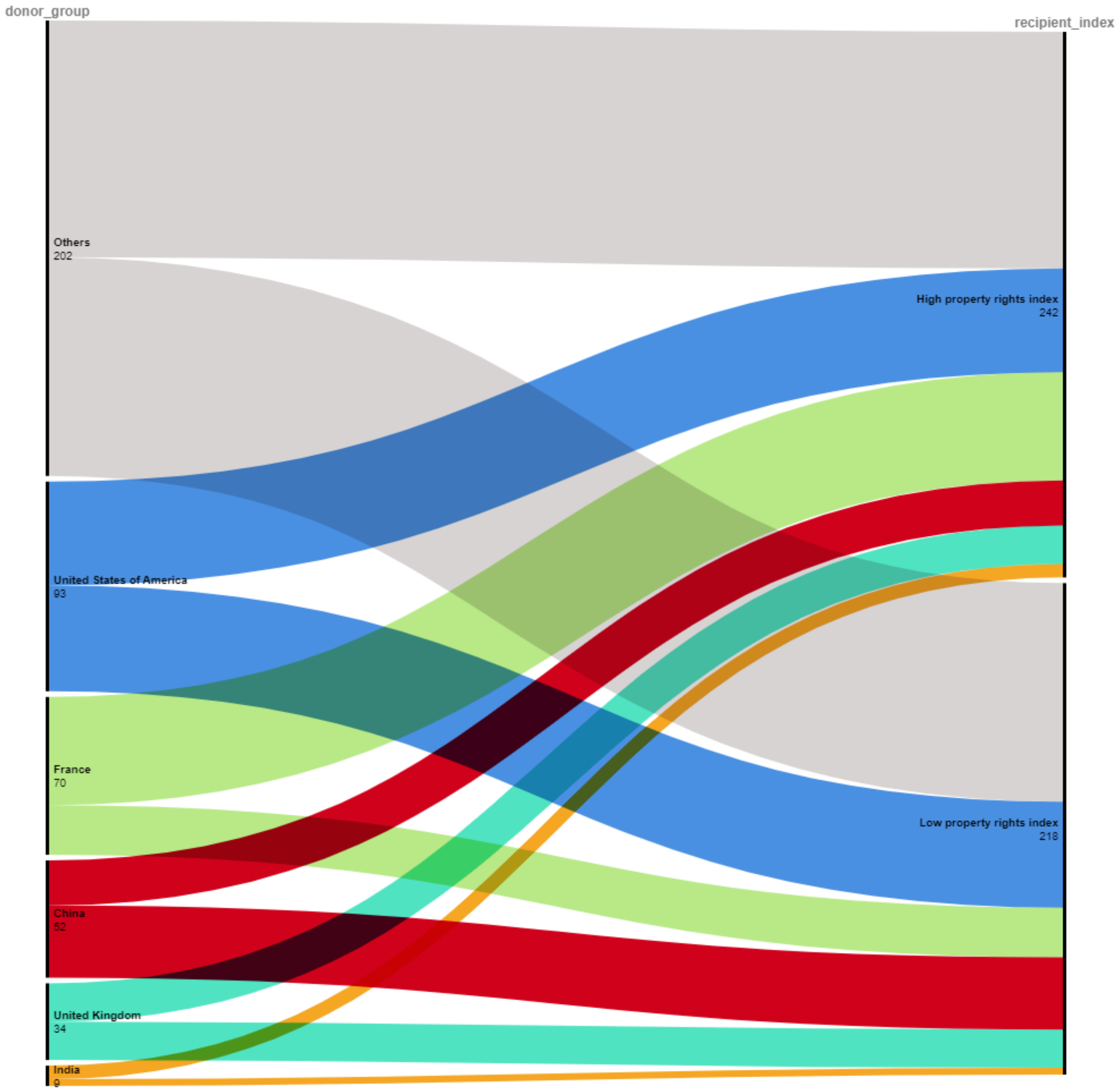
Notes: This alluvial chart represents the Other Official finance flows from each donor country (left nodes) to each African recipient country (right nodes) between 2000-2013.
Source: Own computation using Aiddata.

Figure C.15: Bilateral total official finance flows 2000-2013 across recipient countries' property rights index



