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Conséquences économiques et démographiques des catastrophes naturelles et des déplacements de population

Iverson-Love Joseph

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Normandie Université

THÈSE

Pour obtenir le diplôme de doctorat

Spécialité SCIENCES ECONOMIQUES

Préparée au sein de l'Université de Caen Normandie

Conséquences économiques et démographiques des catastrophes naturelles et des déplacements de population

Présentée et soutenue par
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Thèse soutenue le 07/12/2022
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UNIVERSITÉ
CAEN
NORMANDIE



Conséquences économiques et démographiques des catastrophes naturelles et des déplacements de population

Thèse de Doctorat : Sciences Economiques

De

Iverson-Love JOSEPH

Sous la direction de :

Isabelle LEBON et co-encadrée par **Olivier DAGNELIE**

07 Décembre 2022

Par la présente note, je déclare qu'en dehors des auteurs et documents cités dans cette thèse,
le reste du travail est l'œuvre de l'esprit.

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Cette thèse a été financée à 100% par un contrat doctoral offert par la région Normandie. Le premier **Chapitre** a été présenté à la 17ème conférence annuelle de la Fédération de Recherche “Théorie et Évaluation des Politiques Publiques (TEPP)” qui a eu lieu les 21 et 22 octobre 2021 à l’Université d’Évry. Il a été également présenté à la “Conférence Internationale en Économie du Développement (ICDE)” qui s’est déroulée le 30 juin et le 1er juillet 2022 au Centre d’Études et de Recherches sur le Développement International (CERDI) à Clermont-Ferrand. Le deuxième **Chapitre** a été présenté aux colloques suivant : “36th Eurasia Business and Economics Society (EBES) Conference” (Turkey), 01-03 juillet 2021 ; “IV International Conference on Empirical Economics and Social Science (e-ICEESS’21)”, Bandirma Onyedi Eylul University (Turkey), 03-04 juillet 2021 ; “10èmes DOCTORIADES : Journée de la jeune recherche de l’Université de Toulon”, 14 Octobre 2021 ; “The 20th International Conference of the Japan Economic Policy Association (JEPA2021)”, 06-07 novembre 2021 ; “2^e Workshop Développement et environnement”, Université de Pau et des Pays de l’Adour (TREE-UPPA), 2-3 juin 2022, Bayonne ; “The 70th Congress of the French Economic Association (AFSE)”, 14-16 Juin 2022, Dijon. Le dernier **Chapitre** a été présenté à l’École Thématique sur l’Évaluation des Politiques Publiques (ETEPP), 14-18 mars 2022, Aussois. Ces colloques ont été financés par le Centre de Recherche en Économie et Management (CREM-UMR 6211). Les frais de relecture de ces trois articles ont été également pris en charge par le CREM.

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Je dédie cette thèse,

À ma mère **Agnès Rosemonde PIERRE**

À la mémoire de mon défunt grand frère **Joriscal PIERRE**,
décédé le 12 Janvier 2010.

À mes petits frères **Faldherbe et Gérald Fils BEAUSSEJOUR.**

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✠ Résumé Général ✠

Au niveau mondial, les dommages causés par les catastrophes naturelles de grande ampleur, comme le tremblement de terre du 12 janvier 2010 en Haïti, n'ont cessé d'augmenter au cours des dernières décennies. L'accélération du changement climatique devrait accroître la fréquence, l'ampleur et la gravité des catastrophes environnementales aussi bien que leurs conséquences directes et indirectes. La complexité croissante des changements géologiques, environnementaux, socio-économiques mondiaux et les interconnexions entre les processus à l'échelle mondiale, régionale, nationale et locale, exigent une plus grande connaissance, des différentes dimensions affectées par les désastres naturels ainsi que de la capacité des pays à limiter l'ampleur des pertes immédiates, à se rétablir et se reconstruire durablement. Avec la crise mondiale des réfugiés en constante augmentation, particulièrement dans les pays en développement, les recherches sur leurs conséquences se sont multipliées. Il est donc important d'évaluer leur impact économique et d'analyser les facteurs susceptibles de rendre les réfugiés plus bénéfiques aux communautés qui les accueillent. Cette thèse vise à identifier, examiner, et évaluer ces différents aspects de la vie sociale, démographique, économique en Haïti et dans certains pays africains.

La recherche prend la forme d'une analyse empirique qui inclut les modèles de différences de différences (Chapitres I et II), des modèles vectoriels autorégressifs de panel (Chapitre II), des MCO standards et une approche par variable instrumentale (Chapitre III). Cette thèse produit des estimations de relations causales en s'appuyant sur les données de l'intensité du séisme avec celles des enquêtes démographiques et de santé (Chapitre I), les données des intensités lumineuses de nuit, et les données de la population (Chapitre II). Dans le dernier chapitre les données des lumières émises la nuit et captées par satellite, collectées et mises à disposition par la NOAA's National Centers for Environmental Information, du Haut Commissariat des Nations Unies pour les Réfugiés (UNHCR), de la Uppsala Conflict Data Program (UCDP) ont, entre autres, été utilisées.

Les analyses empiriques sur Haïti révèlent une augmentation du nombre de naissances durant le premier mois suivant le séisme, ainsi qu'une hausse de la fertilité et de la mortalité infantile dans les camps (Chapitre I). Ce séisme a également réduit considérablement la croissance économique à court et à long terme dans les zones fortement touchées (Chapitre II). Le troisième chapitre, consacré à l'évaluation de l'impact des réfugiés, montre une baisse de la croissance économique locale dans les zones proches des camps. L'effet est néanmoins négligeable d'un point de vue économique. Il indique également que l'impact économique dépend fortement de la capacité d'absorption approximée par le revenu national brut par habitant et de la politique migratoire en place dans les pays d'accueil. Des recommandations de politiques publiques ont été discutées dans les trois chapitres ainsi que les limites, et des perspectives pour des recherches futures.

Mots clés : Haïti, Catastrophes naturelles, Tremblement de terre, Fertilité, Mortalités néonatale et infantile, Activité économique, Conflits, Personnes déplacées de force, Réfugiés, Afrique.

Globally, the damage caused by large-scale natural disasters, such as the January 12, 2010 earthquake in Haïti, has been steadily increasing over the past decades. The acceleration of climate change is expected to increase the frequency, scale and severity of environmental disasters as well as their direct and indirect consequences. Further, the increasing complexity of global geological, environmental, and socio-economic changes and the interconnections between global, regional, and local processes require a greater understanding of the different dimensions affected by natural disasters, as well as the capacity of countries to limit the magnitude of immediate losses, and to recover and rebuild sustainably. With the global refugee crisis on the rise, particularly in developing countries, research on the consequences of these disasters has multiplied. It is therefore important to assess their economic impact and to analyze the factors that can make refugees more beneficial to the communities that host them. This thesis aims to identify, evaluate, and examine these different aspects of social, demographic, and economic life in Haiti and in some African countries.

The research takes the form of an empirical analysis that includes difference-in-differences models (Chapters I and II), panel vector autoregressive models (Chapter II), standard OLS and an instrumental variable approach (Chapter III). This work produces estimates of causal relationships using earthquake intensity data with demographic and health survey data (Chapter I), and night light data (Chapter II). In the last chapter, satellite data on nighttime light emissions collected and made available by NOAA's National Centers for environmental Information, the United Nations High Commissioner for Refugees (UNHCR), and the Uppsala Conflict Data Program (UCDP) were used, among others.

Empirical analyses in Haïti reveal an increase in the number of births in the first month after the earthquake, and a rise in both fertility and infant mortality in the camps (Chapter I). This earthquake also considerably reduced short and long term economic growth in the heavily affected areas (Chapter II). The third chapter, devoted to the evaluation of the impact of the refugees, shows a decrease in local economic growth in the areas close to the camps. The effect is nevertheless negligible from an economic point of view. It also indicates that the economic impact depends strongly on the approximate absorptive capacity of the gross national income per capita and on the migration policy in place in

the host countries. Policy recommendations have been discussed in the three chapters as well as limitations, and perspectives for future research.

Key words : Haïti, Natural disasters, Earthquake, Fertility, Neonatal and infant mortality, Economic activity, Conflict, Forcibly displaced persons, Refugees, Africa.

✠ Introduction Générale ✠

Des études récentes révèlent une augmentation significative des catastrophes naturelles et de leurs conséquences sociales, démographiques, et économiques dans le monde, accéléré par le réchauffement climatique, notamment dans les pays en développement. Ces derniers sont particulièrement vulnérables aux désastres naturels—qu’il s’agisse de processus lents comme l’érosion côtière, l’élévation du niveau de la mer, et le changement climatique—ou de perturbations rapides à grande échelle comme les ouragans/cyclones, les inondations, les tsunamis et les tremblements de terre. Ces événements tragiques fragilisent les populations affectées, amplifient les précarités sanitaires, sociales, économiques, et minent les perspectives de développement durable de ces pays. Située dans la Caraïbe insulaire, la République d’Haïti est l’un des pays les plus touchés par ces désastres dont le plus dévastateur a été le tremblement de terre du 12 janvier 2010, en termes du nombre de décès par rapport à la population.¹ D’importants dommages à l’infrastructure économique du pays ont été enregistrés, estimés à plus de 100 % du PIB de 2009 (Cavallo et al., 2010 ; Government of the Republic of Haiti, 2010). Ce séisme a altéré les processus économiques, sociaux et démographiques, en particulier la fertilité, la mortalité, la migration et la délocalisation des populations affectées (Behrman and Weitzman, 2016 ; Cavallo et al., 2010 ; DesRoches et al., 2011 ; Doocy et al., 2013).

Outre les désastres naturels de grande ampleur, d’autres chocs majeurs aggravant la vulnérabilité socio-économique des populations touchées comme les persécutions, les violences, ou les conflits engendrent des déplacements massifs de populations dont des réfugiés dans les pays africains en particulier (UNHCR, 2021a).² Ces deux phénomènes combinés ou pris séparément peuvent entraîner des changements importants dans les domaines de

1. Ce séisme a tué plus de 250 000 personnes, blessé plus de 300 000, engendré plus de 1.3 millions de déplacées, et a causé des pertes massives de biens et d’actifs civiques (DesRoches et al., 2011 ; Government of the Republic of Haiti, 2010).

2. On estime à plus 89,2 millions le nombre de personnes déplacées dans le monde à la fin de l’année 2021, le plus haut niveau jamais enregistré, dont 27,5 millions sont reconnues comme des réfugiés, beaucoup ayant fui leur foyer et leur pays face à la violence (UNHCR, 2021a).

la santé, la démographie, et de l'économie (Cavallo and Noy, 2011 ; Frankenberg and Thomas, 2014 ; Verme and Schuettler, 2021). Il est donc important d'évaluer leurs impacts et d'identifier les canaux de transmission.

La problématique relative aux catastrophes et aux déplacements de population présente des enjeux majeurs pour les pays en développement d'Afrique et des Caraïbes en particulier. L'objectif de cette thèse a été d'une part de modéliser, de quantifier et d'analyser les conséquences économiques et démographiques du tremblement de terre de 2010 en Haïti, et d'autre part d'évaluer et d'examiner l'impact économique des camps de réfugiés dans les communautés d'accueil en Afrique. Plus spécifiquement, dans les Chapitres I et II nous avons profité des caractères aléatoire et exogène de l'intensité avec laquelle les différentes zones du pays ont été touchées par le séisme, pour estimer son impact et produire des estimations causales de ses effets sur des paramètres du monde réel tels que le niveau de la fertilité, la mortalité néonatale et infantile, et l'activité économique au niveau local. Ensuite, nous avons identifié et quantifié l'impact économique des réfugiés sur le continent africain en couvrant une quarantaine de pays dans le Chapitre III. En évaluant également la croissance et le redressement économique suite au séisme, la thèse aide à comprendre comment les pays en développement se redressent suite aux catastrophes naturelles dont l'aggravation et la multiplication sont prévues par les experts du climat, afin d'améliorer les stratégies de prévention et d'atténuation, et de mieux orienter la relance économique locale après les désastres de grande ampleur. Elle permet également de connaître les conséquences que les réfugiés ont sur les communautés qui les accueillent dans les pays en développement afin de transformer leur présence en opportunité de développement.

Nos principales conclusions peuvent être résumées comme suit.

Le **Chapitre I** intitulé "*The impacts of the 2010 Haiti earthquake on fertility, neonatal and infant mortality*", évalue empiriquement les conséquences démographiques du tremblement de terre de 2010 en Haïti. L'objectif est de comprendre les dynamiques démographiques résultant du séisme, en tenant compte des migrations internes induites par ce désastre—en particulier la localisation des personnes qui vivaient dans les camps. A cet

effet, la méthodologie exploite le fait que l'on peut combiner les données des Enquêtes Démographiques et de Santé (DHS : 2012, 2016-17, selon son acronyme en anglais) et l'intensité du tremblement de terre enregistré sur l'échelle de Mercalli – The Modified Mercalli Intensity Scale – utilisée comme proxy du niveau local des dommages dans le pays. Nous avons utilisé un cadre d'expérience naturelle via un modèle de différences de différences à effets fixes afin de déterminer si le choc causé par le séisme a entraîné une variation substantielle du niveau de la fertilité, de la mortalité néonatale et infantile dans les zones fortement touchées. Les problèmes de sélection, de l'hétérogénéité observée et non observée ont été pris en compte. Ce faisant, le présent chapitre suggère que les effets perturbateurs d'une catastrophe naturelle comme le tremblement de terre de 2010, peuvent avoir un effet positif sur la fertilité et la mortalité infantile. Il met également en évidence une variation considérable des effets démographiques du séisme selon le lieu, l'âge et le niveau de scolarisation des femmes dans les camps de déplacés. Ces résultats sont particulièrement utiles pour les gouvernements centraux et locaux, les services d'urgence et les travailleurs humanitaires afin qu'ils puissent répondre efficacement et déployer les ressources là où elles sont le plus nécessaires. Ce chapitre a été co-écrit avec Olivier Dagnelie.

Le **Chapter II** ayant pour titre "*The effect of natural disaster on economic growth : evidence from a major earthquake in Haiti*", analyse les conséquences du séisme sur la croissance et le redressement économiques à court et à long terme. L'objectif est d'évaluer les pertes en termes de croissance/activité économique du tremblement de terre et d'examiner comment les différentes régions d'Haïti se sont redressées suite à ce choc négatif. Les données d'intensité du tremblement de terre fournies par l'Institut d'Études Géologiques des États-Unis (USGS, d'après son acronyme en anglais) et les lumières émises la nuit et captées par satellite—DMSP-OLS Nighttime Lights—ont été combinées afin d'évaluer l'impact de la catastrophe naturelle. En comparant les arrondissements fortement touchés et légèrement affectés par le séisme à travers un modèle de différences de différences à effets fixes, et des fonctions de réponses au choc au niveau local—Local Impulse Response Functions (IRF), ce chapitre montre des évidences claires que la dynamique de développement a été ralentie par le tremblement de terre. De plus, le pays n'a pas pu se remettre de ce choc négatif pendant de nombreuses années contrairement à certaines publications antérieures sur les impacts économiques à long terme des catastrophes naturelles. Ces

résultats sont robustes à différentes techniques d'estimations, y compris l'utilisation d'un modèle spatial. De telles évidences empiriques remettent en lumière ce désastre naturel qui a laissé tant de morts dans son sillage et plus généralement les problématiques environnementales actuelles et leurs conséquences dans les pays en développement. Ce chapitre a été réalisé seul, et est publié dans la revue *World Development*.

Le **Chapitre III** intitulé "*The economic impact of refugees in Africa*", s'écarte des chapitres précédents en ce sens qu'il s'agit d'un article consacré aux problématiques liées à la présence des réfugiés dans les pays en développement. Il examine l'impact des réfugiés sur la croissance économique locale en Afrique de 2000 à 2016. L'objectif est d'une part, d'identifier et de quantifier l'impact des camps de réfugiés sur l'activité économique locale, et d'autre part, d'analyser les facteurs qui pourraient conduire à des conséquences économiques positives ou négatives de l'accueil des réfugiés. Pour cela, nous avons utilisé la base de données de l'Agence des Nations Unies pour les Réfugiés (UNHCR de son acronyme en anglais) et les données des lumières de nuits utilisées comme une proxy pour l'activité économique dans les pays d'accueil. La combinaison d'un modèle quasi-expérimental de type MCO et l'utilisation des méthodes de variables instrumentales incluant des effets fixes géographiques et temporels, nous a permis de contrôler l'endogénéité, l'hétérogénéité observée et non observée, et produire des estimations causales. Notre analyse empirique révèle que la présence des réfugiés dans les camps de déplacés est associée à une baisse significative de la croissance économique locale dans un rayon de 150 km autour des camps. L'effet est cependant négligeable d'un point de vue économique et dépend largement de la capacité d'absorption des pays et des politiques mises en place envers les réfugiés dans les pays d'accueil. Les réfugiés affectent négativement l'activité économique dans les pays à faibles revenus, tandis que l'effet est en revanche positif et significatif dans les pays à revenus intermédiaires, et dans les pays ayant des politiques libérale en termes d'accès aux moyens de subsistance (propriété, la terre, et l'emploi). Ces résultats supportent fortement l'analyse théorique suggérant que la capacité d'absorption, et les politiques migratoires (en particulier les politiques d'asile) déterminent le signe et la magnitude des relations entre l'activité économique et les réfugiés. Ce chapitre est basé sur un papier co-écrit avec Olivier Dagnelie et Jean-François Maystadt.