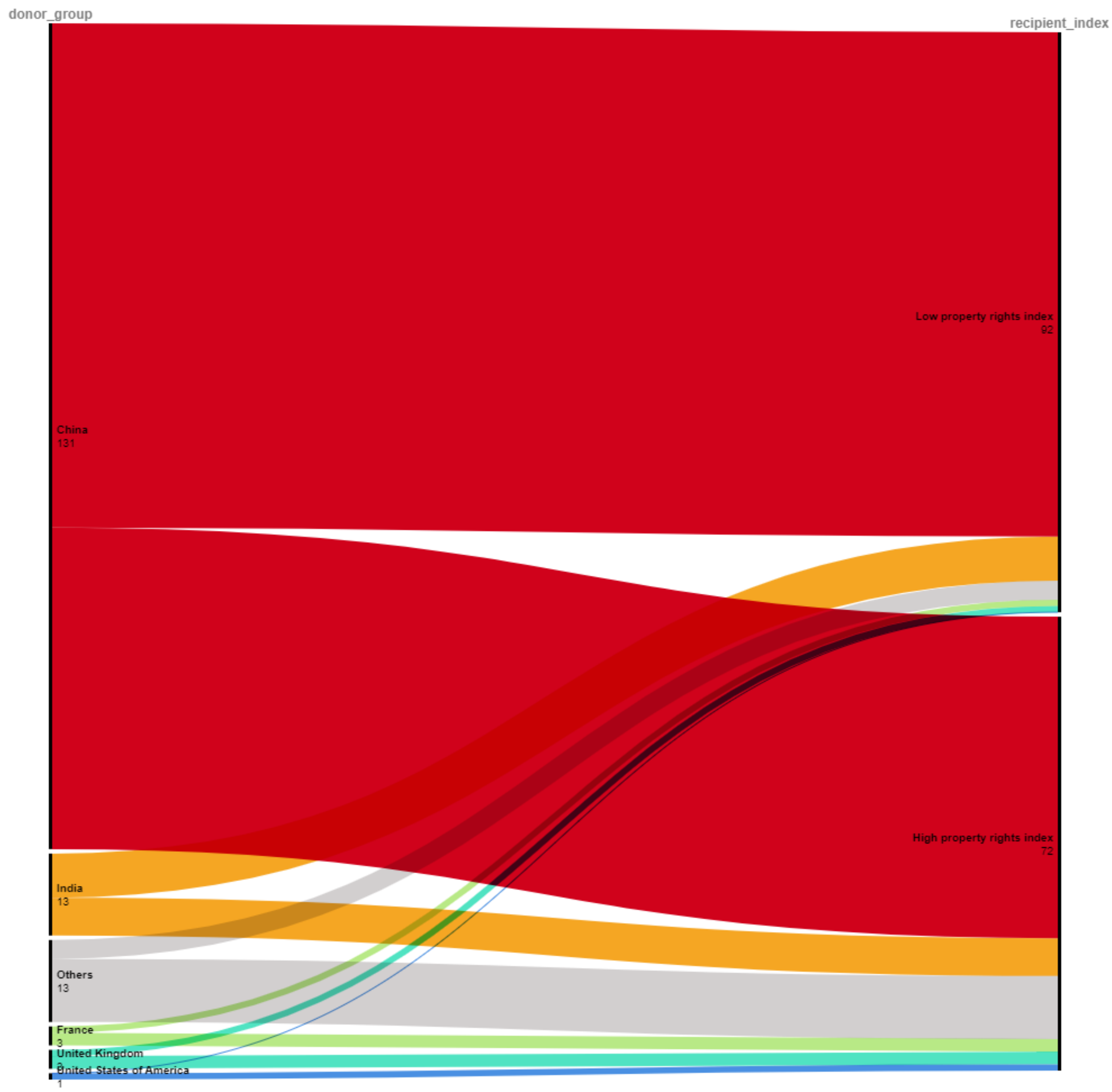
Notes: This alluvial chart represents the total bilateral official finance flows from each donor country (left nodes) to each African recipient country according to them being above or below the median property right index in 2010 (right nodes) between 2000-2013. The exact list of corresponding countries can be found in table C.3.
Source: Own computation using Aiddata and the Mo Ibrahim Index.

Figure C.16: Bilateral ODA flows across recipient countries' property rights index, over 2000-2013



Notes: This alluvial chart represents the Official Development Finance flows from each donor country (left nodes) to each African recipient country according to them being above or below the median property right index in 2010 (right nodes) between 2000-2013. The exact list of corresponding countries can be found in table C.3.
Source: Own computation using Aiddata and the Mo Ibrahim Index.

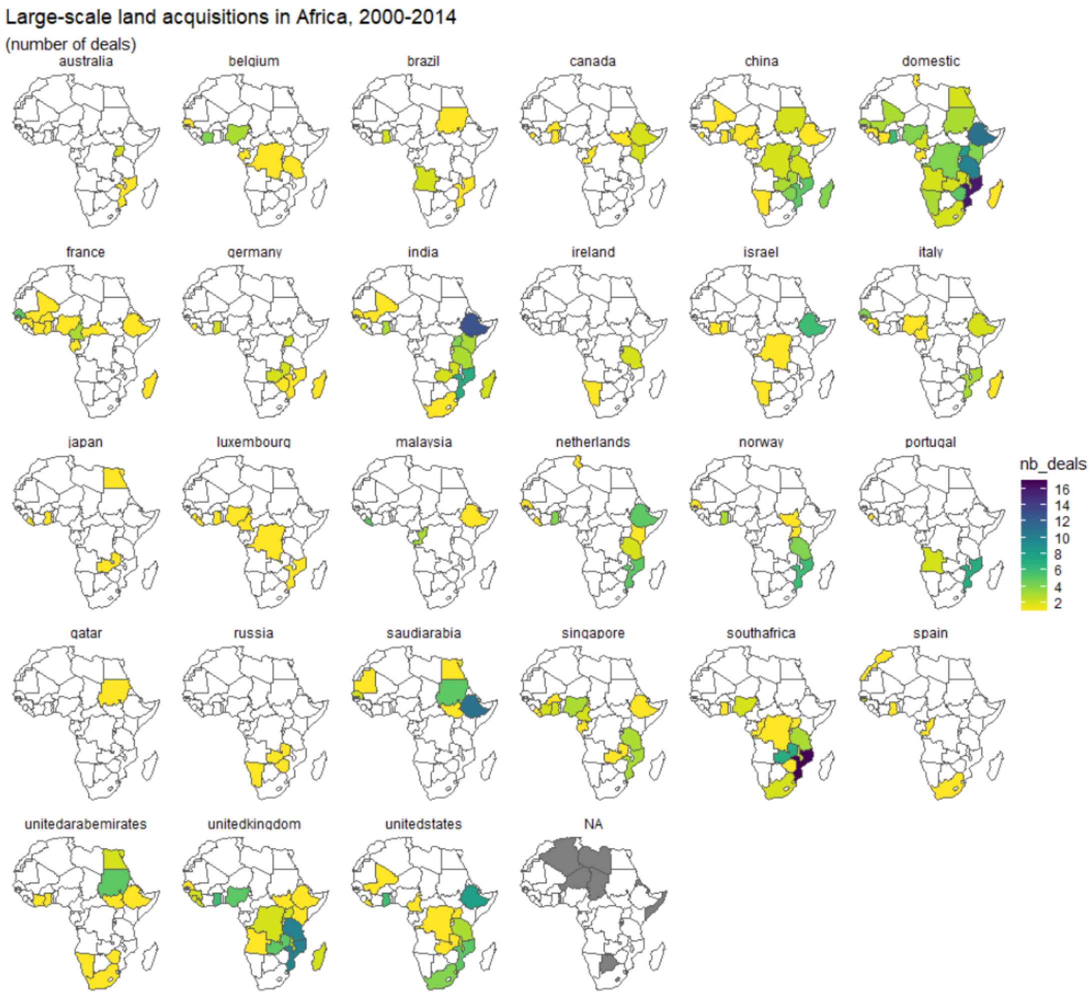
Figure C.17: Bilateral other official finance (OOF) flows across recipient countries' property rights index, over 2000-2013



Notes: This alluvial chart represents the other official finance flows from each donor country (left nodes) to each African recipient country according to them being above or below the median property right index in 2010 (right nodes) between 2000-2013. The exact list of corresponding countries can be found in table C.3.

Source: Own computation using Aiddata and the Mo Ibrahim Index.

Figure C.18: Number of deals by investor



Notes: This map represents the total number of large-scale land acquisitions (2000-2014) by all the investors, even for those we do not have Official Finance flows on. NA in grey, indicates countries with no land deal recorded in the Land Matrix dataset.
Source: Own elaboration using the Land Matrix data.

C.7 Heterogeneity analysis

Table C.6: Hypothesis 2: Complementary and substitution effects of French financial flows across recipient countries' property rights level

Outcome	Share (Donor's cumulated land deals)$_t$					
Competing donor country	France					
Flow type	Total		ODA		OOF	
Recipient's property rights index	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
Sh(DonorCum.OF)$_{t-1}$×Sh(CompetFlowType)$_{t-1}$	-0.0263	0.343	-0.0830	0.307	0.0174	-0.0367
	[0.148]	[0.252]	[0.126]	[0.210]	[0.200]	[0.298]
Sh(DonorCum.OF)$_{t-1}$	0.0321	0.0450	0.0408	0.0426	0.0283	0.0731
	[0.0352]	[0.0580]	[0.0372]	[0.0594]	[0.0309]	[0.0502]
Sh(CompetFlowType)$_{t-1}$	0.0143	0.0216	0.0194*	0.0134	0.0174	-0.0367
	[0.0114]	[0.0229]	[0.0102]	[0.0224]	[0.200]	[0.298]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Donor FE	Yes	Yes	Yes	Yes	Yes	Yes
Recipient FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.112	0.139	0.112	0.139	0.112	0.139
Outcome	0.0261	0.0271	0.0261	0.0271	0.0261	0.0271
N	5,716	5,432	5,716	5,432	5,716	5,432

Notes: This table presents the results from regression 3.2 to test Hypothesis 2 for land deals. The main coefficient of interest is α_3 associated with $Sh(DonorCum.OF)_{t-1}$×Sh(CompetFlowType)$_{t-1}$. $\alpha_3 < 0$ notes a substitution effect and $\alpha_3 > 0$ marks a complementary effect. All cumulated total official finance flows (Cum. OF) and large-scale land acquisitions (LSLA) deals are at the recipient-year level. The cumulative land deals start in 2000 and stop in 2014. Controls include the log distance between recipient and donor countries, the existence of a colonial or dependency relationship, the GDP per capita and the log of the population at the recipient level during year t. Standard errors are clustered at the recipient-year level, $^{*}p < 0.1$,$^{**}p < 0.05$,$^{***}p < 0.01$.

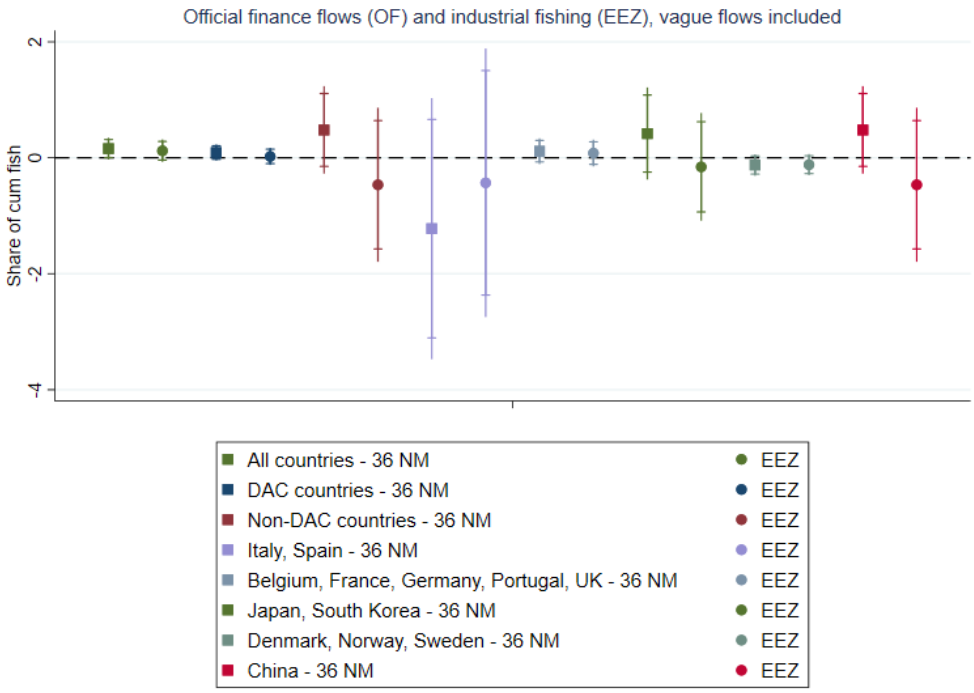
C.7.1 Industrial fishing

Table C.7: Hypothesis 1: Influence of Official Finance on industrial fishing activity