The impacts of the 2010 Haïti earthquake on fertility, neonatal and infant mortality

RÉSUMÉ

Cette étude évalue les effets du tremblement de terre de 2010 sur la fertilité, la mortalité néonatale et infantile en utilisant les données des enquêtes démographiques et de santé (DHS, 2012, 2016-17) et de l'Institut d'études géologiques des États-Unis (USGS, 2010). Nous utilisons les modèles de différence de différences et contrôlons pour l'hétérogénéité non observée à travers un ensemble d'effets fixes, afin de produire des estimations causales des effets du séisme sur les paramètres démographiques. Nous trouvons que ce dernier a entraîné une augmentation significative du nombre de naissances durant le mois de janvier 2010, un effet compatible avec les accouchements prématurés. Les résultats suggèrent une augmentation de la fertilité dans les camps de déplacés, commençant approximativement à partir du vingt et unième mois suivant le séisme. Les effets sont prononcés particulièrement chez les moins jeunes, les moins scolarisées, et les femmes vivant dans les zones rurales. Nous constatons également que ces femmes avaient une probabilité plus élevée de voir leurs enfants mourir avant d'atteindre l'âge d'un an. Ces résultats mettent en évidence des variations considérables des conséquences démographiques du tremblement de terre selon les caractéristiques socio-économiques des femmes touchées, et appellent à des politiques et interventions nationales et internationales renforçant les systèmes de santé du pays, et améliorant les conditions de vie de la population.

Mots clés : Tremblement de terre, Haïti, Fertilité, Mortalités néonatale et infantile.

JEL Codes : Q54 R11 O10 O4 .

ABSTRACT

This study evaluates the effects of the 2010 Haïti earthquake on fertility, neonatal and infant mortality employing data from the Demographic and Health Surveys (DHS, 2012, 2016-17) and the United States Geological Survey (USGS, 2010). We use difference-in-difference regression models and control for unobserved heterogeneity with different sets of fixed effects to provide causal estimates of the earthquake effects on demographic issues. We reveal that the earthquake led to significant rises in the number of births at the time of the earthquake; an effect compatible with before term deliveries. Findings also suggest an increase in live births beginning approximately twenty-one months after the quake that is tratisfied across rural, young and primary-schooled women living in displaced camps. We also observe that these women had a higher probability of seeing their children die before the age of 1. These results highlight considerable variations in the earthquake's demographic impacts depending on women's socio-economic characteristics, and call for national and international policies and interventions strengthening the country's health care systems, and improving the population's living conditions.

Key words : Earthquake, Haïti, Fertility, Neonatal and Infant mortality

JEL Codes : J10, J11, J13, J16, O15, O18

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1.1. Introduction and Background

On January 12, 2010, the Republic of Haïti, a country of 9.6 million inhabitants prior to the earthquake spread over 27,750 km², was devastated by a powerful earthquake of moment magnitude Mw 7.0 which caused significant loss of human life and considerable material damage.^{3, 4} The hypocenter of the earthquake was close to the earth's, surface (10 km deep) and its epicenter was close to the city of Léogâne, about 25 km southwest of the densely populated capital, Port-au-Prince (United States Geological Survey, 2010). More than 250,000 (or 2.54% of the 2009 population) people were reported killed, about 300,000 (3.09%) injured, and over 1.3 million (13.54%) homeless (DesRoches et al., 2011 ; Government of the Republic of Haiti, 2010), as well as major direct economic losses accounting for between USD 8.1 billion (123.01% of 2009 GDP) and USD 13.9 billion

3. The moment magnitude scale (Mw) is the current standard scale for measuring earthquake strength replacing the better-known Richter scale since 2002. In particular, for very large earthquakes, moment magnitude gives the most reliable estimate of earthquake size (USGS, 2002).

4. Population estimated in 2009 by the World Bank (2019).

(211.09%) (Cavallo et al., 2010). By analysing the short- and long-term economic impacts of the quake, and post-disaster recovery, Joseph (2022) evidenced that Haiti experience strongly negative growth effects, which are still present ten years later.

Beyond causing direct loss of life, health, and income or wealth (Cavallo and Noy, 2011 ; Frankenberg and Thomas, 2014), academic attention towards large natural disasters has increased considerably in recent years, with many scholars seeking to understand whether natural disasters have any impact on demographic structure of affected areas (Doocy et al., 2013 ; Fotso et al., 2013 ; Frankenberg et al., 2008).⁵ For instance, natural disasters may have indirect effects on demographic outcomes such as fertility through several mechanisms, including infant mortality, displacement, access to reproductive health care, and the need for more children (Seltzer and Nobles, 2017). As such, they may increase fertility (Behrman and Weitzman, 2016 ; Davis, 2017 ; Nandi et al., 2018 ; Nobles et al., 2015), decline birth weight (Kim et al., 2017 ; Torche, 2011) and gestational age (Torche and Kleinhaus, 2012) or reduce birth spacing (Nandi et al., 2018). As opposed to the above findings, fertility may also decrease after large disasters such as the tsunami in Japan (Lin, 2010). From a perspective based in psychology, other evidence suggests a depression of fertility behavior due to lower psychological capacity of women for child-bearing, a higher incidence of miscarriages (Norris and Elrod, 2006), or reduced desire for children (Agadjanian and Prata, 2002 ; Frankenberg and Thomas, 2014 ; Hapsari et al., 2009).⁶ Past economic research suggests that the population-level effects following natural disasters may not be large (Frankenberg and Thomas, 2014). Empirical evidence on both sides of the discussion is sparse.

On the other hand, natural disasters have a range of direct and indirect effects on children's health and, consequently, on child mortality (Datar et al., 2013 ; Fotso et al., 2013 ; Frankenberg et al., 2011 ; Khanal, 2022). Death and post-disaster mortality are often concentrated among poor populations due to pre-existing social, economic and health vulnerabilities in low-income countries (Cutter et al., 2003 ; Jiang and Hardee, 2011 ;

5. Demographic dynamics may be impacted by the disaster itself directly or indirectly, as well as by pre- and post-disaster policy programs (for a review, see Frankenberg and Thomas (2014)).

6. This because people are often affected by disaster events and fear that they may lose their children in the future due to more frequent and natural disasters (Agadjanian and Prata, 2002).

Kahn, 2005). Natural disasters may also exacerbate preexisting gender and socioeconomic inequalities (Farmer et al., 2012 ; Hartman and Squires, 2006 ; Neumayer and Plümper, 2007). Although numerous studies have focused on the economic, social and psychological impacts of hurricanes, floods, tornadoes, earthquakes, and other natural disasters in the developing world, little theoretical or empirical works examine local demographic consequences of the 2010 Haiti earthquake that left death and destruction in its wake. This event has profound psychological, social (Green and Miles, 2011), and economic (Joseph, 2022) impacts on the stricken individuals and communities. In this respect, we seek to understand how affected populations respond to this shock and how it alters the life of course trajectories of those affected.

Using a natural experiment design, this paper investigates the impact of this earthquake on fertility, neonatal, and infant mortality which all determined how the country could recover. We explore whether changes in the timing of fertility and the effects on fertility immediately after an earthquake are greater than in later periods. We use data from Demographic and Health Survey (DHS, 2012, 2016–17), and employ difference-in-difference (DID) regression models that compare the outcomes on a monthly basis for 5-year periods before and after the earthquake in heavily impacted and less affected zones of the country. Our results show that the earthquake led to significant rises in the number of births at the time of the earthquake. Our empirical analysis also demonstrates that internally displaced persons camps (IDP) are driving the positive effects of the earthquake on the fertility of hard-hit women. This average positive impact on fertility is coupled with an increase among rural, younger, and less-schooled women. Further, we find that the earthquake resulted in an increase in the rate of neonatal death of only some mothers.⁷ Our results also reveal that the earthquake is associated with a rise in infant mortality, specifically among rural and less-schooled women living in camps. Beside its specific estimates, we make an important contribution to a small but growing literature on the demographic effects of natural disasters by evaluating the very short- and medium-term demographic effects of the 2010 Haiti earthquake. Specifically, this paper contributes to two strands of literatures : (1) effects of early life exposure to natural disaster shocks on fertility, neonatal, and infant mortality, and (2) heterogeneous effects among population

7. In the overall sample, for some mothers only, there is a decrease in infant mortality rates about twelve months after the disaster in primary sampling units struck with an intensity greater than 7.

subgroups.

The remainder of the paper goes as follows : next section gives descriptive demographic and background information on Haiti before the earthquake. The two main sections of this paper are Section 1.3, detailing our empirical strategy, the data we use and the models we turn to, and Section 1.4 putting forward the results, and exploring the mechanisms through which the earthquake could affect demographic outcomes. Section 1.5 concludes with a discussion of the results and outlook.

1.2. The 2010 Haïti earthquake and its impact

The Haitian earthquake of 2010 was the most destructive event any country has experienced in modern times when measured in terms of the number of people killed as a percentage of the country's population (Cavallo et al., 2010).⁸ The earthquake leveled the capital city, delivering a severe blow to an already vulnerable Haitian economy and infrastructure, and severely impeding nation-building efforts in the country.⁹ The effects of the earthquake were felt mainly in three of the country's ten departments (Ouest, Sud-Est and Nippes). These administrative units experienced significant destruction of their basic infrastructure. It is estimated that more than 80 to 90% of buildings were severely damaged or destroyed in areas close to the epicenter (DesRoches et al., 2011 ; Government of the Republic of Haiti, 2010). Around 3 million people were affected by the quake, which damaged or totally destroyed approximately 310,000 homes (Government of the Republic of Haiti, 2010), and forcing hundreds of thousands of Haitians into displacement (DesRoches et al., 2011). Furthermore, the quake has led to significant population movements within the country (Bengtsson et al., 2011 ; Lu et al., 2012), which may lead to significant increases in morbidity and mortality.¹⁰ Although, population movements are sometimes incomplete or even misleading, as large-scale disasters result in a series of temporary as well as permanent movements (Smith, 1996), population reloca-

8. The Haiti earthquake destroyed the physical infrastructure of many of the organizations with pre-defined response and humanitarian aid roles and killed many of their key employees. These impacts both degraded the capacity of official response and created conditions for emergent response (Green and Miles, 2011).

9. The country is located in a zone where the seismic, climatic (cyclone/flood, drought, Hurricanes,...) (Anton et al., 2019), and health risks are high, making its population very vulnerable to natural disasters (Farmer et al., 2012 ; Frankel et al., 2011).

10. Analysis of cellular network data found most long-term migration occurred within the Ouest department (Lu et al., 2012).

tion has been taken into account in the regressions as discussed in Section 1.3. Further internally displaced persons camps (see Figure 1.1 for localisation of IDP camps) were built in the affected areas, mainly in the Port-au-Prince metropolitan region (Comfort et al., 2011 ; Government of the Republic of Haiti, 2010 ; IDMC, 2012 ; NRC, 2016).¹¹ A year later, these camps were still in place, with approximately 1.3 million people living in tents or under tarps. These camps have, over time, been transformed into shanty towns.¹²

Population displacements have disrupted societal codes implying that young people have the opportunity to live alone in the camps without work, without leisure and without access to contraception. These precarious living conditions, coupled with the disruption of health services and the availability of clean drinking water can be expected to have changed the country's demographic dynamics. Demographically, prior to the earthquake, Haiti had an annual population growth rate of 1.37% for the period 2017-2018 and maternal mortality was 53 deaths per 1,000 live births in 2010-2017 while the contraceptive prevalence rate was less than 40% (IHE, 2017). The availability of services, costs and the actual quality of care in Haiti are major obstacles to the use of health services, particularly by pregnant women. These constraints were exacerbated after the earthquake as evidenced by Weitzman and Behrman (2016), and may have had an impact on demographic outcomes such as fertility and children's mortality in the country.

1.3. Empirical Strategy

In order to identify the causal effect of the 2010 earthquake on fertility and the evolution of neonatal and infant mortality in the country, we used, as a treatment variable in a difference-in-difference (DID) regression model, the intensity with which different areas of the country were hit (Behrman and Weitzman, 2016 ; Torche, 2011). The objective is to take advantage of the random and exogenous nature of earthquake intensity as a natural experiment. Other parameters are also used to measure earthquake damage such as Maximum Ground Acceleration (MGA) or Maximum Ground Speed (MGV), which are all correlated to damage (United States Geological Survey, 2010). We use ShakeMaps

11. The physical, sanitary, and economic conditions of IDP camps present continuing health and security risks for these vulnerable populations (Comfort et al., 2011).

12. Six years later, there were still nearly 62,600 people living in deteriorating conditions in 36 displacement camps in and around Port-au-Prince (NRC, 2016).

from the United Geological Survey (USGS), which are automatically generated maps providing these key parameters.¹³

The Modified Mercalli Scale (MMI) is a measure based on the extent of damage observed at a given location, on natural objects, industrial facilities and humans.¹⁴ Because the Richter scale is only weakly correlated to the associated damage, this geophysical methodology was devised to classify seismic damage on twelve notches from ‘instrumental’ (I) to ‘catastrophic’ (XII) (Porcelli and Trezzi, 2019 ; United States Geological Survey, 2010).¹⁵ In Haiti, the level of intensity of the 2010 earthquake varies from 8.6 at the epicenter (Commune of Leogane) and its surroundings to 3.4 in the least affected areas.

1.3.1. Data and Descriptive Statistics

In order to assess and analyse the impact of the earthquake on fertility and child mortality in Haiti, we turned to data from two waves of the Demographic and Health Surveys (DHS) which are nationally representative and geo-localized. They were collected in 2012 and 2016-17 after the natural disaster but contain the complete maternal history of all women. The 2012 survey was conducted from January to June 2012 and includes 13,181 households, of which 9,493 men and 14,287 women. The 2016 survey, conducted from November 2016 to April 2017, consists of 13,405 households, divided in 9,795 men and 14,371 women. All women are 15-49 years old in the 2012 survey and 15-64 in the 2016-2017 wave. The surveys gathered information on the date of birth, sex and birth order of the child, and whether the child was alive at the time of the survey. Several questionnaires were distributed, including the household questionnaire, which records all household members with some of their characteristics such as relationship to the head of household, sex, age, religion, place of residence, marital status, along with information on educational attainment of each household member. They also contain information on household living conditions such as access to television, radio, basic means of transport (for instance bicycle, car), electricity, toilets, availability of drinking water, use of mosquito

13. More specifically, the ShakeMaps provide near-real-time maps of ground motion and shaking intensity following significant earthquakes (United States Geological Survey, 2010).

14. The intensity scale consists of a series of certain key responses such as people awakening, movement of furniture, damage to chimneys, and finally - total destruction (Porcelli and Trezzi, 2019 ; United States Geological Survey, 2010).

15. The Richter scale measures the earthquake size (magnitude) but says nothing of the associated damages (Porcelli and Trezzi, 2019 ; United States Geological Survey, 2010).

nets, use of health services, number of rooms, and the quality of housing construction.

To study fertility, we combined the individual women files from the 2012 and 2016-17 surveys to construct a panel dataset where the unit of observation is a woman-cmc (century month code) from 2005 to 2015. Concerning infant mortality, the individual files of children from the two surveys have been put together. DHS Data provide an accurate measure of the geographical location of clusters.¹⁶ These data were merged with the earthquake intensity map provided by the United Geological Survey (UGSS) to produce a measure of the treatment.¹⁷

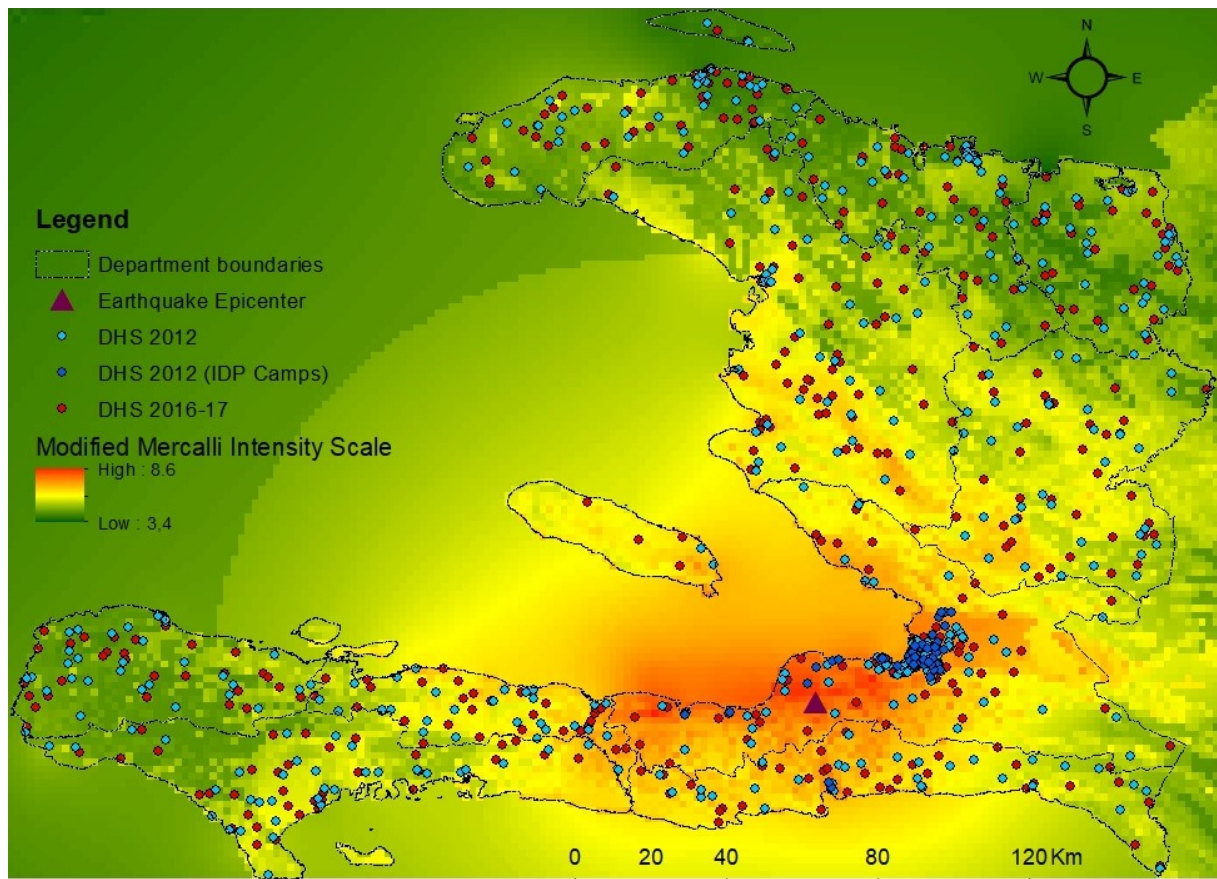
Figure 1.1 displays a map presenting the Modified Mercalli Intensity zones and the location of the 2012 and 2016-17 DHS clusters. GADM data were merged with DHS cluster locations to attribute to each cluster a department, arrondissement, commune and commune section.¹⁸ Therefore, as a first step, the treatment group will include all clusters where the earthquake struck with an MMI magnitude greater than 5 or 5.5, and progressively include only the clusters that experienced more severe damage : $MMI > 6$ or 6.5 (a “strong” earthquake, which causes slight damage to buildings) as a second step, and $MMI > 7$ or 7.5 (a “very strong” earthquake, which can cause considerable damage in badly designed structures) as a third step, and $MMI > 8$ (“violent” earthquake) as a final step (see Table 1.7 for descriptive statistics of these treated and control groups).