Outcome	Share(Donor's cumulated industrial fishing hours)$_t$							
Maritime zone	36 NM				EEZ			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sh(Donor Cum. OF)$_{t-1}$	0.160*	0.160*	0.159*	0.159*	0.120	0.120	0.122	0.122
	[0.0928]	[0.0928]	[0.0935]	[0.0882]	[0.0965]	[0.0966]	[0.0970]	[0.0887]
Log(Dist)	-0.0496**	-0.0496**	-0.0496**	-0.0496**	-0.0891***	-0.0891***	-0.0889***	-0.0889***
	[0.0207]	[0.0207]	[0.0207]	[0.0206]	[0.0192]	[0.0192]	[0.0192]	[0.0213]
Col. or dep. ever	-0.0144	-0.0144	-0.0144	-0.0144	0.0298	0.0298	0.0302	0.0302
	[0.0225]	[0.0225]	[0.0226]	[0.0206]	[0.0290]	[0.0290]	[0.0291]	[0.0255]
Log(GDPcap)$_{rt}$	-0.0121	0.00591	0.00639	0.00639	0.0410**	0.0397*	0.0489**	0.0489
	[0.0197]	[0.0197]	[0.0192]	[0.0529]	[0.0205]	[0.0206]	[0.0210]	[0.0590]
Log(Pop)$_{rt}$	0.0315	0.0199	0.0300	0.0300	0.00842	0.00794	-0.00104	-0.00104
	[0.0313]	[0.0250]	[0.0338]	[0.0989]	[0.0148]	[0.0146]	[0.0178]	[0.0982]
Log(Cum. fish. hours zone)$_{rt}$		0.00274	0.000715	0.000715	-0.00165	-0.00309	-0.00309	
		[0.00171]	[0.00205]	[0.00329]	[0.00134]	[0.00192]	[0.00413]	
Log(Cum. ODA)$_{r,t-1}$			-0.0167	-0.0167			-0.0579*	-0.0579
			[0.0305]	[0.0377]			[0.0302]	[0.0450]
Log(Cum. OOF)$_{r,t-1}$			0.00840	0.00840			0.00564	0.00564
			[0.00857]	[0.0134]			[0.00904]	[0.0134]
Log(Cum. Vague)$_{r,t-1}$			0.00826***	0.00826			0.00547*	0.00547
			[0.00312]	[0.00782]			[0.00309]	[0.00909]
Donor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Recipient FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.130	0.134	0.134	0.239	0.115	0.132	0.135	0.135
0.236	0.105							
Outcome mean	0.0164	0.0164	0.0164	0.0150	0.0152	0.0142	0.0142	0.0142
0.0130	0.0131							
N	1,780	1,780	1,780	1,780	1,780	1,780	1,780	1,780

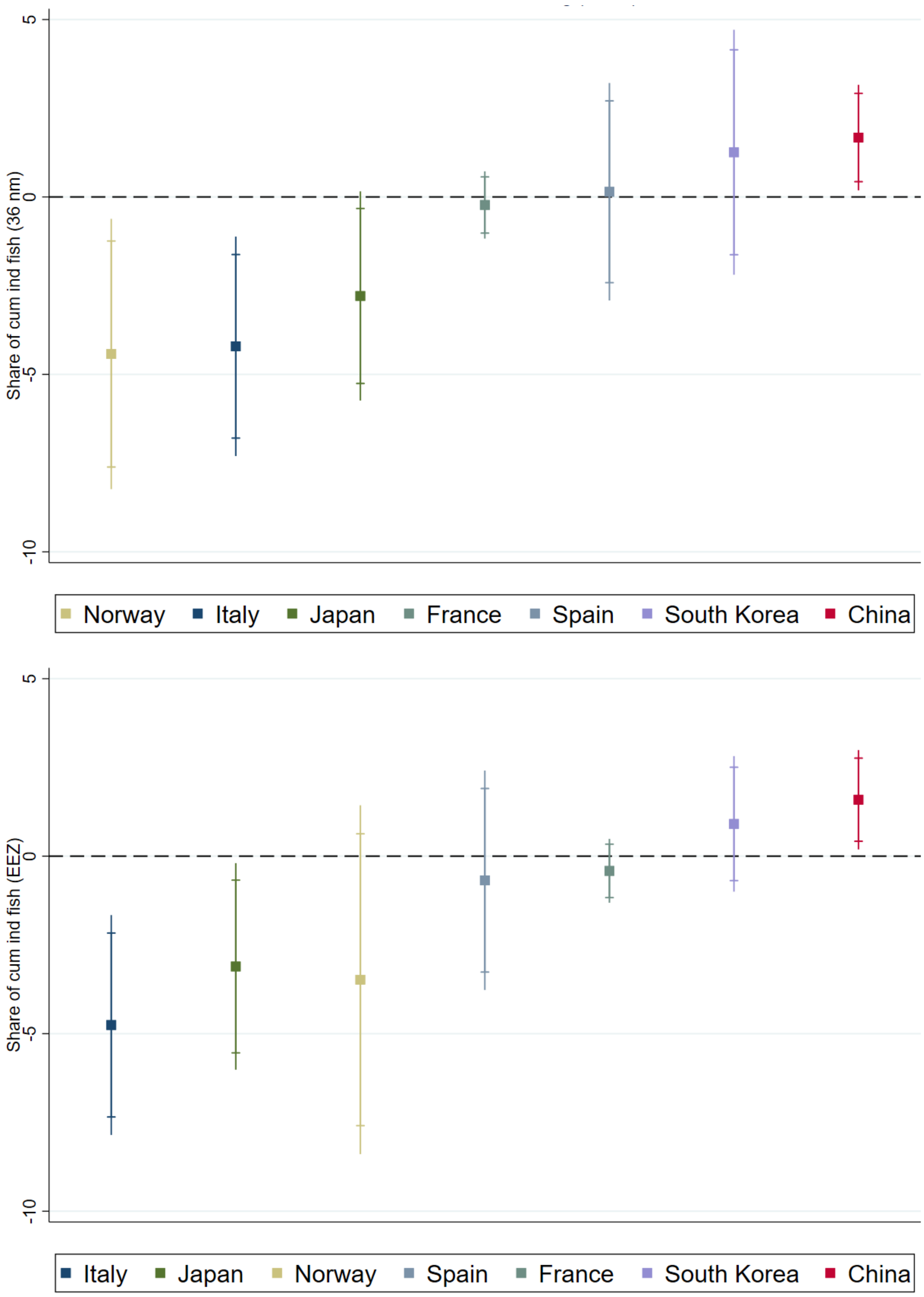
Notes: This table presents the results from regression 3.1 for industrial fishing activity. The main coefficient of interest is α_1, associated to Sh(Donor Cum.OF). All cumulated total official finance flows (Cum. OF) and industrial fishing hours are at the recipient-year level. The cumulative industrial fishing hours start in 2012 and stop in 2014. $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

Figure C.19: Hypothesis 1: Influence of official finance flows on industrial fishing



Notes: This graph displays the coefficients α_1 in equation 3.1, i.e. the correlation between each donor's share of cumulated official finance flows and their share of the cumulated number of industrial fishing hours within a recipient country's close maritime zone (36 NM, square) and EEZ (circle). Each coefficient comes from a separate regression ran across each subset of donor countries.

Figure C.20: Hypothesis 2: Complementarity and substitution effects on industrial fishing activity (36 NM - upper graph and EEZ- lower graph)



Notes: These graphs display the coefficients α_3 from equation 3.2 of the interaction between the share of each competing donor's official finance flow type (total, ODA or OOF) and the share of all other donors. $\alpha_3 > 0$ denotes a complementary effect and $\alpha_3 < 0$ a substitution effect. Each coefficient comes from a separate regression.

Table C.8: Hypothesis 1: Influence of Official Finance on industrial fishing activity (36 nm), by group of donor countries

Outcome	Share(Donor's cumulated industrial fishing hours (36 nm))$_t$							
				DAC				Non-DAC
Group of countries	All	DAC	Non-DAC	Italy Spain Portugal, UK	Germany, France Netherlands	Japan South Korea	Denmark, Finland Norway, Sweden	China
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sh(Donor Cum. OF)$_{t-1}$	0.159*	0.0908	0.481	-1.222	0.114	0.419	-0.125	0.481
	[0.0935]	[0.0701]	[0.375]	[1.134]	[0.112]	[0.400]	[0.0934]	[0.375]
Log(Cum. fish. hours 36nm)$_{rt}$	0.000715	-0.00196	0.0524*	0.00115	-0.00603	-0.00184	-0.00690	0.0524*
	[0.00205]	[0.00148]	[0.0296]	[0.00734]	[0.00457]	[0.0115]	[0.00454]	[0.0296]
Log(Cum. ODA)$_{r,t-1}$	-0.0167	-0.0222	-0.138	0.107	-0.00698	0.0335	-0.0199	-0.138
	[0.0305]	[0.0326]	[0.279]	[0.195]	[0.0358]	[0.320]	[0.0290]	[0.279]
Log(Cum. OOF)$_{r,t-1}$	0.00840	0.0111	-0.0700	0.0663*	-0.00792	0.0758	0.00608	-0.0700
	[0.00857]	[0.00851]	[0.0623]	[0.0368]	[0.0112]	[0.0987]	[0.00563]	[0.0623]
Log(Cum. Vague)$_{r,t-1}$	0.00826***	0.0128***	-0.0622**	-0.0113	0.0504***	0.0106	0.00773	-0.0622**
	[0.00312]	[0.00296]	[0.0299]	[0.00836]	[0.0111]	[0.00810]	[0.00496]	[0.0299]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Donor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Recipient FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.112	0.120	0.736	0.635	0.195	0.334	0.165	0.736
Outcome mean	0.0235	0.0224	0.0465	0.0777	0.0167	0.0738	0.00517	0.0465
N	1780	1691	85	178	445	178	356	85

Notes: This table presents the results from regression 3.1 for industrial fishing activity. The main coefficient of interest is α_1, associated to Sh(Donor Cum.OF). All cumulated total official finance flows (Cum. OF) and industrial fishing hours are at the recipient-year level. The cumulative industrial fishing hours start in 2012 and stop in 2014. Controls include the log distance between recipient and donor countries, the existence of a colonial or dependency relationship, the GDP per capita and the log of the population at the recipient level during year t. Standard errors are clustered at the recipient-year level, $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

Table C.9: Hypothesis 1: Influence of Official Finance on industrial fishing activity (EEZ), by group of donor countries

Outcome	Share(Donor's cumulated industrial fishing hours (EEZ))$_t$							
				DAC				Non-DAC
Group of countries	All	DAC	Non-DAC	Italy Spain Portugal, UK	Germany, France Netherlands	Japan South Korea	Denmark, Finland Norway, Sweden	China
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sh(Donor Cum. OF)$_{t-1}$	0.122	0.0238	-0.465	-0.431	0.0816	-0.156	-0.118	-0.465
	[0.0970]	[0.0748]	[0.660]	[1.165]	[0.117]	[0.468]	[0.0925]	[0.660]
Log(Cum. fish. hours EEZ)$_{rt}$	-0.00309	-0.00377*	0.00355	-0.0207**	-0.0150**	0.0298**	-0.0101	0.00355
	[0.00192]	[0.00204]	[0.0195]	[0.00937]	[0.00696]	[0.0113]	[0.00648]	[0.0195]
Log(Cum. ODA)$_{r,t-1}$	-0.0579*	-0.0554*	-0.161	-0.184	0.00339	-0.225	-0.00314	-0.161
	[0.0302]	[0.0329]	[0.231]	[0.201]	[0.0381]	[0.317]	[0.0223]	[0.231]
Log(Cum. OOF)$_{r,t-1}$	0.00564	0.00656	0.124	0.0205	-0.0210*	0.108	0.00614	0.124
	[0.00904]	[0.00900]	[0.161]	[0.0429]	[0.0109]	[0.100]	[0.00625]	[0.161]
Log(Cum. Vague)$_{r,t-1}$	0.00547*	0.00789**	-0.00716	-0.0517***	0.0545***	-0.00366	0.00930	-0.00716
	[0.00309]	[0.00337]	[0.0282]	[0.0150]	[0.0121]	[0.00889]	[0.00635]	[0.0282]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Donor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Recipient FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.172	0.186	0.661	0.643	0.228	0.363	0.162	0.661
Outcome mean	0.0302	0.0293	0.0484	0.122	0.0188	0.0949	0.00478	0.0484
N	1,780	1,691	85	178	445	178	356	85

Notes: This table presents the results from regression 3.1 for industrial fishing activity. The main coefficient of interest is α_1, associated to Sh(Donor Cum.OF). All cumulated total official finance flows (Cum. OF) and industrial fishing hours are at the recipient-year level. The cumulative industrial fishing hours start in 2012 and stop in 2014. Controls include the log distance between recipient and donor countries, the existence of a colonial or dependency relationship, the GDP per capita and the log of the population at the recipient level during year t. Standard errors are clustered at the recipient-year level, $^{*}p < 0.1$,** $p < 0.05$,*** $p <$ 0.01.