Table 1.1 displays the descriptive statistics of our sample. The first four variables are our dependent variables. They are followed by our control variables while the last three variables give information on the location of respondents at the time of interview. With

16. In most recent DHS surveys, the groupings of households that participated in the survey, known as clusters, are geo referenced. In total, households were grouped into 895 clusters (445 in 2012 and 450 in 2016-17), 45 of which are located in IDP camps (5.03%), mainly in the two departments worst hit by the earthquake : the *Ouest* (43 camps) and the *Sud-Est* (2 camps). Note that in the 2016-17 wave, we have no information on displacement camps.

17. In order to ensure that respondent confidentiality is maintained, the GPS latitude/longitude positions for all DHS surveys are randomly displaced so that : Urban clusters are displaced up to 2 kilometers. Rural clusters are displaced up to 5 kilometers, with 1% of the rural clusters displaced up to 10 kilometers. This random error can substantively affect analysis results, where analysis questions look at small geographic areas, as is the case in this paper.

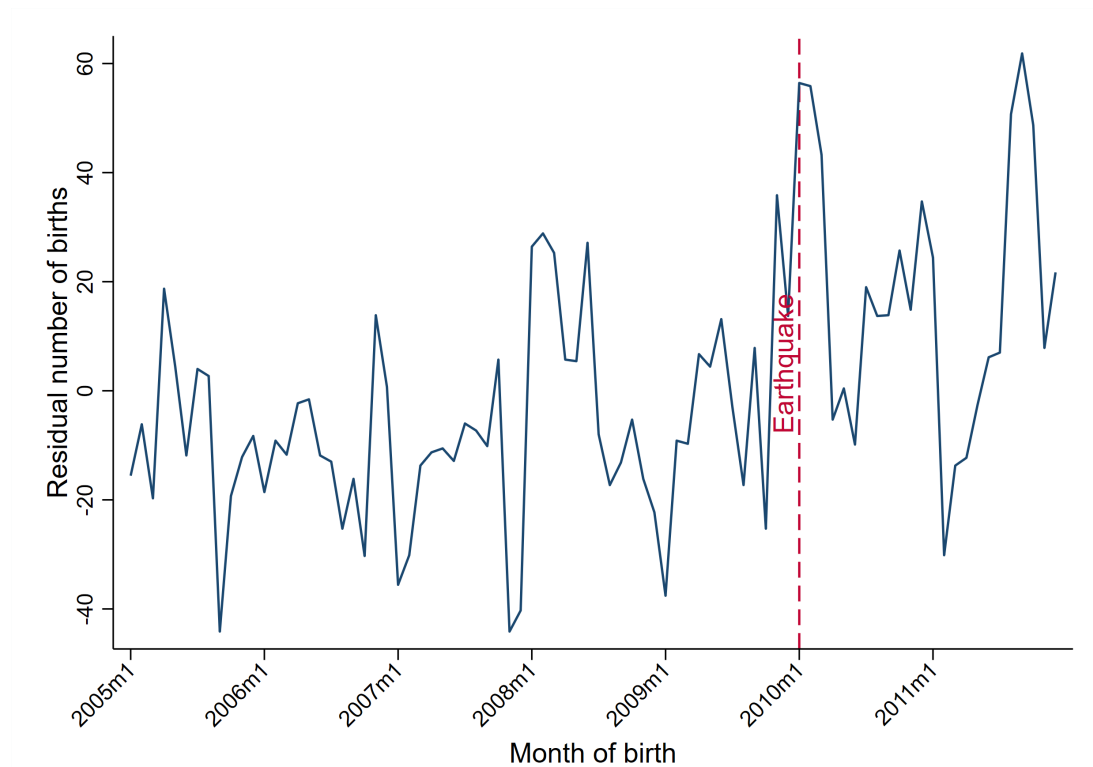
18. Coordinates (0;0) were assigned to eight (8) clusters in the 2012 survey whose location data could not be fully verified. These clusters were removed from the final sample as the analysis is conducted at the primary sampling unit level.



Notes : Created using GADM map data from www.gadm.org. Mercalli scores are assigned to the GADM map by plotting the map of intensity provided by the United States Geological Survey (2010). Survey clusters from 2012 are represented by sky blue dots, and red is for 2016 DHS clusters. Cretan blue dots show the location of IDP camps in the 2012 survey. The triangle indicates the epicenter.

Figure 1.1 – Map of intensity on Mercalli score of 2010 Haiti earthquake and geographical distribution of the Demographic and Health Survey clusters (2012, 2016–17)

the exception of regressions including women living in camps, we restrict our sample on individuals who remained in their accommodation after the earthquake. This enables us to ensure that earthquake intensity is correctly attributed to the women of our sample (modulo the location error introduced by DHS). The regressions produced on this sample evacuate the issues linked to selective migration. Our findings are robust to sensitivity analysis (discussed later) in which we use the full sample of usual residents. As to individuals living in camps, a piece of information present in the 2012 survey (see cretan blue dots in Figure 1.1), all located in primary sampling units of MMI greater or equal than 7.4, we make the realistic assumption that they used to live close to the camp location and therefore that they experienced a very high earthquake intensity.

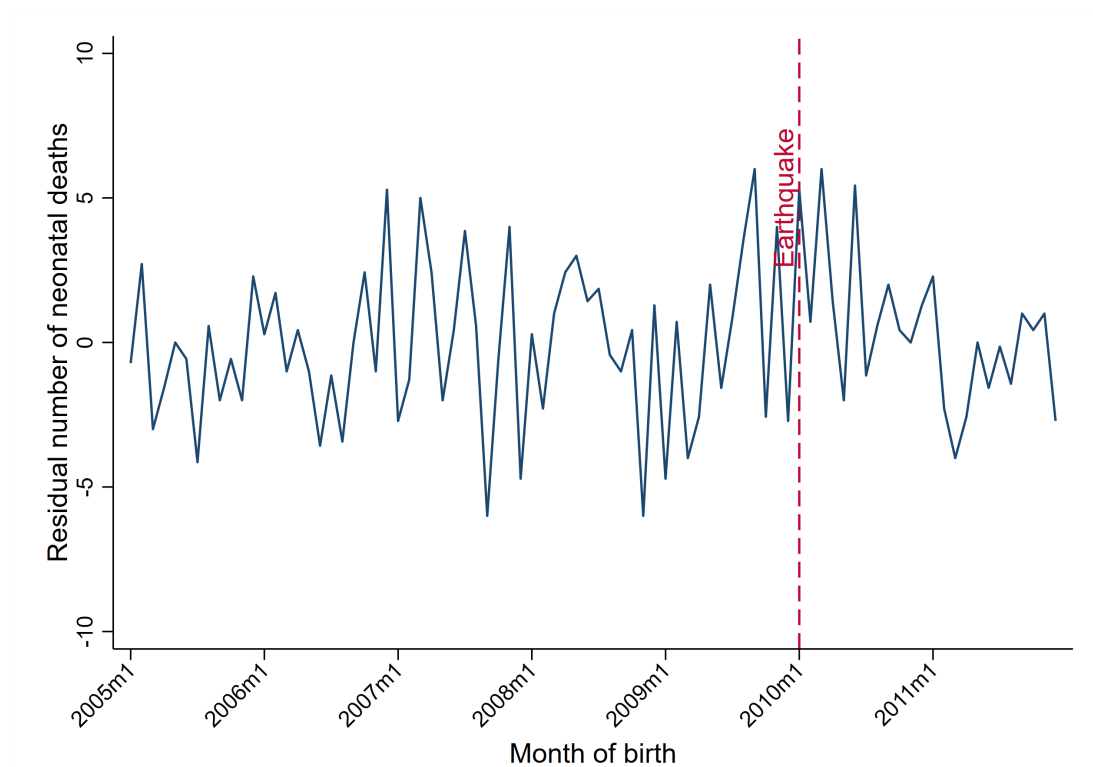


Note : Data are from DHS (2012, 2016–17)

Figure 1.2 – Monthly residual of childbirth, 2005–2011

Figure 1.2 exhibits the distribution of months of birth on the full sample. One can note a high number of births on the month of the earthquake.¹⁹ On Figures 1.3 and 1.4, no peaks in the distribution of months of death were observed for neonatal and infant mortality at the time of the earthquake. Figure 1.5 displays a comparison of the number of births and infant deaths for women in and out of the camps. There seem to be increasing in births around the time of the earthquake in both cases, while the increase in infant mortality is noticeable only in the panel of women living outside the camps (see Figure 1.7 for more details). It also indicates that there is a selection issue in the camps as the death rate is much higher even if nothing happens before the earthquake. Our findings may depend on the selection of women residing in the camps for the post-earthquake period (see Table 1.8 for selection in camps). We test the robustness of our results using either coarsened exact matching or mother fixed effects regression models.

19. It is worth noting that there is also a peak in the number of births during the month of september 2011. However, in the overall sample (Tables 1.2), the results do not show significant effects at this time. However, in the IDP camps, there is an increase in fertility beginning approximately 21 months after the earthquake (see Col. (2) of Table 1.3), which corresponds to the peak observed in Figure 1.2.

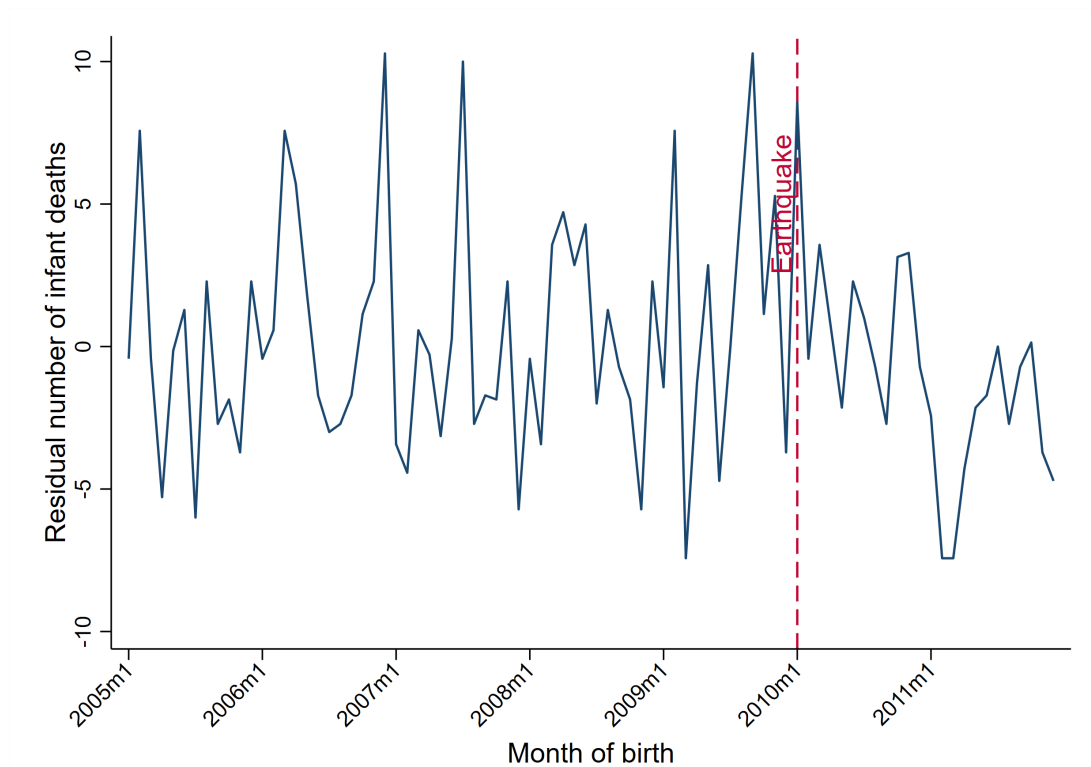


Note : Data are from DHS (2012, 2016–17).

Figure 1.3 – Monthly residual of neonatal mortality between January 2005 and December 2011

In Table 1.6, one can see that almost 90% of the primary sampling units are considered to be in zones where the earthquake intensity reached at least 5, which is described on the USGS website as ‘felt by nearly everyone; many awakened. Some dishes, windows broken. Unstable objects overturned. Pendulum clocks may stop’ (USGS, 1989). Almost 6% of the primary sampling units are located in areas severely hit by the earthquake ($MMI > 8$). The description of the effects goes as follows : ‘Damage slight in specially designed structures; considerable damage in ordinary substantial buildings with partial collapse. Damage great in poorly built structures. Fall of chimneys, factory stacks, columns, monuments, walls. Heavy furniture overturned’.

The following Table 1.7, puts forward the variation in terms of earthquake intensity by administrative regions as mentioned by GADM, from administrative level 1 : Department to administrative level 4 : Commune section, and primary sampling units (PSU). This gives an indication as to the influence of location fixed effects on the treatment variable (MMI). Figures 1.2 to 1.5 contain initial evidence of the earthquake effect. We next conduct a regression of the monthly incidence of childbirth of each woman during 2009–2011 on the

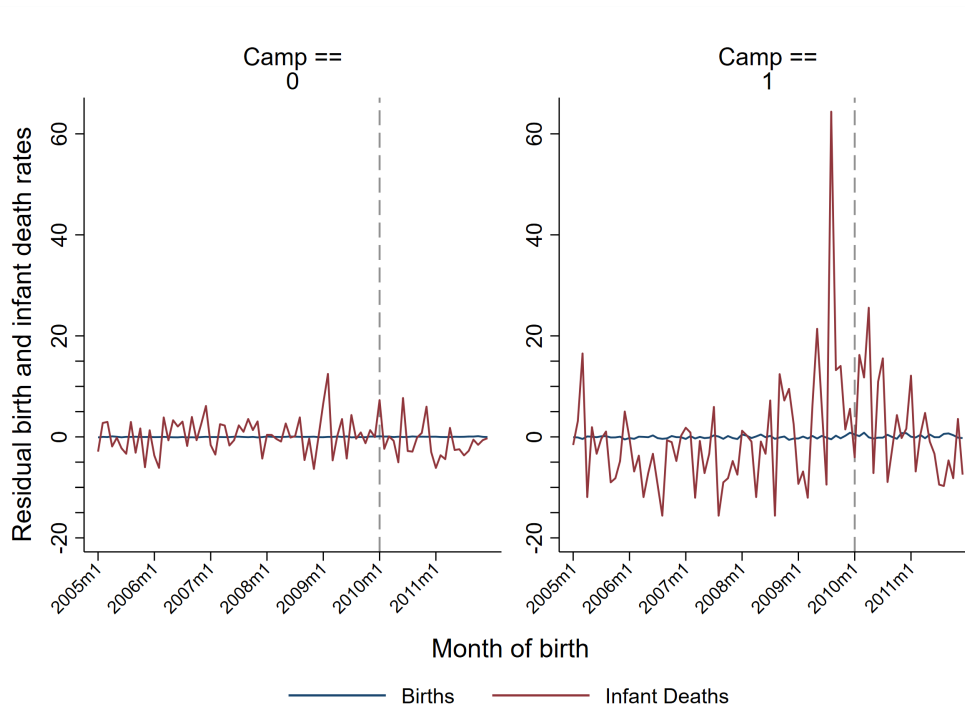


Note : Data are from DHS (2012, 2016–17).

Figure 1.4 – Monthly residual of infant mortality between January 2005 and December 2011

set of covariates X in Eq. 1.1. The estimated coefficients along with their 95% confidence intervals are presented in Figure 1.6.²⁰ The coefficients of the MMI-cmc interaction terms from these regression models show whether the outcomes differed from month to month between the treatment and control groups, after controlling for other factors. The higher estimate of cmc-specific coefficients for children born during the month of the quake reflects the higher premature births of highly affected women. Figure 1.8 displays the cmc-specific coefficients from a less restrictive version of equation 1.1 with the probability of a live birth as the dependent variable, including a separate interaction term between the MMI magnitude scales and each cmc in a single, instead of seven regressions ($\sum_{j=1}^7 \beta_t(MMI_j \times CMC_t)$). It provides prima facie evidence of a limited effect of the earthquake. The point estimates and significance levels, which are not reported in order to save space, are similar to those presented in Figure 1.6, confirming the increase in the probabi-

20. Formally, the series of $\hat{\beta}_t$ are estimated from $Birth_{ijt} = \alpha + \sum_{j=1}^7 \beta_t(MMI_j \times CMC_t) + \gamma X_i + \delta_{yob} + \delta_{geo} + \delta_{time} + \varepsilon_{ijt}$. MMI_j is a dummy that is equal to 1 for zones struck by an MMI magnitude higher than 5, 5.5, 6, 6.5, 7, 7.5, 8 and 0 otherwise. Full results are available from the authors.



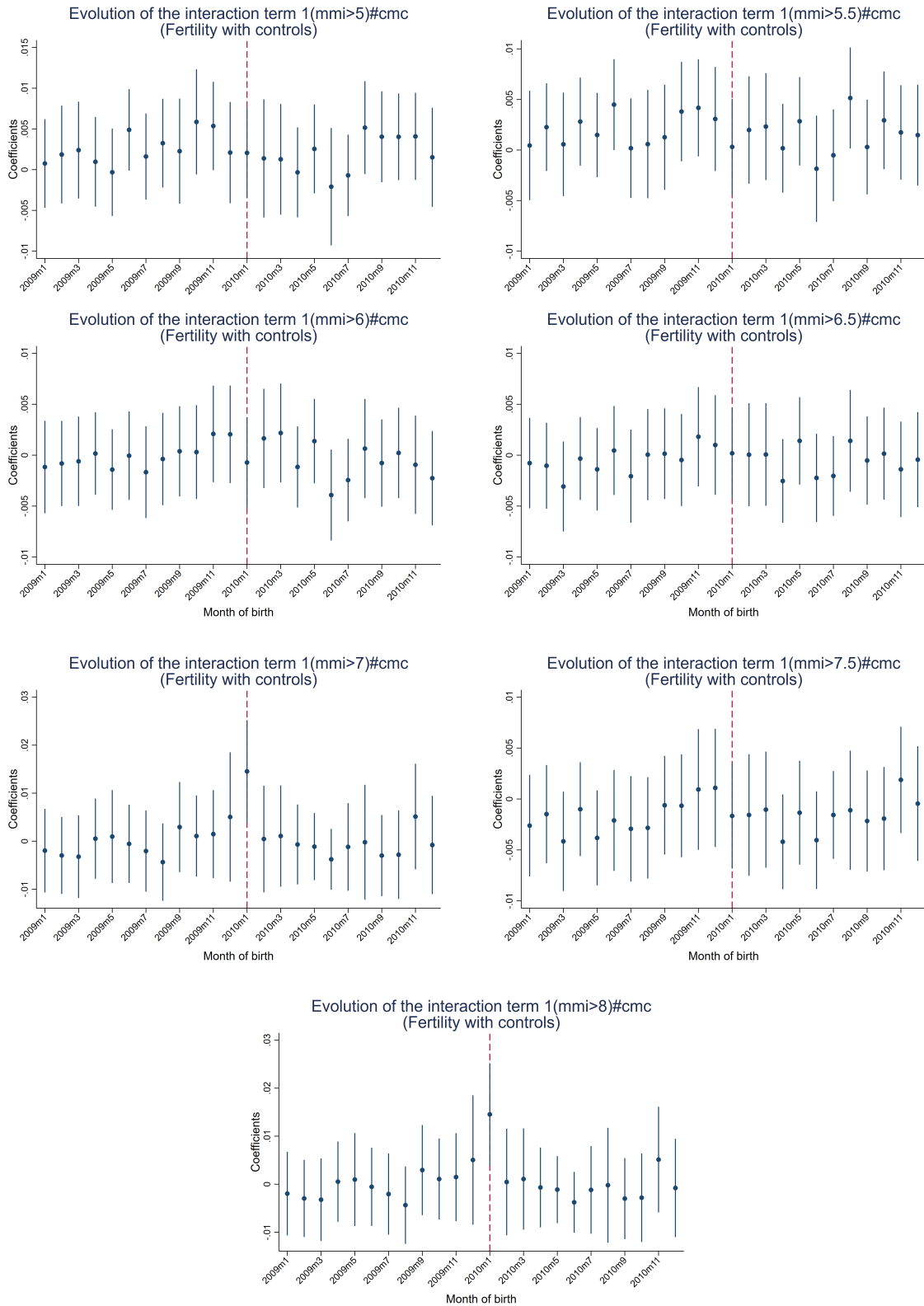
Notes : Data are from DHS (2012, 2016–17). Births in treatment and control groups are included. Graphs by individuals who lived in a camp after the quake. The vertical dotted line indicates the occurrence of the Haiti 2010 earthquake (see Figure 1.7 for more detailed graphs).

Figure 1.5 – Monthly residual of birth and infant mortality rates, 2005–2011

lity of a live birth in the most impacted primary sample units at the time of the disaster.²¹

We also observe that in mostly century month codes, there was no statistical difference in fertility between the treatment and control groups (the confidence intervals are large). In addition, there is no clear time trend in the values of the coefficients, particularly leading up to the earthquake in January 2010. Therefore, we argue that the parallel trends assumption is satisfied for the fertility analysis. All figures show that when looking at those zones where the earthquake was very strong (MMI 8 or higher), the difference is more evident in January 2010. We see that the earthquake caused an increase in premature births in the country during that month, which may explain the decrease in the number of births in the aftermath.

21. The different arbitrarily defined thresholds in the creation of binary variables for intensity levels are : $3.4 \geq \text{MMI} < 5$; $5 \geq \text{MMI} < 5.5$; $5.5 \geq \text{MMI} < 6$; $6 \geq \text{MMI} < 6.5$; $6.5 \geq \text{MMI} < 7$; $7 \geq \text{MMI} < 7.5$; $7.5 \geq \text{MMI} \leq 8$; $\text{MMI} > 8$. $\hat{\beta}_t$ are estimated from $\text{Birth}_{ijt} = \alpha + \sum_{i=2}^{24} \beta_t(\text{MMI}_j \times \text{CMC}_t) + \gamma X_i + \delta_{yob} + \delta_{geo} + \delta_{time} + \varepsilon_{ijt}$. As a further check, we replicate Figure 1.8 by splitting the sample according to these intensity levels. Results, which are not reported in order to save space, do not change meaningfully.



Notes : Data are from DHS (2012, 2016–17). Coefficient and 95% confidence intervals are presented.

Figure 1.6 – Coefficient of interaction between earthquake-affected zones and cmc in regression of monthly rate of childbirth, 2009–2011

Table 1.1 – Summary Statistics, 2005–2015

Variable	N	Mean	Std. Dev.	Minimum	Maximum
Birth : Takes 1 if (at least) a birth this time period	29,258	0.0078	0.0103	0	1
Neonatal death : Takes 1 if child died in the first 28 days of life	13,448	0.0266	0.1344	0	1
Postneonatal death : Takes 1 if child died between 28 days and 365 days after birth	13,448	0.0224	0.1163	0	1
Infant death : Takes 1 if child died in the first year of life	13,448	0.0490	0.1760	0	1
Modified Mercalli intensity	29,001	6.4450	1.1931	3.4	8.6
Number of kids aged 2-, Alive	29,258	0.1565	0.2066	0	3
Number of kids alive	29,258	1.3618	1.9334	0	14
Number of kids	29,258	1.5294	2.2009	0	15
Number of kids dead in the last 24 months	29,258	0.0166	0.0664	0	4
Number of sisters alive	13,448	0.7985	1.1050	0	8
Number of brothers alive	13,448	0.8230	1.1402	0	8
Number of siblings aged 2-	13,448	0.1095	0.2251	0	2
Wealth index factor score combined	29,258	0.1631	1.0350	-1.5817	4.0613
No schooling	29,258	0.1598	0.3664	0	1
Primary	29,258	0.3538	0.4782	0	1
Secondary	29,258	0.4348	0.4957	0	1
Higher	29,258	0.0515	0.2211	0	1
Respondent's year of birth	29,258	1984.9666	10.4457	1960	2002
Individuals who were at location during earthquake	29,258	0.6933	0.4611	0	1
Respondent is a usual resident of the household	29,258	0.9793	0.1423	0	1
Camps	29,258	0.0411	0.1986	0	1

Source : Author's calculations based on DHS datasets and USGS data.

1.3.2. Methodology and Model Specification

The models we turn to are variations of the Difference in Difference model (DID) :

$$Y_{ijt} = \beta_1 treatment_j + \beta_2 post_t + \beta_3 (treatment_j \times post_t) + \gamma X_i + \delta_{yob} + \delta_{geo} + \delta_{time} + \varepsilon_{ijt} \quad (1.1)$$

Where Y_{ijt} is one of our three dependent variable of interest, i.e. birth, neonatal, or infant mortality. $birth_{ijt}$, for instance, is an indicator taking the value of 1 if the woman i living in the primary sampling unit j gave birth in period t . Our treatment measure is either a continuous measure of earthquake intensity, mmi_j —the Modified Mercalli Intensity varying at primary sampling unit level—or a discretization of our continuous measure at different arbitrary cutoffs (going from 5 to 8). The $post_t$ variable takes 1 when our observations are potentially hit by the earthquake. It varies with time and takes 1 from January 2010. It is worth noting that in the fertility analysis, the binary variable is defined according to the data sample used (overall sample or the sub-sample of people residing in camps). Thus, $post_t$ is a dummy that takes the value of 0 in the time period before the earthquake ($post_t < 1321$), and 1 in the period following the disaster ($post_t \geq 1321$ (January 2010)). When focusing on women residing in displacement camps, $post_t = 1$ for $cmc \geq 1330$ (October 2010), and 0 for $cmc < 1330$. Regarding neonatal, and infant mortality, $post_t$ is an indicator that is equal to 1 for respectively $cmc \geq 1320$ (December 2009), $cmc \geq 1309$ (January 2009) and equal to 0 otherwise.

Our coefficient of interest is β_3 , the coefficient of the interaction term, $treatment_j \times post_t$. X_i are controls varying either at the household (woman) or at the child level for mortality. We control for education, a measure of wealth and demographic measures of the household structure. We take account of the number of children aged less than 24 months, the number of dead children in the last 24 months and the number of kids alive in the fertility regressions. As for mortality, we control for multiple births, the rank of the child and the number of brothers and of sisters aged less than 3. δ_{yob} are mother year of birth fixed effects, allowing us to control for mother's age in all fertility and mortality regressions while δ_{geo} , δ_{time} , are respectively location and time fixed effects. We also introduced geographic specific time trends in some specifications for robustness.²²

22. In order to save space the results are not reported, but are available upon request to the authors.

All standard errors are clustered at the primary sampling unit level, which is also the variation level of our treatment variable. This allows us to take account of the error correlation at the most disaggregated geographic level. Given the number of primary sampling units, we never encounter problems related to the number of clusters.²³ Demographic and Health Surveys are meant to be nationally representative. This is the reason why some parts of the population are under/oversampled. In order for our estimates to be independent of the sampling design, we use sampling weights, corresponding to the inverse of the probability of being included in the survey, to rebalance our sample. Note that, for the fertility regressions, a panel is created where the unit of observation is a mother-time period. The $birth_{ijt}$ dummy takes 0 for all periods with no birth and 1 for all t periods when mother i has at least one child. In our mortality specifications, the unit of observation is a child. We consider two measures of child mortality : neonatal mortality measured by a dummy taking 1 if the child died in their first 28 days after birth, and infant mortality, a dummy taking 1 for a death in the first 365 days of life. The difference in difference method enables us to capture the mean effect of treatment by taking the difference between the mean effect for the treated and the mean effect for the non-treated. The advantage of this technique is to take account of time differences and selection issues if all considered groups follow parallel trends.

Thanks to the exogenous and random nature of earthquakes, in most of our regressions, we do not have to worry about selection into treatment issues. On January 12, 2010, nobody could tell that an earthquake would hit the island on the following day. Nobody could know where the earthquake would be more intense and would produce more damage. When paying attention to a specific subsample of individuals, i.e. those who were living in camps in 2012, we must consider selection issues. It is indeed very likely that these people are different from those who could remain at their house. Still, there is an exogenous component in this phenomenon, since camps are located in areas with a MMI intensity of at least 7.4 (with an observed maximum of 8.6). We conduct mother fixed effect regression models, and use matching methods as further robustness checks to overcome these issues.

23. As noted above, we have 887 clusters of observations in our full sample while we still have more than 260 clusters when focussing on camps and reducing our sample to the zones with an earthquake intensity higher or equal to 7.4.

Given the size of the country and of the island, one of the issues we have to deal with is the fact that no region of Haiti was untouched by the earthquake, as shown in the figure 1.1. This means that we have no real counterfactual for our treatment. We have to consider the intensity of treatment, i.e. the Modified Mercalli Intensity scale. For this reason, we rely on a quasi-experimental approach, because close clusters are more likely to share the same cultural, social, and economic characteristics that influence childbirth, neonatal and infant mortality rates. Thus, we define the treated and control groups according to the MMI magnitude data provided by the United States Geological Survey (2010). We use dummies taking 1 when the earthquake intensity is higher than a cutoff as described in Section 1.3.1. In these cases, we make the assumption that zones under this limit intensity were not treated, although they were less severely hit by the earthquake. In robustness checks, we use a continuous measure as our selection variable (treatment).

1.4. Results

1.4.1. Effects of the earthquake on fertility on the main sample

As a first approach to this dataset and following the visual information conveyed by Figures 1.2 through 1.4, we ran regressions aiming to assess the immediate impact of the earthquake on fertility and child mortality, and then progressively widening the period covered by our *post* variable to reach up to 27 months after the earthquake. Regressions from Table 1.2 (Cols. (4) and (8), line (1)) reveal that the most severely hit regions knew an increase in the number of births just after the earthquake. We indeed observe an increase in births in primary sampling units whose MMI is higher than 8. This coefficient goes down and loses significance when we widen the period covered by our post-earthquake (*post*) variable. This is compatible with an effect concentrated at the time of the earthquake.

In Appendix Table 1.9, we perform a sensitivity analysis of this result by dividing the 24-month post-earthquake period into eight (8) binary variables. The estimate is positive and statistically significant at the 10% level (Col. (8)), confirming the increase in births in the first months following the quake as shown in Table 1.2. Using sample of usual residents

as a further robustness check, our results show that the rate of childbirth among women in highly impacted primary sampling units was significantly higher one month after the earthquake, compared to neighboring women living in less severely affected zones (Table 1.10).²⁴ The fertility effects are also uninfluenced by whether we use mother fixed effect regression models as evidenced in Table 1.11. These results indicate that exposure to the January 2010 earthquake resulted in earlier delivery as demonstrated in Figures 1.6 and 1.8). Finally, using our continuous measure of earthquake intensity as an additional checks, we do not detect any significant effect of the earthquake on fertility or mortality in any of the regressions whatever the duration covered by the post-earthquake (*post*) variable. The results are not reported in order to save space, but are available upon request to the authors.

Since the earthquake triggered large post-earthquake population movements, as outlined above in the next subsection, we estimate fertility by comparing women living in camps with residents. Indeed, the effect on the birth rate could be due to the fact that women residing in IDP camps are different from others and may have different fertility behaviors (Table 1.8). Finally, in Section 1.5, we discuss potential selective fertility that may occur after the earthquake.

24. The ‘usually resident of the household’ in our sample is composed of those persons who have their place of usual residence in the country at the survey reference time (2012 or 2016-17), and are not just visiting the household. In this sample, we do not control for potential threat to the validity of our analysis related to internal migration following the earthquake.

Table 1.2 – Difference-in-differences estimation for number of births at diferent intensity magnitudes

Dependent variable :	Birth : Takes 1 if (at least) a birth this time period							
	Resident sample				Resident and Camp sample			
	MMI > 5	MMI > 6	MMI > 7	MMI > 8	MMI > 5	MMI > 6	MMI > 7	MMI > 8
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Earthquake Intensity × Post (1 month)	-0.000158 (0.00214)	-0.000588 (0.00167)	-0.000236 (0.00174)	0.0151*** (0.00490)	-2.27e-05 (0.00213)	-0.000387 (0.00165)	6.68e-05 (0.00169)	0.0141*** (0.00458)
N	1,016,863	1,016,863	1,016,863	1,016,863	1,087,280	1,087,280	1,087,280	1,087,280
Earthquake Intensity × Post (3 months)	-0.000631 (0.00155)	0.00121 (0.00104)	0.000312 (0.00114)	0.00487 (0.00297)	-0.000510 (0.00154)	0.00136 (0.00102)	0.000556 (0.00110)	0.00493* (0.00274)
N	1,052,415	1,052,415	1,052,415	1,052,415	1,125,165	1,125,165	1,125,165	1,125,165
Earthquake Intensity × Post (6 months)	-0.00127 (0.00109)	0.000242 (0.000654)	-0.000144 (0.000690)	0.00118 (0.00150)	-0.00127 (0.00109)	0.000233 (0.000643)	-0.000145 (0.000666)	0.00131 (0.00139)
N	1,105,845	1,105,845	1,105,845	1,105,845	1,182,084	1,182,084	1,182,084	1,182,084
Earthquake Intensity × Post (9 months)	-0.000555 (0.000817)	2.33e-05 (0.000547)	0.000121 (0.000581)	0.000234 (0.00109)	-0.000577 (0.000815)	-1.05e-05 (0.000539)	6.45e-05 (0.000561)	0.000232 (0.00103)
N	1,159,424	1,159,424	1,159,424	1,159,424	1,239,135	1,239,135	1,239,135	1,239,135
Earthquake Intensity × Post (12 months)	-0.000139 (0.000654)	-0.000180 (0.000481)	0.000431 (0.000514)	0.000145 (0.000936)	-0.000137 (0.000652)	-0.000174 (0.000472)	0.000416 (0.000495)	0.000184 (0.000881)
N	1,213,186	1,213,186	1,213,186	1,213,186	1,296,357	1,296,357	1,296,357	1,296,357

Notes : All regressions include cluster, age and birth Century-Month Code (CMC) fixed effects. Estimates weighted using survey weights provided by DHS. Robust standard errors clustered at the primary sampling unit level. The unit of observation is a woman-cmc, starting at the age of 15 for all columns. All columns are linear probability models, and contain control for education level, number of kids, aged 2- (alive), total number of Kids, number of kids dead in the last 24 months, and wealth index. Treated group clusters include those struck by an MMI magnitude greater than those indicated in the header of each column, while the control group includes all the clusters where the earthquake had a MMI magnitude ≤ 5 , ≤ 6 , ≤ 7 , ≤ 8 in columns (1;3), (2;4), (3;7), (4;8) respectively. Coefficients that are statistically significant at *10%, **5%, and ***1% levels.