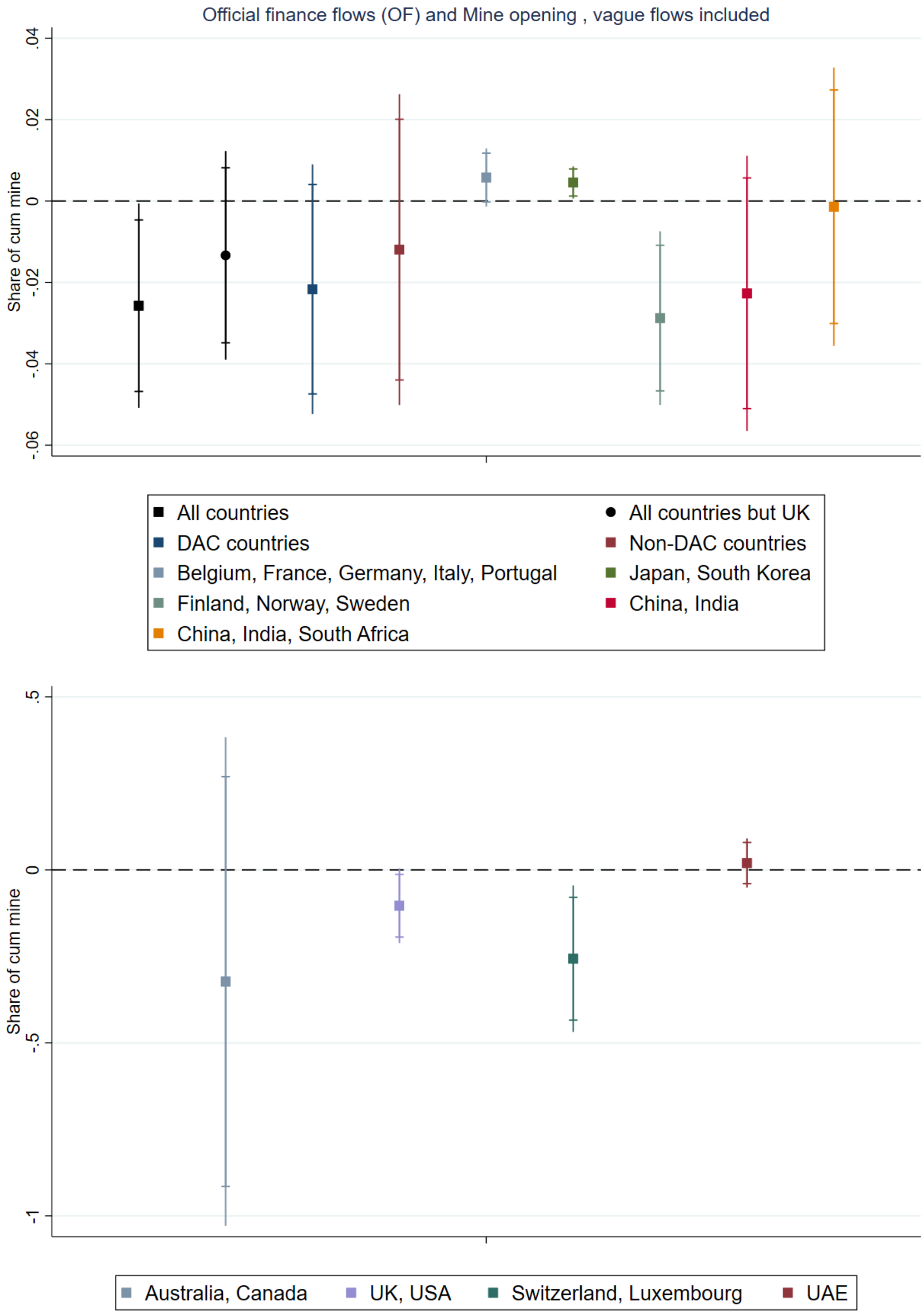
C.7.2 Industrial mining

Table C.10: Hypothesis 1: Influence of Official Finance on industrial mine openings

Outcome	Share (Donor's cumulated open mines)$_t$									
Sample	All countries					All countries but the United Kingdom				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Sh(DonorCum.OF)$_{t-1}$	-0.0423***	-0.0421***	-0.0420***	-0.0257**	-0.0257**	-0.0243**	-0.0241*	-0.0242*	-0.0133	-0.0133
	[0.0126]	[0.0126]	[0.0126]	[0.0128]	[0.0118]	[0.0123]	[0.0123]	[0.0124]	[0.0131]	[0.0120]
Log(Dist)	-0.0150***	-0.0150***	-0.0151***	-0.0133***	-0.0133***	-0.0173***	-0.0173***	-0.0173***	-0.0157***	-0.0157***
	[0.00409]	[0.00409]	[0.00410]	[0.00315]	[0.00337]	[0.00412]	[0.00412]	[0.00413]	[0.00330]	[0.00338]
Col. or dep. ever	0.0362***	0.0362***	0.0362***	0.0176***	0.0176***	0.00892**	0.00889**	0.00890**	-0.00542	-0.00542
	[0.00694]	[0.00694]	[0.00696]	[0.00675]	[0.00638]	[0.00383]	[0.00383]	[0.00384]	[0.00533]	[0.00503]
Log(GDPcap rec)	-0.00148	0.00437*	0.00486*	0.00332	0.00332	-0.00396*	0.000816	0.00106	0.00191	0.00191
	[0.00274]	[0.00240]	[0.00252]	[0.00239]	[0.00354]	[0.00239]	[0.00224]	[0.00236]	[0.00225]	[0.00340]
Log(Pop rec)	0.0193	-0.000842	-0.00191	0.00175	0.00175	0.0105	-0.00605	-0.00625	-0.00904	-0.00904
	[0.0133]	[0.0106]	[0.0109]	[0.0107]	[0.0132]	[0.0103]	[0.00884]	[0.00941]	[0.00861]	[0.0107]
Log(Tot.op.mines)$_{rt}$		0.00505***	0.00502***	0.00384***	0.00384***		0.00413***	0.00411***	0.00326***	0.00326***
		[0.000343]	[0.000347]	[0.000338]	[0.000418]		[0.000329]	[0.000332]	[0.000299]	[0.000400]
Log(Cum.ODA)$_{r,t-1}$			-0.000341	0.000584	0.000584			0.000654	0.00132*	0.00132
			[0.000720]	[0.000801]	[0.00106]			[0.000612]	[0.000674]	[0.000983]
Log(Cum.OOF)$_{r,t-1}$			-0.0000989	0.0000255	0.0000255			-0.000162	-0.0000835	-0.0000835
			[0.000246]	[0.000231]	[0.000336]			[0.000218]	[0.000204]	[0.000310]
Log(Cum.Vague)$_{r,t-1}$			0.000227	0.000408	0.000408			0.000191	0.000396	0.000396
			[0.000273]	[0.000267]	[0.000383]			[0.000286]	[0.000274]	[0.000369]
Sh(D.mines)$_{b.2000}$				0.297***	0.297***				0.268***	0.268***
				[0.0310]	[0.0304]				[0.0310]	[0.0303]
Donor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Recipient FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	15,825	15,825	15,790	15,540	15,540	15,192	15,192	15,158	14,936	14,936