1.4.2. Effects of the earthquake on fertility focusing on camps population

Although our objective is to produce causal estimates, it seems necessary to try and shed some light on the specific population of camp inhabitants. Contrarily to the 2016 wave of the DHS, the 2012 Survey allows us to identify people living in displacement camps. While the timing and intensity of the earthquake are random and therefore prevent us from facing a problem of selection into treatment, we must admit that paying attention to camp inhabitants forces us to depart from the assumption of pure exogeneity. Camp primary sampling units are all located in zones whose intensity is greater or equal than 7.4 (see Figure 1.1). This means that camps are located in the areas most severely hit by the earthquake and this remains exogenous. However, regressions presented in Table 1.8 show that women living in camps are significantly different from those living in their house. They are less educated and more likely to be young, even if not the youngest. We can therefore suspect that they are poorer—this being potentially the reason why they had to leave their house—and thus more likely to see one of their children die. In order to mitigate the problems caused by selection into camps and to have more credible counterfactuals, we restrict our sample to clusters undergoing an earthquake intensity of at least 7.4 and include all controls in all regressions comparing camp inhabitants to residents. Table 1.3 reports the results of the regression estimated for the childbirth rates on this sample. We found a significant increase in fertility after the earthquake for women residing in displacement camps beginning approximately twenty-one months after the event.

To assess the sensitivity of the main findings from Table 1.3, we conduct woman fixed effects DID regression analysis of the childbirth before and after the earthquake. In doing so, we address potential selection bias in our previous results when focusing on displaced persons in camps. The first column of Table 1.12 reports the estimated DID effect in camps. These coefficients are statistically and economically indistinguishable from the baseline results. Second, we test the robustness of our results by using matching methods. To begin our Coarsened Exact Matching (CEM) analysis, we first choose a reasonable coarsening for each of the following variables : education, religion, wealth index combined, type of place of residence, woman's age and earthquake intensity. Then, we used CEM with difference-in-difference models to improve the estimation of causal effects by reducing

Table 1.3 – Earthquake impact on fertility, neonatal and infant mortality in camps

	Dependent variable		
	Fertility	Neonatal Mortality	Infant Mortality
	(1)	(2)	(3)
Camp × Post (1 month)	0.00414 (0.00456)	0.0326 (0.0602)	0.0561 (0.0355)
N	319,575	2,431	2,431
Camp × Post (3 months)	0.00181 (0.00265)	0.0874* (0.0506)	0.0960*** (0.0355)
N	379,560	2,545	2,545
Camp × Post (6 months)	0.00251 (0.00174)	0.0716* (0.0434)	0.0980*** (0.0342)
N	395,980	2,632	2,632
Camp × Post (9 months)	0.00206 (0.00129)	0.0600 (0.0366)	0.108*** (0.0300)
N	412,432	2,770	2,770
Camp × Post (12 months)	0.00382*** (0.00132)	0.0278 (0.0260)	0.0717*** (0.0236)
N	428,921	2,932	2,932
Camp × Post (15 months)	0.00270** (0.00121)	0.0297 (0.0231)	0.0736*** (0.0226)
N	445,449	3,052	3,052
Camp × Post (18 months)	0.00199* (0.00101)	0.0331 (0.0233)	0.0728*** (0.0218)
N	458,712	3,148	3,148

Notes : All regressions include cluster, age and birth Century-Month Code (CMC) fixed effect. Estimates weighted using survey weights provided by DHS. Robust standard errors clustered at the primary sampling unit level. Column (1) contains control for education level, number of kids, aged 2- (alive), total number of kids, number of kids dead in the Last 24m and wealth index. Columns (2) and (3) control for number of twins, birth order, number of sister alive, number of brother alive, education level and Wealth Index. Coefficients that are statistically significant at *10%, **5%, and ***1% levels.

imbalance in covariates between women residing in camps and control groups (Blackwell et al., 2009).²⁵ Table 1.14 replicates estimations of Table 1.3. The analysis performed on the childbirth rate shows a positive and statistically significant DID coefficient from nine (9) months after the earthquake (Column (1)). The estimates of this sensitivity test are qualitatively equivalent to those found in the main results. The point estimates from this analysis are generally larger in magnitude than those in Table 1.3, nevertheless they are broadly similar in sign and significance.

1.4.3. Effects of the earthquake on mortality on the main sample

To examine the effects of the earthquake on neonatal, and infant mortality, we use several specifications. The only effect we detect regarding mortality in the main sample is an increase of death of a live-born baby within the first 28 days of life on the sample of residents in primary sampling units whose MMI is higher than 6 (Table 1.4), approximately six, nine and twelve months after the quake. We find no significant effect of the earthquake on the probability of dying between birth and exactly 1 year of age in the overall sample (as shown in Cols. (1)-(8) of Table 1.4, Panel B).

For confirmation of these results, we include a maternal fixed effects in Eq. 1.1 and report the results in Table 1.13 to control for any time-invariant differences between women.²⁶ In panel A, coefficients of interest fail to be statistically significant across these robustness checks (from three months and more). However, in Column (7) (line (1)), the DID coefficient shows an increase in neonatal mortality in primary sampling units impacted by an intensity greater than 7 at the time of the quake. Regression results including maternal fixed effects also indicate a decrease in infant mortality approximately 12 months after the earthquake in primary sampling unit affected by an intensity greater than 7 (Panel B, Col. (7)) at the 5% conventional level. In all, the alternative specifications do not provide additional support for the main results in terms of magnitude, significance and the

25. Unfortunately, because of the richness of covariates in our sample, CEM produces very few matches (Blackwell et al., 2009).

26. One potential concern with the identification strategy is that women who have births died or live births in the preearthquake period are somehow different than women whose fertility occurs only after the quake, even after controlling for age, education, number twins, birth order, number of brother and sister alive and wealth. The fixed effects help to address endogeneity caused by omitted individual- and time-specific variables that may be important in this study.

temporal variation of the effect. Next, we focus on children living in IDP camps.

Table 1.4 – DID estimation for neonatal and infant mortality at different intensity magnitudes

	Resident sample				Resident and Camp sample			
	MMI > 5	MMI > 6	MMI > 7	MMI > 8	MMI > 5	MMI > 6	MMI > 7	MMI > 8
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A : Neonatal Mortality								
Earthquake Intensity × Post (1 month)	-0.00163 (0.0332)	0.0421* (0.0245)	0.0235 (0.0351)	-0.0414* (0.0227)	0.00119 (0.0330)	0.0446* (0.0234)	0.0281 (0.0318)	-0.00553 (0.0303)
N	9,456	9,456	9,456	9,456	10,129	10,129	10,129	10,129
Earthquake Intensity × Post (3 months)	-0.0315 (0.0262)	0.0219 (0.0154)	0.0180 (0.0203)	-0.0178 (0.0197)	-0.0264 (0.0261)	0.0279* (0.0150)	0.0286 (0.0190)	0.00645 (0.0230)
N	9,844	9,844	9,844	9,844	10,551	10,551	10,551	10,551
Earthquake Intensity × Post (6 months)	-0.0190 (0.0219)	0.0293** (0.0130)	0.0154 (0.0169)	-0.0211 (0.0173)	-0.0157 (0.0218)	0.0333*** (0.0128)	0.0231 (0.0160)	-0.00107 (0.0198)
N	10,257	10,257	10,257	10,257	10,986	10,986	10,986	10,986
Earthquake Intensity × Post (9 months)	-0.00839 (0.0165)	0.0213* (0.0117)	0.0109 (0.0143)	-0.0121 (0.0149)	-0.00578 (0.0164)	0.0244** (0.0115)	0.0168 (0.0136)	0.00622 (0.0170)
N	10,755	10,755	10,755	10,755	11,522	11,522	11,522	11,522
Earthquake Intensity × Post (12 months)	-0.00374 (0.0137)	0.0239** (0.00988)	0.00974 (0.0121)	-0.00903 (0.0171)	-0.00220 (0.0136)	0.0251*** (0.00960)	0.0127 (0.0113)	0.00414 (0.0167)
N	11,302	11,302	11,302	11,302	12,121	12,121	12,121	12,121

Table 1.4 – (Continued) DID estimation for neonatal and mortality at diferent intensity magnitudes

Panel B : Infant Mortality								
Earthquake Intensity × Post (1 month)	-0.0174	0.00565	-0.0183	-0.0230	-0.0156	0.00886	-0.0109	-0.0148
	(0.0169)	(0.0134)	(0.0150)	(0.0249)	(0.0168)	(0.0132)	(0.0143)	(0.0226)
N	9,456	9,456	9,456	9,456	10,129	10,129	10,129	10,129
Earthquake Intensity × Post (3 months)	-0.0295*	0.00298	-0.0136	-0.0182	-0.0255	0.00820	-0.00262	-0.00448
	(0.0165)	(0.0122)	(0.0137)	(0.0225)	(0.0164)	(0.0120)	(0.0132)	(0.0218)
N	9,844	9,844	9,844	9,844	10,551	10,551	10,551	10,551
Earthquake Intensity × Post (6 months)	-0.0298*	0.00652	-0.0109	-0.0187	-0.0261	0.0115	-0.000517	-0.00370
	(0.0162)	(0.0116)	(0.0131)	(0.0211)	(0.0161)	(0.0114)	(0.0126)	(0.0206)
N	10,257	10,257	10,257	10,257	10,986	10,986	10,986	10,986
Earthquake Intensity × Post (9 months)	-0.0260*	0.000471	-0.0130	-0.0153	-0.0221	0.00585	-0.00228	-0.000313
	(0.0149)	(0.0112)	(0.0125)	(0.0211)	(0.0148)	(0.0110)	(0.0120)	(0.0204)
N	10,755	10,755	10,755	10,755	11,522	11,522	11,522	11,522
Earthquake Intensity × Post (12 months)	-0.0178	0.00935	-0.00981	-0.00612	-0.0150	0.0127	-0.00236	0.00503
	(0.0134)	(0.0104)	(0.0115)	(0.0204)	(0.0133)	(0.0101)	(0.0110)	(0.0193)
N	11,302	11,302	11,302	11,302	12,121	12,121	12,121	12,121

Notes : All regressions include cluster, age and birth Century-Month Code fixed effects. Standard errors clustered at the cluster level. All columns contain control for twins, first birth order, number of sister alive, number of brother alive, education level and Wealth Index. Treated group clusters include those struck by an MMI magnitude greater than those indicated in the header of each column, while the control group includes all the clusters where the earthquake had a $MMI \leq 5$, ≤ 6 , ≤ 7 , ≤ 8 in columns (1;3), (2;4), (3;7), (4;8) respectively. Coefficients that are statistically significant at *10%, **5%, and ***1% levels.

1.4.4. Effects of the earthquake on mortality focusing on camps population

We conduct fixed effects DID regression analysis of neonatal mortality in camps and present the results in Table 1.3. We find no significant changes in neonatal mortality rates after the earthquake. Comparing camp inhabitants to residents sample exposed to the same intensity level, we note that their children have a higher probability of dying when the *post* variable covers a period from 3 to 18 months after the earthquake. As for fertility analysis, we also run mother fixed effects DID regression analysis of the newborn and infant deaths before and after the earthquake. In the last two columns in Table 1.12, we present the estimated DID effect of the earthquake from the mother fixed effect regressions, separately for neonatal and infant mortality. The results from these regressions mirror those presented in this section, providing evidence of the robustness of Table 1.3's findings. Last, we check robustness using matching methods. We find no significant effect of the earthquake on neonatal and infant deaths (as shown in the two last columns of Table 1.14 using these techniques).

Finally, we test robustness of fertility and mortality results to different types of fixed effects. As before, the treated group progressively excludes primary sampling units according to the highest MMI recorded. Unreported results available from the authors of the DID estimates suggest that the results are quite similar whether *arrondissement*, *commune*, and *commune section* fixed effects is used or not. The coefficients on ($treatment_j \times post_t$) or ($Camp \times post_t$) are remarkably stable in sign and magnitude.

Heterogenous Effects

Having established the robustness of the basic setups, we build the remainder of the empirical analysis on the more detailed specification in column 4 and line 15 of Table 1.3 that exploits geographic variation in earthquake exposure on infant mortality, fertility, from one or nine months after the disaster respectively. Indeed, the mechanisms through which the earthquake could affect fertility, neonatal and infant mortality can also be examined in the light of heterogeneous treatment effects (Marteletto et al., 2020 ; Nandi et al., 2018). Although some research has shown increase current pregnancy following the 2010 earthquake in Haiti (Behrman and Weitzman, 2016), it is unclear whether such tendencies, or

overall fertility were homogenous across women ages or educational groups, or whether they led to increase fertility in areas affected differently by the earthquake. Changes in fertility and mortality after the 2010 earthquake may vary between local communities due to their socioeconomic and demographic characteristics.

Researchers may wish to probe the patterns of heterogeneity and see if there is a reasonable interpretation. To do so, we further stratify our sample between rural and urban women, uneducated, less and women with a higher educational level. We also split our sample by women's age. Finally, we separately estimate the DID effect of the earthquake based on these different characteristics. Table 1.5 summarizes the results for our coefficient of interest, separately for each location, age group and education level of women.²⁷

Results show a large and striking increase in fertility for rural women, which drives their increase in total fertility. Specifically, we find that women residing in rural camps experienced an increase in birth rates, while in urban areas we see no significant effect of the earthquake on fertility. With regard to the age group of women, the increase in fertility is observed only among the youngest (women under 20). Results by level of education of women reveal that those with primary education experienced a 0.005 percentage point increase in the monthly childbirth rate.

Further analysis by type of residence and educational attainment of women shows a highly significant increase in infant mortality rate among mothers living in rural areas of the camps, and among those with primary education. Overall, these results show that there are significant differences in the increase in fertility, and infant mortality based on the socioeconomic characteristics of women living in the very high earthquake intensity areas. The DID analysis indicates that the earthquake had heterogeneous effects on demographic outcomes, and also suggests that the poor are disproportionately affected, an important topic, that requires further study.

27. We report only the coefficient associated with interactions $Camp \times Post_t$, but all other results are available upon request.

Table 1.5 – Heterogeneous treatment effects by woman characteristics

	Location		Woman's age at the time of the survey			Woman's education			
	Rural (1)	Urban (2)	Age ≤ 20 years (3)	Age > 20 to ≤30 years (4)	Age > 30 years (5)	No education (6)	Primary (7)	Secondary (8)	Higher (9)
Probability of a live birth									
Camp × Post (12 months)	0.00463*** (0.00147)	0.00218 (0.00269)	0.00686** (0.00309)	0.00263 (0.00204)	0.00127 (0.00219)	0.00458 (0.00506)	0.00496*** (0.00190)	0.00278 (0.00173)	0.00853 (0.00690)
N	287,165	141,756	73,696	165,841	189,384	49,037	126,444	212,605	40,835
Probability of dying between birth and exactly 1 year of age									
Camp × Post (12 months)	0.0756*** (0.0268)	0.0346 (0.0301)	-0.0828 (0.295)	0.0530 (0.0306)	0.140* (0.0750)	0.0369 (0.0272)	0.112** (0.0447)	0.0541 (0.0431)	
N	3,508	8,612	110	3,971	7,798	3,610	5,200	2,806	
Cluster and CMC FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Woman's age	YES	YES	NO	NO	NO	YES	YES	YES	YES

Notes : In fertility analysis, columns (1)-(5) contain control for number of kids, aged 2- (alive), total number of kids, number of kids dead in the last 24 months, education level and wealth index. Regarding mortality analysis, columns (1)-(5) include number of twins, first birth order, number of sister alive, number of brother alive, education level and Wealth Index as explanatory variables. Regressions in columns (6) through (9) include the same set of control variables for fertility and mortality respectively except for education level. Coefficients that are statistically significant at *10%, **5%, and ***1% levels.

1.5. Discussion and Research Perspectives

Employing a DID identification strategy, we find greater post-disaster increases in the number of births in the most severely impacted primary sampling units at the time of the earthquake. In camps, our findings reveal an increment in live births beginning approximately from nine to twenty-one months after the quake, that is stratified across location, age, and educational level. The positive fertility impact in this study is similar to the findings of some other studies on natural disasters. For example, Nandi et al. (2018) found that the Gujarat earthquake of 2001 led to significant rises in childbirth rates by comparing the outcomes across earthquake-affected districts and their neighbouring districts during 5 years before and after the earthquake. Finlay (2009) also found positive fertility effects of earthquakes in Pakistan and Turkey. In Haiti, Behrman and Weitzman (2016) found that living in a violently or severely affected area positively affected current pregnancy and negatively affected current contraceptive use, with effects particularly pronounced for less-schooled women. Regarding the probability of dying within the first month of life. We find no robust significant effect of the earthquake in the overall sample as well as in camps. As for infant mortality, we find a significant increase in IDP camps. The significantly positive coefficients after the third month following the quake on infant mortality is consistent with the link between the level of development and natural disasters found by Djafri et al. (2015) and Kolbe et al. (2010).

Our study has several limitations that should be recognized and inform future research. First and foremost, the key demographic outcomes we have considered can be affected by policies and programs related to disaster preparedness and response as concurrent health, nutrition program, or any aid program that targeted the most heavily affected regions in Haïti could lead to biased estimates of the earthquake effect. Frankenberg and Thomas (2014) argued that emergency assistance and longer-term recovery efforts can shape how outcomes unfold in a disaster's aftermath while El-Shal et al. (2022) showed that emergency preparedness and response can prevent negative effects.²⁸ Further, other mitigators, namely, water, sanitation, and hygiene coverage, universal health coverage, education, gender equality, and financial inclusion could mitigate these impacts. Through CMC effects,

28. El-Shal et al. (2022) showed that health system capacity, public health infrastructure, health care coverage and financing, and social determinants of health can mitigate disaster effects like increase maternal, under-5, and neonatal mortalities.

we control for any nationwide changes in each year-month that affected all primary sampling units in a uniform way. Any time-invariant differences among administrative unit regions are controlled for with location fixed effects. One potential direction would be to consider whether such measures alter the immediate or indirect consequences of natural disasters for women fertility, infant and more broadly for child health and assess the causal effects remain an avenue for future research.

A second potential concern with our identification strategy is that women who have live births in the pre-earthquake period are somehow different than women living in camps or not, whose fertility occurs only after the earthquake, even after controlling for education and number of children live or death. The age and cluster fixed effects models in Tables 1.2-1.4 and 1.9-1.14 control for any time and location-invariant differences between women. There may be concerns about giving a causal interpretation to the estimated coefficients from OLS standard estimation approach. In order to mitigate possible biases originating from unobserved factors, we also use DID mother and matching fixed effect regression models. The maternal fixed effects control for any time-invariant differences between women. Hence, the interaction of the dummy variable indicating the time when the treatment started with the binary camp variable can be interpreted as causal effects. Although our matching fixed effect models leave the main fertility result unaffected. An issue derived from this sensitivity analysis is the lack of sufficient observations in neonatal and infant mortality regressions (Cols. (2)-(3) of Table 1.14). Scholars, in the future, might conduct research with large samples to unearth these potential relationships.

A third threat to the validity of our analysis is whether earthquake-induced mortality altered the population composition in a way that biases our estimates. First, as evidenced by Kolbe et al. (2010) and Doocy et al. (2013), earthquake fatalities were largely concentrated in the Ouest department. Second, earthquake in the high-intensity area may have induced a compositional change based on unobserved characteristics of women. In addition, a cholera outbreak broke out in October 2010 in the department of Artibonite and spread across the country, leading to high mortality among the population in all categories (Farmer et al., 2012 ; OCHA, 2017).²⁹ Finally although DHS data are na-

29. Post-disaster mortality is often concentrated among poorer populations because of pre-existing social, economic, and health vulnerabilities (Cutter et al., 2003).

tionally representative and all estimates weighted using survey weights, our constructed dataset may clearly underestimate the true natality or child death rates in Haiti for at least two main reasons. Due to information not available in our DHS data, it was not possible to include children whose mothers did not survive the earthquake. Additionally children born after the earthquake whose parents migrated to other countries were not included. Future research therefore, ought to examine in what extent these factors impact the demographic outcome in Haiti. Further, in our data sample, only 0.18% of mothers lost a child at the time of the earthquake, suggesting that the majority of children who died that day or in the days following were with their parents. Thus, there is selection in the sample. A potential direction would be to examine and assess earthquake-related adult mortality at the national/regional or local level using the DHS maternal mortality module, and compare it to official statistics, in order to test the validity of the DHS sample.

Another issue is the potential for bias from earthquake-induced migration in the country (Most affected areas to other regions of Haiti or international migration). In particular, the earthquake may have been followed by selected out-migration, altering the composition of the babies eligible for life birth. If migration between treatment and control areas were high, it might distort our findings. Moreover, the damage to residential shelters and debris blockages led to significant residential displacement and migration out of the heavily damaged metropolitan region of Port-au-Prince (Green and Miles, 2011). However, analysis of cellular network data found that over 70 percent of people who moved after the earthquake stayed within 50 kilometers of the center of Port-au-Prince (Lu et al., 2012). Even if the influence of selective out-migration cannot be fully ruled out, and given Haiti is a poor country, international migration following the 2010 earthquake until 2012 was minimal, we believe, if it exists, it should be minor. Nonetheless, concerns about migration-related bias are mitigated by the fact that we limit the sample to women who have ‘always lived in the same house and those residing in internally displaced person camps’. This strategy reduces concern about selective migration. Future research could examine whether the earthquake may have been followed by selected out-migration.

Finally, in additional analyses, we examine the potential selective fertility that may occur in the aftermath of the quake. For instance, women or family who experienced the death

of a child as a result of the 2010 earthquake might be more likely to increase their fertility rates as suggested by the replacement theory of fertility (Nobles et al., 2015). We compare maternal characteristics of infants conceived in the first nine months following the disaster with the composition of woman/maternal attributes in the rest of the sample period (Brown, 2020). To do this, we create five maternal characteristics : an indicator for whether the mother lost at least one death at the time of the earthquake, an indicator for each level of mother education (no schooling, primary, secondary, or higher).³⁰ Using DHS birth data for 2005–2010, we find that the mothers who conceived children after the disaster are not globally significantly different than the mothers from the previous cohort (Table 1.15). Specifically, mothers who lost a child at the time of the quake are more likely to give birth. We do not find any statistically significant differences by education level. Given the bias that would be caused by including infants from mothers that are endogenously self-selected in a way that is positively correlated with childbirth, we believe that the choice to use mother fixed effect regression models, and matching estimations techniques help preserve the randomness needed for identification.

All in all, we provide causal estimates of the earthquake exposure on demographic issues in Haiti by using a set of fixed effects difference-in-difference models. To our knowledge, this is the first time that a micro-level dataset with individual-level information on population and health has been transformed to a monthly panel data to investigate the effects of disasters on demographic outcomes. One of the strenghts of this study is a focus on population living in IDP camps. As far as we know, to date, no other study has previously analysed post-disaster demographic outcomes in IDP camps. In doing so, our results contribute to the large empirical literature of the effect of natural disasters on indirect demographic changes.

Deciphering the underlying relationship between disasters, child mortality and fertility through a sub-national pre- and post-earthquake comparison provided a better unders-

30. The regression used in this analysis is as follows :

$$Z_{ijt} = \alpha + \beta post + \gamma_t + \gamma_j + \epsilon_{ijt} \quad (1.2)$$

where Z_{ijt} is one of our four dependent variables as defined earlier. $post$ is an indicator for being conceived in the first nine months after the quake. γ_j and γ_t are location and time fixed effects respectively. Maternal characteristic controls are excluded from these regressions.

tanding of the needs of local populations. These results call for national and international policies and interventions that strengthen the country's health care systems and improve the living conditions of the population in an era of very rapid climate change and increasingly violent natural disasters in Haïti and the rest of the world. Guided by insights from disaster demography models on the channels through which natural disasters may affect demographic processes, this study went as well beyond the averages and explored the effects of the earthquake on a monthly basis by eliminating any bias from migration.

1.5.1. Appendix A : Descriptive statistics

Table 1.6 – Descriptive statistics on earthquake intensity

	N	Mean	Std. Dev.	Min	Max
Modified Mercalli Intensity	887	6.447802	1.169193	3.4	8.6
Takes 1 if Earthquake Intensity > 5	887	0.8703495	0.336108	0	1
Takes 1 if Earthquake Intensity > 5.5	887	0.7361894	0.4409464	0	1
Takes 1 if Earthquake Intensity > 6	887	0.5636979	0.4962058	0	1
Takes 1 if Earthquake Intensity > 6.5	887	0.4509583	0.4978698	0	1
Takes 1 if Earthquake Intensity > 7	887	0.3325817	0.4714039	0	1
Takes 1 if Earthquake Intensity > 7.5	887	0.2660654	0.4421482	0	1
Takes 1 if Earthquake Intensity > 8	887	0.0586246	0.2350532	0	1

Source : Data are from United States Geological Survey (2010).

Table 1.7 – Number of distinct values of MMI by administrative regions

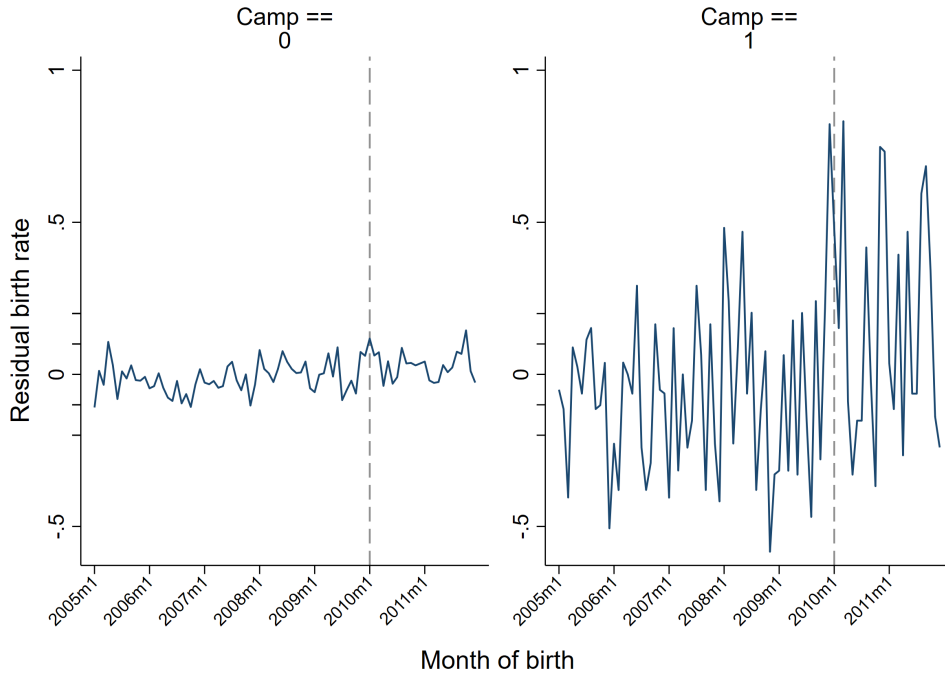
	N	Number	Mean	Std. Dev.	Min	Max
Number of distinct values of mmi by department	887	10	12.91995	2.243455	7	15
Number of distinct values of mmi by arrondissement	887	41	7.257046	2.22072	3	12
Number of distinct values of mmi by commune	887	131	4.140924	1.97255	1	11
Number of distinct values of mmi by commune section	887	346	2.217587	1.113738	1	6
Number of distinct values of mmi by PSU	887	887	1	0	1	1

Source : GADM map from www.gadm.org/, United States Geological Survey (2010) and Demographic and Health Surveys data (DHS 2012, 16-17).

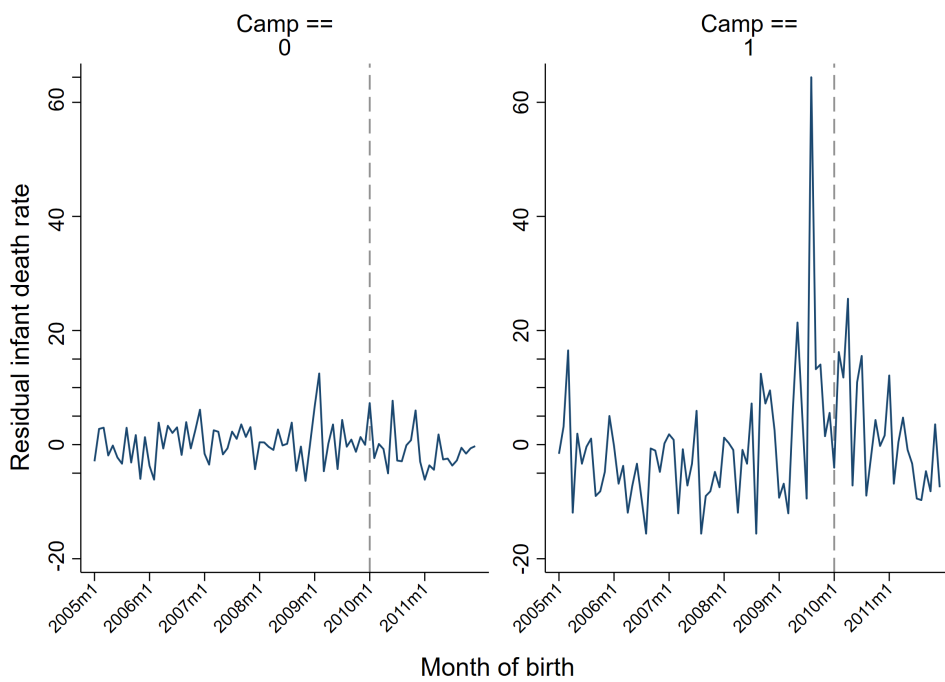
Table 1.8 – Selection in camps

Dependent variable :	Camp : Takes 1 if lived in a camp in 2012		
	(1)	(2)	(3)
Age just before the earthquake	-.000577*** (.000168)	-.000537*** (.000148)	-.000599*** (.000146)
Age * age	-9.45e-07*** (2.75e-07)	-9.07e-07*** (2.48e-07)	-1.02e-06*** (2.48e-07)
Total number of Kids	.00125 (.00406)	.00156 (.004)	.000623 (.0033)
Number of kids Alive	.000656 (.00398)	.000875 (.00404)	.00207 (.00337)
Woman's education (omitted = No schooling)			
Primary	-.00478 (.00814)	-.00978 (.00774)	-.0106 (.00682)
Secondary	-.0326** (.0145)	-.0423*** (.0145)	-.045*** (.0136)
Higher	-.0864*** (.0218)	-.101*** (.0228)	-.102*** (.0221)
N	10163	10163	10163
Arrondissement FE	✓		
Communes FE		✓	
Commune section FE			✓

Notes : Standard errors clustered at the cluster level. Sampling weights. *** p < 0.01, ** p < 0.05, * p < 0.1; FE = fixed effects.



(a)

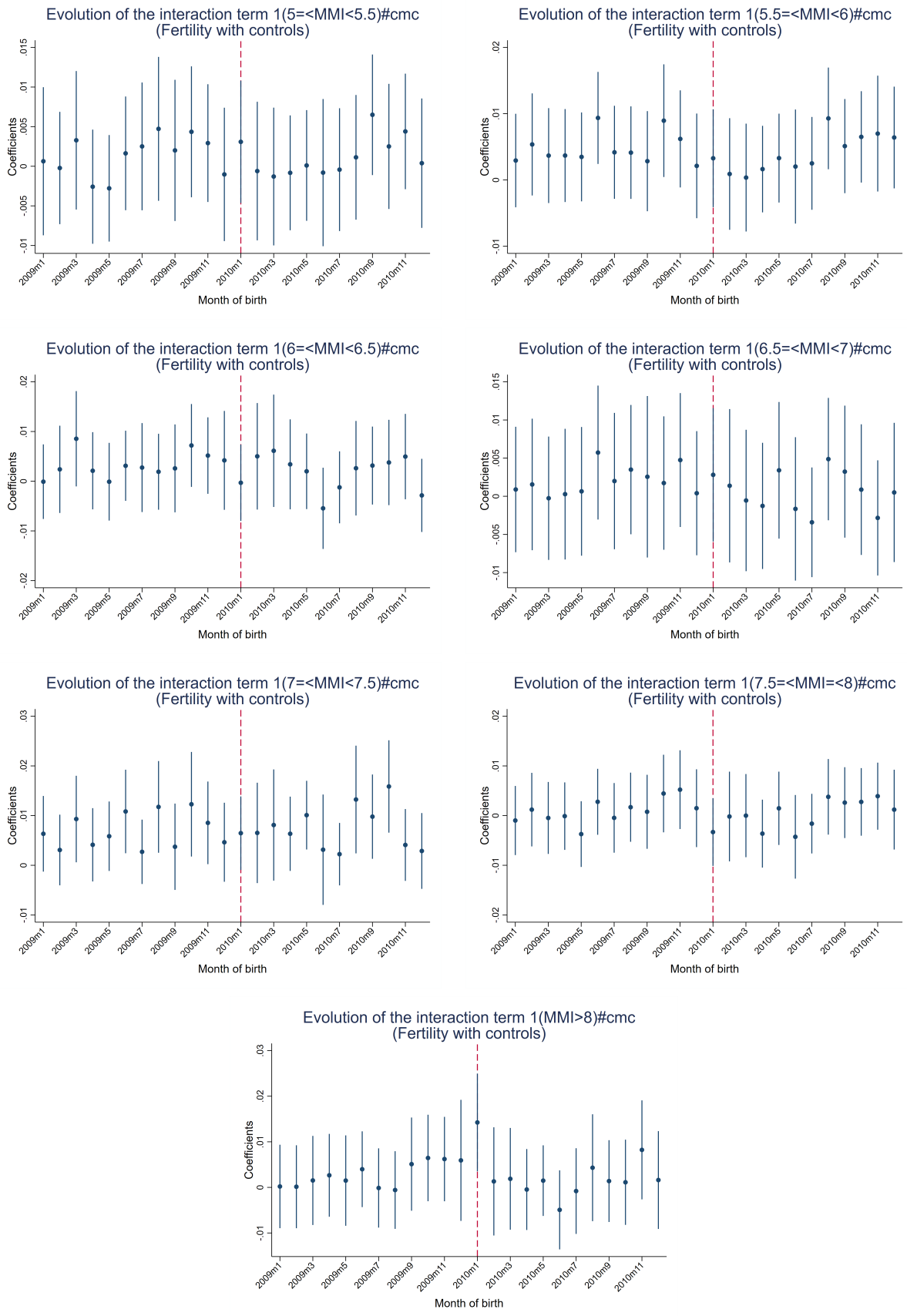


(b)

Note : The added vertical line indicates 2010 Haiti earthquake.