Notes: This table presents the results from regression 3.1 for industrial mining. The main coefficient of interest is α_1, associated to Sh(Donor Cum.OF). All cumulated total official finance flows (Cum. OF) and the number of open mines are at the recipient-year level. The cumulative mining starts in 2000 and stops in 2014. $Sh(D.mines)_{b.2000}$ represents the donor's share of mines that have opened in the recipient country before 2000. Standard errors are clustered at the recipient-year level, $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

Figure C.21: Hypothesis 1: Influence of official finance flows on industrial mine openings



Notes: This graph displays the coefficients α_1 in equation 3.1, i.e. the correlation between each donor's share of cumulated official finance flows and their share of industrial mine openings within a recipient country. Each coefficient comes from a separate regression ran across each subset of donor countries.

Table C.11: Hypothesis 2: Complementary effect of UK flows on other DAC donors' industrial mining activity

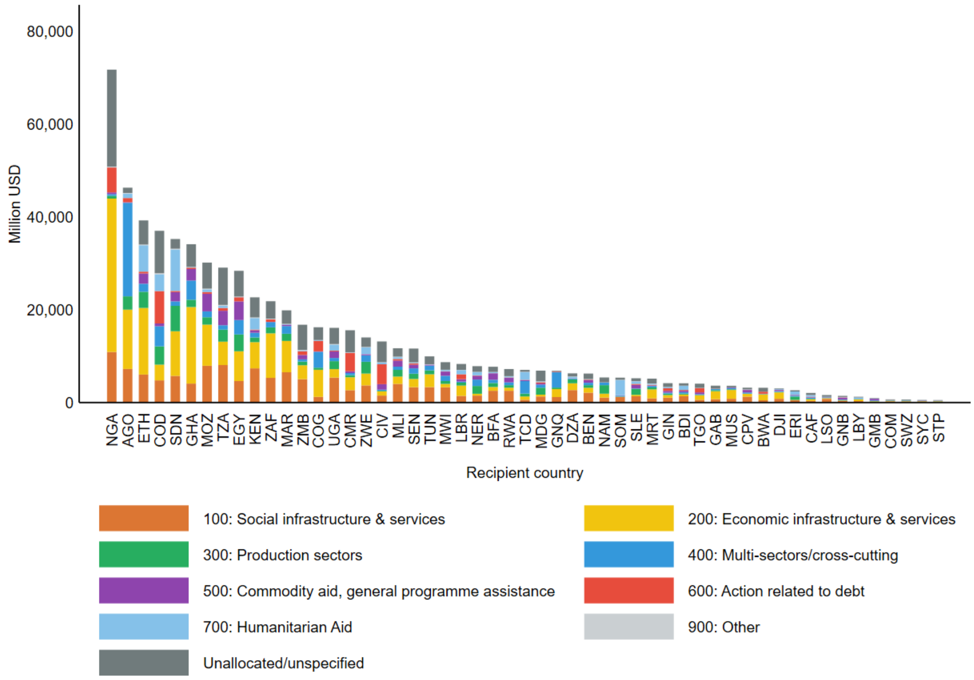
Outcome	Share (Donor's cumulated open mines)$_t$								
UK Flows	Total			ODA			OOF		
Donors' sample	All	DAC	Non-DAC	All	DAC	Non-DAC	All	DAC	Non-DAC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sh(DonorCum.OF)$_{t-1}$×Sh(DonorCum.UK flows)$_{t-1}$	0.809***	1.036***	-0.0706	0.835***	1.287***	0.0301	0.0518	0.0334	0.0985
	[0.299]	[0.376]	[0.170]	[0.243]	[0.389]	[0.108]	[0.0700]	[0.0730]	[0.307]
Sh(DonorCum.OF)$_{t-1}$	-0.0407***	-0.0413**	-0.0105	-0.0472***	-0.0501***	-0.0129	-0.0163	-0.00254	-0.0116
	[0.0150]	[0.0188]	[0.0203]	[0.0149]	[0.0185]	[0.0209]	[0.0135]	[0.0177]	[0.0196]
Sh(DonorCum.UK flows)$_{t-1}$	-0.0232**	-0.0269**	-0.0377*	-0.0249**	-0.0292**	-0.0617**	-0.00801**	-0.00785**	-0.00506
	[0.00919]	[0.0112]	[0.0204]	[0.0115]	[0.0135]	[0.0297]	[0.00333]	[0.00379]	[0.00688]
Log(Tot.op.mines)$_{rt}$	0.00328***	0.00295***	0.00500***	0.00326***	0.00294***	0.00499***	0.00328***	0.00293***	0.00501***
	[0.000298]	[0.000310]	[0.000924]	[0.000297]	[0.000307]	[0.000932]	[0.000296]	[0.000306]	[0.000912]
Sh(D.mines)$_{b.2000}$	0.267***	0.268***	0.0880	0.267***	0.268***	0.0870	0.268***	0.268***	0.0864
	[0.0310]	[0.0345]	[0.0654]	[0.0310]	[0.0345]	[0.0656]	[0.0311]	[0.0345]	[0.0652]
Log(Cum.ODA)$_{r,t-1}$	0.00145**	0.00141*	0.00108	0.00148**	0.00138*	0.00104	0.00136**	0.00134	0.00106
	[0.000657]	[0.000819]	[0.00171]	[0.000647]	[0.000810]	[0.00170]	[0.000666]	[0.000832]	[0.00172]
Log(Cum.OOF)$_{r,t-1}$	-0.0000533	-0.000167	0.000736	-0.0000734	-0.000179	0.000749	-0.0000348	-0.000114	0.000656
	[0.000205]	[0.000232]	[0.000649]	[0.000203]	[0.000226]	[0.000650]	[0.000203]	[0.000234]	[0.000642]
Log(Cum.Vague)$_{r,t-1}$	0.000370	0.000106	0.00194***	0.000364	0.000106	0.00197***	0.000339	0.0000617	0.00200***
	[0.000273]	[0.000289]	[0.000706]	[0.000275]	[0.000289]	[0.000701]	[0.000275]	[0.000295]	[0.000708]
R2	0.234	0.261	0.307	0.235	0.264	0.307	0.231	0.256	0.307
Outcome mean	0.0130	0.0118	0.0186	0.0130	0.0118	0.0186	0.0130	0.0118	0.0186
N	14,936	12,467	2,469	14,936	12,467	2,469	14,936	12,467	2,469