Figure 1.7 – Monthly residual of childbirth (a), and infant mortality (b)

1.5.2. Appendix B : Figures and Tables of the Robustness Analysis



Notes : Coefficient and 95% confidence intervals are presented.

Figure 1.8 – Coefficient of interaction between earthquake-affected zones and cmc in regression of monthly rate of childbirth (2009–2010)

Table 1.9 – Difference-in-differences estimation for number of births at different intensity magnitudes

Dependent variable :	Birth : Takes 1 if (at least) a birth this time period						
	MMI > 5	MMI > 5.5	MMI > 6	MMI > 6.5	MMI > 7	MMI > 7.5	MMI > 8
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Earthquake Intensity × Post (3 months)	-0.000502 (0.00153)	-9.29e-05 (0.00112)	0.00141 (0.00101)	0.000676 (0.00105)	0.000510 (0.00110)	0.000325 (0.00116)	0.00480* (0.00272)
Earthquake Intensity × Post (4–6 months)	-0.00203 (0.00148)	-0.00125 (0.000976)	-0.000862 (0.000821)	-0.000544 (0.000798)	-0.000910 (0.000827)	-0.00145* (0.000864)	-0.00242* (0.00124)
Earthquake Intensity × Post (7–9 months)	0.000790 (0.00112)	2.31e-05 (0.000929)	-0.000466 (0.000931)	0.000203 (0.000927)	0.000418 (0.000956)	0.000147 (0.000999)	-0.00204 (0.00185)
Earthquake Intensity × Post (10–12 months)	0.00117 (0.00107)	0.000434 (0.000937)	-0.000612 (0.000940)	2.49e-05 (0.000964)	0.00144 (0.00103)	0.00158 (0.00111)	-7.21e-05 (0.00214)
Earthquake Intensity × Post (13–15 months)	-0.00106 (0.00101)	-0.000292 (0.000841)	0.000180 (0.000781)	-0.000507 (0.000783)	-9.70e-05 (0.000787)	-0.000485 (0.000805)	-0.000702 (0.00147)
Earthquake Intensity × Post (16–18 months)	5.41e-05 (0.00101)	3.57e-05 (0.000833)	0.000526 (0.000821)	0.000172 (0.000856)	0.000219 (0.000919)	-0.000289 (0.000932)	-0.000538 (0.00186)
Earthquake Intensity × Post (19–21 months)	0.000254 (0.00116)	-0.000161 (0.00103)	-0.00119 (0.00104)	-0.000312 (0.00103)	-0.000193 (0.00105)	-0.000165 (0.00109)	0.00265 (0.00241)
Earthquake Intensity × Post (22–24 months)	-0.000479 (0.00117)	-0.00128 (0.00104)	0.000282 (0.000949)	0.000509 (0.000975)	0.000358 (0.00103)	0.000670 (0.00110)	0.00281 (0.00263)
Observations	1,462,936	1,462,936	1,462,936	1,462,936	1,462,936	1,462,936	1,462,936

Notes : All regressions include cluster, age and birth Century-Month Code (CMC) fixed effects. Estimates weighted using survey weights provided by DHS. Robust standard errors clustered at the primary sampling unit level. The unit of observation is a woman-cmc, starting at the age of 15 for all columns. All columns are linear probability models, and contain control for education level, number of kids, aged 2- (alive), total number of Kids, number of kids dead in the last 24 months, and wealth index. Treated group clusters include those struck by an MMI magnitude greater than those indicated in the header of each column, while the control group includes all the clusters where the earthquake had a MMI magnitude ≤ 5 , ≤ 5.5 , ≤ 6 , ≤ 6.5 , ≤ 7 , ≤ 7.5 , ≤ 8 in columns 1, 2, ..., 7 respectively. Coefficients that are statistically significant at *10%, **5%, and ***1% levels.

Table 1.10 – Earthquake impact on fertility, using sample of usual residents

Dependent variable :	Birth : Takes 1 if (at least) a birth or child dies this time period											
	Fertility				Neonatal Mortality				Infant Mortality			
	MMI > 5	MMI > 6	MMI > 7	MMI > 8	MMI > 5	MMI > 6	MMI > 7	MMI > 8	MMI > 5	MMI > 6	MMI > 7	MMI > 8
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Earthquake Intensity × Post (1 month)	-0.000588 (0.00194)	0.000436 (0.00153)	0.00171 (0.00164)	0.0137*** (0.00407)	-0.0125 (0.0288)	0.0294 (0.0179)	0.0135 (0.0211)	-0.0134 (0.0209)	-0.0127 (0.0174)	0.0246** (0.0125)	0.0153 (0.0144)	0.00912 (0.0217)
N	1,449,259	1,449,259	1,449,259	1,449,259	13,137	13,137	13,137	13,137	13,137	13,137	13,137	13,137
Earthquake Intensity × Post (3 months)	-0.00140 (0.00141)	0.000710 (0.000880)	0.000258 (0.000907)	0.00339* (0.00185)	-0.0225 (0.0219)	0.0191 (0.0118)	0.0171 (0.0138)	0.000385 (0.0166)	-0.0226 (0.0154)	0.0201* (0.0112)	0.0183 (0.0131)	0.0165 (0.0215)
N	1,500,026	1,500,026	1,500,026	1,500,026	13,666	13,666	13,666	13,666	13,666	13,666	13,666	13,666
Earthquake Intensity × Post (6 months)	-0.00126 (0.000906)	0.000146 (0.000563)	-6.46e-05 (0.000573)	0.000869 (0.00107)	-0.0159 (0.0201)	0.0256** (0.0115)	0.0202 (0.0138)	-0.00262 (0.0139)	-0.0250 (0.0152)	0.0216** (0.0107)	0.0211* (0.0125)	0.0140 (0.0201)
N	1,576,325	1,576,325	1,576,325	1,576,325	14,252	14,252	14,252	14,252	14,252	14,252	14,252	14,252
Earthquake Intensity × Post (9 months)	-0.000656 (0.000709)	-5.43e-05 (0.000477)	0.000319 (0.000488)	0.000734 (0.000858)	-0.00387 (0.0152)	0.0127 (0.0109)	0.00850 (0.0117)	-0.00584 (0.0118)	-0.0178 (0.0141)	0.0124 (0.0105)	0.0143 (0.0119)	0.00324 (0.0194)
N	1,652,858	1,652,858	1,652,858	1,652,858	14,962	14,962	14,962	14,962	14,962	14,962	14,962	14,962
Earthquake Intensity × Post (12 months)	-0.000286 (0.000587)	-2.61e-05 (0.000413)	0.000605 (0.000425)	0.000535 (0.000688)	-0.00705 (0.0130)	0.0135 (0.00891)	0.00681 (0.00948)	-0.00855 (0.0116)	-0.0153 (0.0126)	0.0145 (0.00958)	0.0109 (0.0106)	0.00460 (0.0194)
N	1,729,705	1,729,705	1,729,705	1,729,705	15,773	15,773	15,773	15,773	15,773	15,773	15,773	15,773

Notes : All regressions include cluster, age, and birth Century-Month Code (CMC) fixed effects. Sampling weights. Estimates weighted using survey weights provided by DHS. Robust standard errors clustered at the primary sampling unit level. Columns (1)-(4) contain control for education level, number of kids, Aged 2- (Alive), total number of Kids, Number of Kids Dead in the Last 24m and Wealth Index. Columns (5)-(12) control for number of twins, birth order, number of sister alive, number of brother alive, education level and Wealth Index. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 1.11 – Mother fixed effect regressions on the number of births at different intensity magnitudes

Dependent variable :	Birth : Takes 1 if (at least) a birth this time period							
	Resident sample				Resident and Camp sample			
	MMI > 5 (1)	MMI > 6 (2)	MMI > 7 (3)	MMI > 8 (4)	MMI > 5 (5)	MMI > 6 (6)	MMI > 7 (7)	MMI > 8 (8)
Earthquake Intensity × Post (1 month)	-0.000125 (0.00214)	-0.000763 (0.00168)	-0.000598 (0.00175)	0.0151*** (0.00497)	7.00e-06 (0.00213)	-0.000564 (0.00166)	-0.000287 (0.00170)	0.0140*** (0.00464)
N	1,016,804	1,016,804	1,016,804	1,016,804	1,087,221	1,087,221	1,087,221	1,087,221
Earthquake Intensity × Post (3 months)	-0.000621 (0.00156)	0.00106 (0.00105)	-4.53e-05 (0.00116)	0.00474 (0.00293)	-0.000502 (0.00155)	0.00120 (0.00103)	0.000210 (0.00111)	0.00476* (0.00269)
N	1,052,354	1,052,354	1,052,354	1,052,354	1,125,104	1,125,104	1,125,104	1,125,104
Earthquake Intensity × Post (6 months)	-0.00133 (0.00109)	4.52e-05 (0.000657)	-0.000508 (0.000696)	0.00102 (0.00143)	-0.00133 (0.00108)	3.72e-05 (0.000645)	-0.000497 (0.000670)	0.00112 (0.00133)
N	1,105,802	1,105,802	1,105,802	1,105,802	1,182,041	1,182,041	1,182,041	1,182,041
Earthquake Intensity × Post (9 months)	-0.000580 (0.000805)	-0.000176 (0.000552)	-0.000220 (0.000589)	9.02e-05 (0.00106)	-0.000602 (0.000802)	-0.000207 (0.000542)	-0.000262 (0.000567)	5.99e-05 (0.000999)
N	1,159,377	1,159,377	1,159,377	1,159,377	1,239,088	1,239,088	1,239,088	1,239,088
Earthquake Intensity × Post (13 months)	-0.000168 (0.000632)	-0.000382 (0.000481)	0.000115 (0.000514)	3.47e-05 (0.000916)	-0.000164 (0.000629)	-0.000370 (0.000472)	0.000119 (0.000495)	4.62e-05 (0.000865)
N	1,213,126	1,213,126	1,213,126	1,213,126	1,296,297	1,296,297	1,296,297	1,296,297

Notes : All regressions include mother, and birth Century-Month Code (CMC) fixed effects. Sampling weights. Estimates weighted using survey weights provided by DHS. Robust standard errors clustered at the primary sampling unit level. The unit of observation is a woman-cmc, starting at the age of 15 for all columns.

*** p < 0.01, ** p < 0.05, * p < 0.1.

Table 1.12 – Mother fixed effect regressions of fertility, neonatal, and infant mortality

Dependent variable :	Fertility	Neonatal Mortality	Infant Mortality
	(1)	(2)	(3)
Camp × Post (1 month)	0.00421 (0.00461)	0.0250 (0.101)	0.0766 (0.0657)
N	319,564	1,103	1,103
Camp × Post (3 months)	0.00210 (0.00270)	0.0598 (0.0625)	0.139** (0.0629)
N	379,548	1,216	1,216
Camp × Post (6 months)	0.00276 (0.00175)	0.0442 (0.0505)	0.123** (0.0567)
N	395,974	1,289	1,289
Camp × Post (9 months)	0.00230* (0.00129)	0.0225 (0.0412)	0.107** (0.0494)
N	412,426	1,416	1,416
Camp × Post (12 months)	0.00403*** (0.00131)	0.0334 (0.0333)	0.0963** (0.0444)
N	428,907	1,565	1,565
Camp × Post (15 months)	0.00283** (0.00119)	0.0401 (0.0324)	0.106** (0.0422)
N	445,436	1,679	1,679
Camp × Post (18 months)	0.00210** (0.000986)	0.0432 (0.0363)	0.121*** (0.0388)
N	458,709	1,776	1,776

Notes : All regressions include mother and birth Century-Month Code (CMC) fixed effect. Sampling weights. Estimates weighted using survey weights provided by DHS. Robust standard errors clustered at the primary sampling unit level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 1.13 – Difference-in-differences estimation for neonatal and infant mortality at different intensity magnitudes using mother fixed effects

Dependent variable :	Birth : Takes 1 if (at least) a death at this time period							
	Resident sample				Resident and Camp sample			
	MMI > 5 (1)	MMI > 6 (2)	MMI > 7 (3)	MMI > 8 (4)	MMI > 5 (5)	MMI > 6 (6)	MMI > 7 (7)	MMI > 8 (8)
Panel A : Neonatal Mortality								
Earthquake Intensity × Post (1 month)	0.0735 (0.0803)	0.0662* (0.0376)	0.0879* (0.0459)	0.00884 (0.0305)	0.0775 (0.0804)	0.0706* (0.0371)	0.0922** (0.0433)	0.0354 (0.0401)
N	5,282	5,282	5,282	5,282	5,590	5,590	5,590	5,590
Earthquake Intensity × Post (3 months)	-0.0247 (0.0504)	0.0234 (0.0243)	0.0352 (0.0289)	0.0125 (0.0191)	-0.0215 (0.0504)	0.0275 (0.0239)	0.0416 (0.0271)	0.0205 (0.0232)
N	5,687	5,687	5,687	5,687	6,029	6,029	6,029	6,029
Earthquake Intensity × Post (6 months)	-0.0126 (0.0354)	0.0285 (0.0179)	0.0285 (0.0225)	0.00805 (0.0163)	-0.0101 (0.0354)	0.0314* (0.0176)	0.0337 (0.0213)	0.0147 (0.0195)
N	6,112	6,112	6,112	6,112	6,475	6,475	6,475	6,475
Earthquake Intensity × Post (9 months)	-0.0127 (0.0283)	0.0183 (0.0164)	0.0194 (0.0196)	0.0164 (0.0191)	-0.0111 (0.0283)	0.0202 (0.0161)	0.0231 (0.0185)	0.0207 (0.0205)
N	6,608	6,608	6,608	6,608	7,010	7,010	7,010	7,010
Earthquake Intensity × Post (12 months)	-0.00835 (0.0236)	0.0120 (0.0135)	0.00126 (0.0162)	0.00959 (0.0177)	-0.00720 (0.0236)	0.0135 (0.0132)	0.00483 (0.0152)	0.0105 (0.0186)
N	7,108	7,108	7,108	7,108	7,556	7,556	7,556	7,556

Table 1.13 (Continued) Difference-in-differences estimation for neonatal and mortality at different intensity magnitudes

Panel B : Infant Mortality								
Earthquake Intensity × Post (1 month)	0.00623	0.0223	-0.0384	-0.0862	0.00736	0.0230	-0.0335	-0.0603
	(0.0343)	(0.0250)	(0.0313)	(0.0717)	(0.0341)	(0.0244)	(0.0293)	(0.0648)
N	5,282	5,282	5,282	5,282	5,590	5,590	5,590	5,590
Earthquake Intensity × Post (3 months)	-0.0258	0.00751	-0.0443	-0.0592	-0.0219	0.0107	-0.0343	-0.0357
	(0.0316)	(0.0221)	(0.0272)	(0.0581)	(0.0314)	(0.0216)	(0.0257)	(0.0536)
N	5,687	5,687	5,687	5,687	6,029	6,029	6,029	6,029
Earthquake Intensity × Post (6 months)	-0.0170	0.0174	-0.0388	-0.0549	-0.0136	0.0200	-0.0300	-0.0334
	(0.0281)	(0.0194)	(0.0246)	(0.0534)	(0.0279)	(0.0190)	(0.0232)	(0.0492)
N	6,112	6,112	6,112	6,112	6,475	6,475	6,475	6,475
Earthquake Intensity × Post (9 months)	-0.0240	0.00626	-0.0396*	-0.0414	-0.0209	0.00885	-0.0315	-0.0225
	(0.0257)	(0.0176)	(0.0221)	(0.0532)	(0.0256)	(0.0173)	(0.0209)	(0.0487)
N	6,608	6,608	6,608	6,608	7,010	7,010	7,010	7,010
Earthquake Intensity × Post (12 months)	-0.0158	0.00962	-0.0452**	-0.0357	-0.0130	0.0116	-0.0376**	-0.0223
	(0.0230)	(0.0155)	(0.0191)	(0.0495)	(0.0228)	(0.0151)	(0.0181)	(0.0455)
N	7,108	7,108	7,108	7,108	7,556	7,556	7,556	7,556

Notes : All regressions include cluster, age and birth Century-Month Code (CMC) fixed effects. Sampling weights. Estimates weighted using survey weights provided by DHS. Robust standard errors clustered at the primary sampling unit level. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 1.14 – Impact of earthquake on fertility, neonatal and infant mortality using Coarsened Exact Matching difference-in-difference

Dependent variable	Fertility (1)	Neonatal mortality (2)	Infant mortality (3)
Camps × Post (1 month)	-0.00198 (.00787)	0.0955 (0.105)	0.0536 (0.0606)
N	54,522	506	506
Camps × Post (3 months)	-0.00182 (0.00509)	0.0973 (0.0833)	0.0849* (0.0495)
N	64,808	535	535
Camps × Post (6 months)	0.00240 (0.00317)	0.0368 (0.0792)	0.0615 (0.0490)
N	67,617	550	550
Camps × Post (9 months)	0.00552** (0.00230)	0.00882 (0.0730)	0.0155 (0.0531)
	70,424	575	575
Camps × Post (12 months)	0.00653*** (0.00230)	0.0235 (0.0594)	-0.0408 (0.0553)
N	73,227	617	617
Camps × Post (15 months)	0.00433** (0.00206)	0.0280 (0.0533)	-0.0521 (0.0537)
	76,032	641	641
Camps × Post (18 months)	0.00343* (0.00194)	0.0335 (0.0526)	-0.0415 (0.0525)
N	78,109	660	660

Notes : All regressions include century month code and cluster fixed effects. Estimates weighted using survey weights provided by DHS. Robust standard errors clustered at the primary sampling unit level. We control for education, the number of children aged less than 24 months, the number of dead children in the last 24 months and the number of kids alive in the fertility regressions. As for mortality, we control for multiple births, the rank of the child and the number of brothers and of sisters aged less than 3 and the intensity of the quake. Individuals are matched to their place of residence (camp or not). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 1.15 – Change in woman characteristics for infants conceived after the 2010 Haiti earthquake

Dependent variable :	Woman characteristics				
	At least one death at the month of the quake	Education level			
		No schooling	Primary	Secondary	Higher
	(1)	(2)	(3)	(4)	(5)
	Women with children				
Post-Earthquake (Jan. - Oct. 2010)	0.00843*** (0.00237)	0.00633 (0.00960)	-0.0116 (0.0117)	0.00344 (0.0108)	0.00186 (0.00444)
Observations	806,941	806,941	806,941	806,941	806,941
	All woman				
Post-Earthquake (Jan. - Oct. 2010)	0.00843*** (0.00237)	0.0637*** (0.00991)	0.0249** (0.0121)	-0.0736*** (0.0115)	-0.0149*** (0.00507)
Observations	1,204,851	1,204,851	1,204,851	1,204,851	1,204,851

Notes : Estimates weighted using survey weights provided by DHS. Robust standard errors clustered at the woman level. Each regression controls for conception cmc and cluster fixed effects. We note that among the 17,228 women with children in our sample, only 0.15% lost at least one child during the month of the earthquake. Coefficients that are statistically significant at *10%, **5%, and ***1% levels.