Notes: This table presents the results from regression 3.2 to test Hypothesis 2 for industrial mining. The main coefficient of interest is α_3 associated with $Sh(DonorCum.OF)_{t-1}$×Sh(CompetFlowType)$_{t-1}$. $\alpha_3 < 0$ notes a substitution effect and $\alpha_3 > 0$ marks a complementary effect. All cumulated total official finance flows (Cum. OF) and the number of open mines are at the recipient-year level. The cumulative mining starts in 2000 and stops in 2014. $Sh(D.mines)_{b.2000}$ represents the donor's share of mines that have opened in the recipient country before 2000. Standard errors are clustered at the recipient-year level, $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

C.8 Discussion

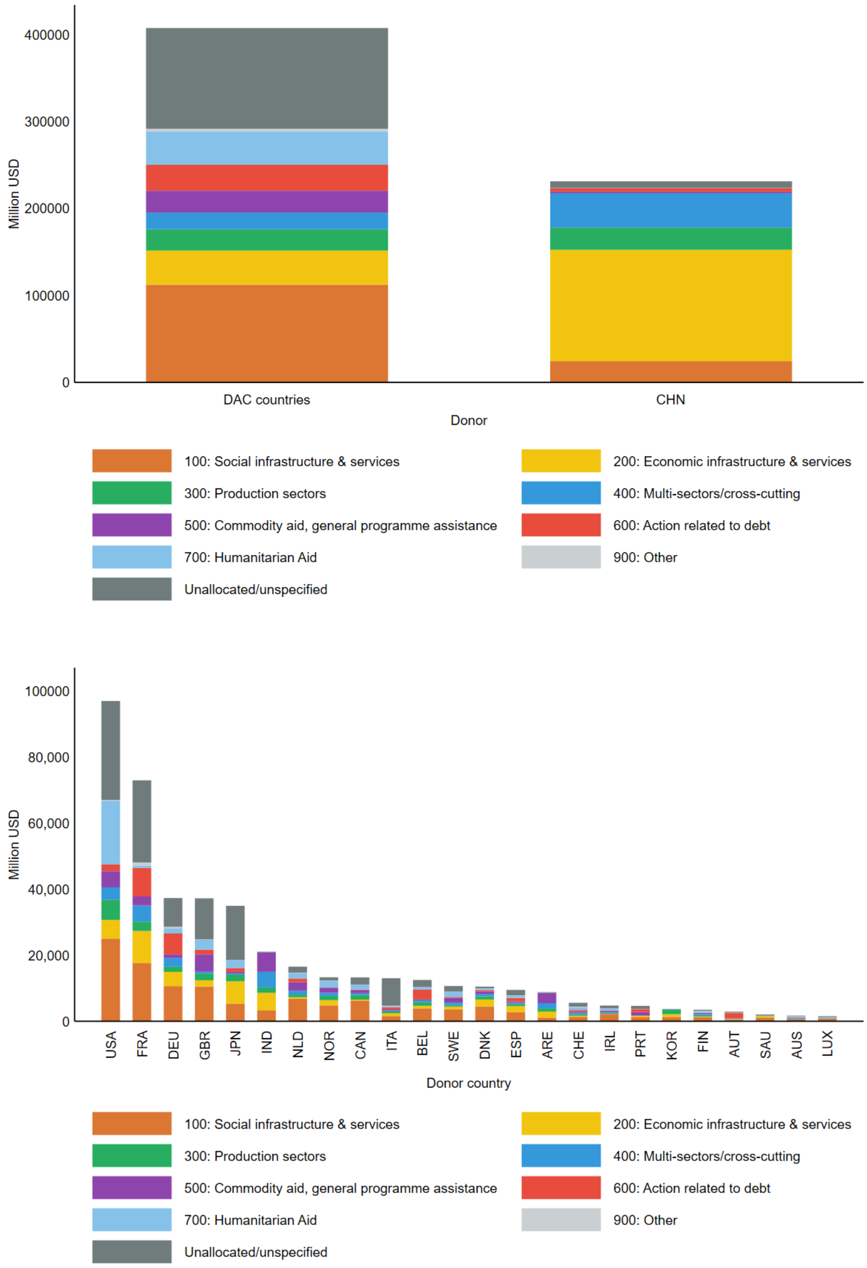
The analysis included in the current paper so far only accounts for flows of different classes (ODA and OOF), but it is also possible for future research to make the distinction across the sectors of each flow. The following figures provide a preliminary description to shed light on the potential of such an analysis.

Figure C.22: Sectoral decomposition of received financial flows (2000-2013)



Notes: This graph represents the official finance flows received by each African recipient country over the 2000-2013 period. It makes the distinction between the sectors to which each flow was attributed, following the OECD sectoral decomposition.

Figure C.23: Sectoral decomposition of all donor countries' financial flows towards Africa (2000-2013)



Notes: These graphs represent the official finance flows from each donor country to all African country recipients over the 2000-2013 period. The upper graph compares China with all DAC countries, and the lower graph represent all individual countries but without China, for a matter of scale. Distinction is made between the sectors to which each flow was attributed to, following the OECD sectoral decomposition.
Source: Own elaboration using Core, China, and India Aiddata.

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