1.6. Appendix C : Data Sources

Data Availability Statement : The individual survey data are from the Demographic and Health Surveys (DHS) conducted in 2012 and 2016–2017 (Institut Haïtien de l'Enfance (IHE) and ICF). The geocoded earthquake intensity data are from the United States Geological Survey (USGS) available at <https://earthquake.usgs.gov/earthquakes/eventpage/usp000h60h/shakemap/intensity>, accessed on 30 September 2019.

The effect of natural disaster on economic growth : evidence from a major earthquake in Haïti

RÉSUMÉ

Nous examinons l'impact causal moyen du tremblement de terre de 2010 en Haïti sur la croissance et la reprise économiques en menant une analyse empirique désagrégée au niveau sous-national. Pour ce faire, nous optons pour un modèle de différence dans les différences à effets fixes et des fonctions de réponse aux chocs en utilisant l'intensité du tremblement de terre comme principale variable exogène et les données des lumières émises la nuit et captées par satellite comme une approximation de l'activité économique de 1992 à 2019. Les résultats indiquent que le tremblement de terre a provoqué une baisse significative de la croissance économique du pays à court terme. Nous montrons également que l'effet négatif observé sur l'activité économique a persisté plus de dix ans après la catastrophe. Dans l'ensemble, les estimations fournissent de nouvelles informations sur les effets des catastrophes naturelles majeures sur la croissance économique à court et à long terme. Par conséquent, notre analyse des effets de l'intensité du séisme sur la croissance des lumières de nuit est une contribution importante à la littérature. Les résultats, les implications et les pistes de recherches futures ont été discutés dans la dernière section.

Mots clés : Lumières de nuit, Intensité du tremblement de terre, Activité économique, Modèle de différences dans les différences, Fonctions de réponse aux chocs, Haïti

JEL Codes : Q54 R11 O10 O4.

ABSTRACT

We examine the average causal impact of the 2010 earthquake in Haiti on economic growth and recovery by conducting a disaggregated empirical analysis at the subnational level. To achieve this, we opt for a fixed effects difference-in-differences model and impulse response functions by using the earthquake's intensity as the main exogenous variable and nighttime light data as a proxy for economic activity from 1992 to 2019. Results indicate a robust evidence that the earthquake caused a significant decrease in the country's economic growth in the short-term. We also reveal that such declines in growth persisted ten years after the disaster. Overall, estimates provide new insights on the short and long-run economic growth effects of major natural disasters. Therefore, our analysis of the effects of earthquake intensity on the growth of night lights is an important contribution to disaster economics. In the concluding reflections, the findings, implications, and avenues for future research are discussed.

Key words : Nighttime lights, earthquake intensity, economic activity, difference-in-differences model, impulse response functions, Haïti.

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2.1. Introduction

Disasters occur frequently all over the world and affect both developed and developing countries. Damage from natural disasters has increased globally over the past two decades and the vast majority of lives lost or affected are in low-income countries (Kahn, 2005 ; Zorn, 2018). These disasters, whether natural or not, inherently have a social and economic dimension, exacerbating pre-existing inequalities and disrupting social norms and institutions for long periods of time (Wagner-Pacifici, 2003). They typically lead to a

disruption of economic and social development in hard-hit areas and can result in a sharp increase in poverty if appropriate recovery measures are not adopted (Kreimer, 2001).

A growing number of studies have already documented the relationship between natural disasters and economic growth in different regions of the world (Cavallo and Noy, 2011 ; Cavallo et al., 2010 ; Skidmore and Toya, 2002,0).² These existing studies typically find that natural disasters have negative economic consequences, resulting in, at best, a recovery to trend after initial losses or, at worst, longer term sustained losses (Cavallo et al., 2013 ; Cavallo and Noy, 2011 ; Cavallo et al., 2010 ; Noy, 2009). Few studies find continuous positive economic effects in the aftermath of disasters (Cavallo and Noy, 2011 ; Loayza et al., 2012 ; Skidmore and Toya, 2002). The most recent is from Heger and Neumayer (2019) on the impact of the single largest aid and reconstruction effort of any developing world region ever afflicted by a natural disaster. It shows that aid triggered a higher long-term economic output than if the tsunami in the Indian Ocean had not occurred.

Others have studied the impact of financial and political crises and wars on growth and economic recovery (Cerra and Saxena, 2008). These authors have shown that a crisis, whether political, monetary, financial or war-related, is generally associated with a slowdown in economic growth in heavily affected areas. However, almost all of these studies have not explored the Haitian case, particularly with regard to economic growth and recovery. This leads us to focus on the economic consequences of the 2010 Haiti earthquake in the short and long term. This article will examine the losses in terms of economic activity, and how different regions of the country recovered from the negative shock induced by the powerful earthquake.

To do this, following the literature, we used a geophysical methodology designed to mea-

2. Skidmore and Toya (2002) showed that natural disasters can promote the adoption of new technologies leading to improved total factor productivity in affected countries. In 2007, they proved that countries with higher incomes, higher educational attainment, greater openness and strong financial systems suffered less from natural disasters.

Cavallo et al. (2010) studied the average causal impact of natural disasters on economic growth in Haiti and found that extremely severe disasters have a negative effect on output in both the short and long run. For an excellent survey of the literature see Cavallo and Noy (2011).

sure seismic damage in order to study the development dynamics following the earthquake through a difference-in-differences model and impulse response functions (Cerra and Saxena, 2008). The earthquake was used as a natural experiment and the nighttime satellite lights collected and made available by NASA as an indicator of economic activity (Bluhm and Krause, 2022 ; Ghosh, 2009 ; Henderson et al., 2012 ; Lee, 2018), given the lack of local data and statistics available in Haiti. Bruederle and Hodler (2018) have proven that these data are a good proxy for the production of goods and services, and are useful for measuring economic growth at subnational and national levels.

The remainder of this paper is organized as follows. We review the main economic consequences of the Haiti earthquake of 2010 and other disasters around the world in Section 2.1. Then follows the description of the data sources, some descriptive statistics in Section 2.2 and the econometric framework in Section 2.3. We next present the main empirical results in Section 2.4, while Section 2.5 reports robustness checks. In Subsection 2.5.2, we discuss a spatial version of our estimates. The discussion is offered in Section 2.6, and lastly the conclusion in Section 2.7.

2.1.1. Overview of the 2010 earthquake in Haïti

On January 12, 2010, following the earthquake of magnitude 7.0 Mw that devastated the country and caused extensive damage, approximately 1.3 million people (13.27% of the 2009 population) lived in temporary shelters in the metropolitan area of Port-au-Prince and more than 500,000 (5.10%) migrated to less affected areas (Government of the Republic of Haiti, 2010 ; United States Geological Survey, 2010).^{3 4} By analysing cellular network data, Lu et al. (2012) estimated that more than 70 percent of the people who moved after the quake stayed within 50 kilometers of the center of Port-au-Prince. The latter, the capital city (close to the epicenter), was hit hard and Haiti experienced significant destruction of basic infrastructure : health (over 50% of hospitals were destroyed or damaged), sports, education (80% of schools cracked or collapsed) (DesRoches et al., 2011 ; Government of the Republic of Haiti, 2010).

3. The metropolitan area was defined as the communes of Port-au-Prince, Carrefour, Pétion-ville, Delmas, Tabarre, Cité Soleil and Kenscoff, and covered 152.02 km².

4. The moment magnitude (Mw) scale provides an estimate of the earthquake size that is valid for the entire magnitude range and is the current standard scale used to measure earthquake strength since 2002 (United States Geological Survey, 2020).

The areas where the intensity of the earthquake was the highest (8 to 9), included all or part of 10 communes, containing three cities of about 20,000 inhabitants (Carrefour, Léogâne and Petit-Goâve), i.e. approximately 0.2% of the 2009 population. Fourteen other communes in the West Department, the most densely populated and the most affected by the earthquake (Table 2.1), were located in an intensity zone ranging from 7.0 to 7.9 (Figure 2.1) and accounted for 28% of the country's total population (United States Census Bureau, 2010 ; WorldPop, 2018). As a result of the earthquake that destroyed the downtown area of the capital, the country experienced the lowest growth rate of its Gross Domestic Product (GDP) in the last 30 years, -3.805%, except for the period during which an embargo was imposed on the country in 1994 (-11.951%) following the military coup of 1991 (World Bank, 2021a).

Cavallo et al. (2010) estimated the damage to range from 8.1 billion (123.01% of the 2009 GDP) to 13.9 billion US dollars (211.09%) for 250,000 deaths (2.54% of the total 2009 population)⁵. Furthermore, over 300,000 injuries were recorded (3.09%) (Government of the Republic of Haiti, 2010). The effects of the earthquake were felt primarily in three of the country's ten departments (West, South-East, Nippes), where between 80 and 90% of buildings were severely damaged or destroyed in areas near the epicenter located in Léogâne (25.3 km from Port-au-Prince) (DesRoches et al., 2011 ; Government of the Republic of Haiti, 2010).⁶ The earthquake also caused a significant increase in outward migration, job destruction and loss of human capital. These consequences could well slow down the economic recovery. By combining information from comparative case studies and employing a treatment effect framework using a synthetic control method to examine the short and long run average causal impact of catastrophic natural disasters on economic growth, Cavallo et al. (2013) suggest that the earthquake significantly affected the subsequent average performance of the Haitian economy. They estimated that per

5. Cavallo et al. (2010) estimated the direct economic damage of the Haiti earthquake using measures of primary initial damage such as mortality, morbidity, or capital losses, a measure of disaster magnitude (the Richter Scale), and control variables to predict, out-of-sample, the dollar amount of direct damage of the 2010 Haiti earthquake.

6. The aforementioned DesRoches et al. (2011) study simply provided an overview of the historical, seismological, geotechnical, structural, lifeline-related, and socio-economic factors that contributed to the catastrophe and described some of the many challenges that must be overcome to enable Haiti to recover from this event through a qualitative, not empirical, theoretical analysis.

capita income would have been \$410 higher in 2020 (about 40 percent of its 2013 level) if Haiti had not suffered one of the worst earthquakes in recent decades. However, the empirical implementation of comparative case studies is plagued by inferential challenges and ambiguity about the choice of valid control groups (Abadie et al., 2010).

Some would argue that these studies do not take into account the economic recovery process following the disaster and that the growth forecasts may turn out to be wrong. Furthermore, between 2010 and 2013, it is too early to indirectly examine the effects of public aid received and capture the true long-term consequences of the earthquake. In addition, these studies were conducted with macroeconomic level data prior to the earthquake and the Richter Scale. However, the moment-magnitude (measured by the Richter Scale) is typically employed as a strictly exogenous regressor and is only weakly correlated to the severity and extent of the damage, which varies depending on a large number of factors. The latter include the depth of the epicenter, the type of seismic waves (undulatory vs. sussultory), and the vulnerability of the buildings (Porcelli and Trezzi, 2018). Hence the need to conduct a study at the local level by using the level of damage to a specific site in the country measured by the Modified Mercalli Intensity Scale. However, having data before and after the earthquake, we address these analytical limitations in our study. We analyzed the short-term impact and economic recovery with greater hindsight, which allowed us to indirectly assess the effectiveness of public policies implemented in the country after the disaster and, in particular, the public aid received in response to it.

The main contribution of this paper is, on the one hand, the use of nighttime lights to assess the consequences of natural disasters in countries where spatial and disaggregated data are not available. On the other hand, unlike the papers cited above in the context on the Haiti earthquake, our article evaluates the long-term economic activity and post-earthquake recovery. We used the difference-in-differences method, which, according to the literature, better assesses the average causal effect of the earthquake given its strictly exogenous nature.

2.2. Data Description

We combine various sources of data : DMSP-OLS Nighttime light data from the Natio-

nal Geophysical Data Center (NGDC) and Colorado School of Mines, Population from WorldPop, the Land area from the Center for International Earth Science Information Network (CIESIN) and the Earthquake Intensity data from the United States Geological Survey (USGS). Our reference dataset is a balanced panel of 41 districts observed over the period 1992–2019 at an annual frequency for a total of 1641 observations. Below, we describe how these data have been used to define our analytical sample and our main variables of interest.

Nighttime light data. In the absence of systematic subnational statistics, we used available annual data on the intensity of nighttime lights to assess the losses in terms of economic growth and recovery as a result of the Haitian 2010 earthquake.⁷ Nighttime lights are unique among global remote sensing data products due to their high correlation to human activities (Hsu et al., 2015). Furthermore, nighttime lights are measured with consistent quality in countries with very different institutional capacities and are not susceptible to manipulation for political reasons. These data, calculated from weather satellite recordings, are increasingly used by social scientists as a proxy for economic activity or economic development in subnational regions of developing countries where disaggregated data from statistical offices are not available (Bruederle and Hodler, 2018 ; Donaldson and Storeygard, 2016 ; Henderson et al., 2012). Although the advantages of nighttime DMSP/OLS data are commonly recognized, several disadvantages in using this sensor to observe nighttime emissions have been identified, such as : relatively low spatial resolution, absence of onboard calibration, lack of intercalibration, lack of records of in-flight gain changes, limited 6-bit quantization of digital numbers ; light saturation in highly populated urban center, free zones or highly illuminated locations ; the blooming effect and limited accessibility to high-quality daily OLS data (Abrahams et al., 2018 ; Elvidge et al., 2013 ; Huang et al., 2014). Saturation occurs when pixels in bright areas, such as city centers, reach the highest possible digital number (DN) value (DN=63) and no further details can be recognized.

The data come from the National Oceanic and Atmospheric Administration using the

7. Nighttime light data is a reliable proxy for formal (Bluhm and Krause, 2022 ; Bruederle and Hodler, 2018 ; Henderson et al., 2012), informal economic activity (Ghosh, 2009), evaluating damage from natural disasters (Heger and Neumayer, 2019 ; Kohiyama et al., 2004 ; Nguyen and Noy, 2019).

Defense Meteorological Satellite Program (DMSP), and Colorado School of Mines, Payne Institute for Public Policy. The final data product is gridded in 30 arc-second by 30 arc-second pixels (approximately $1\text{km} \times 1\text{km}$ at the equator) that spans -180° to 180° longitude and 65° to 75° latitude, and is available for the years since 1992. Annual values were then constructed on the daily grid values, and are available from 1992 to 2019. These composites provide an average digital number (DN) for each 30 arc-second output pixel, where DN values are 6-bit digital numbers that range from 0 to 63, with higher numbers indicating greater brightness.

The visible pixels are relative values and not exactly proportional to the physical amount of light received (called true radiance) due to the scaling factor applied to the sensor during its conversion. These pixel values are not strictly comparable from one year to the next since the sensors used do not have the same calibration on board. However, time fixed effects overcome the problem of inter-annual and inter-satellite calibrations and ensure the comparability and consistency of data (Henderson et al., 2012 ; Lee, 2018).⁸ We use the annual time series of stable light images in this study which include lights from cities, towns, and sites with persistent lighting, and discard ephemeral events such as fires. The original processing by NOAA's National Geophysical Data Center (2020) scientists also excluded (at a pixel level) images for nights affected by clouds, moonlight, sunlight and other glare (Baugh et al., 2010 ; Elvidge et al., 2009).⁹ Elvidge et al. (1997) and the NOAA provide a detailed description of nighttime light data and instruments used, satellites and sensor attachment, data collection and processing methods, and their applications.

The original global nighttime lights time series from DMSP was produced using OLS data from six individual satellites (F12-F18), with some overlap across years from 1992 to 2013. However, since April 2021, NOAA added extra years to the DMSP Nighttime Lights and

8. We used fixed effects (or within) models. The fixed effect of the satellites combined with those of the year eliminates all differences between sensors and across years, making the nighttime light intensities comparable. In statistics, this procedure is equivalent to using one of the multiple data intercalibration methods developed in recent studies (Gibson et al., 2021 ; Henderson et al., 2012 ; Lee, 2018).

9. Monthly Visible Infrared Imaging Radiometer Suite (VIIRS) data became available recently (2013-present), four years after the earthquake. As we have no monthly data available before the earthquake, we cannot use a difference-in-differences model. The same is true for the daily series. Nevertheless, in a robustness check, we include DMSP-like Nighttime Lights Derived from VIIRS Nighttime Light (VNL) (Table 2.9).

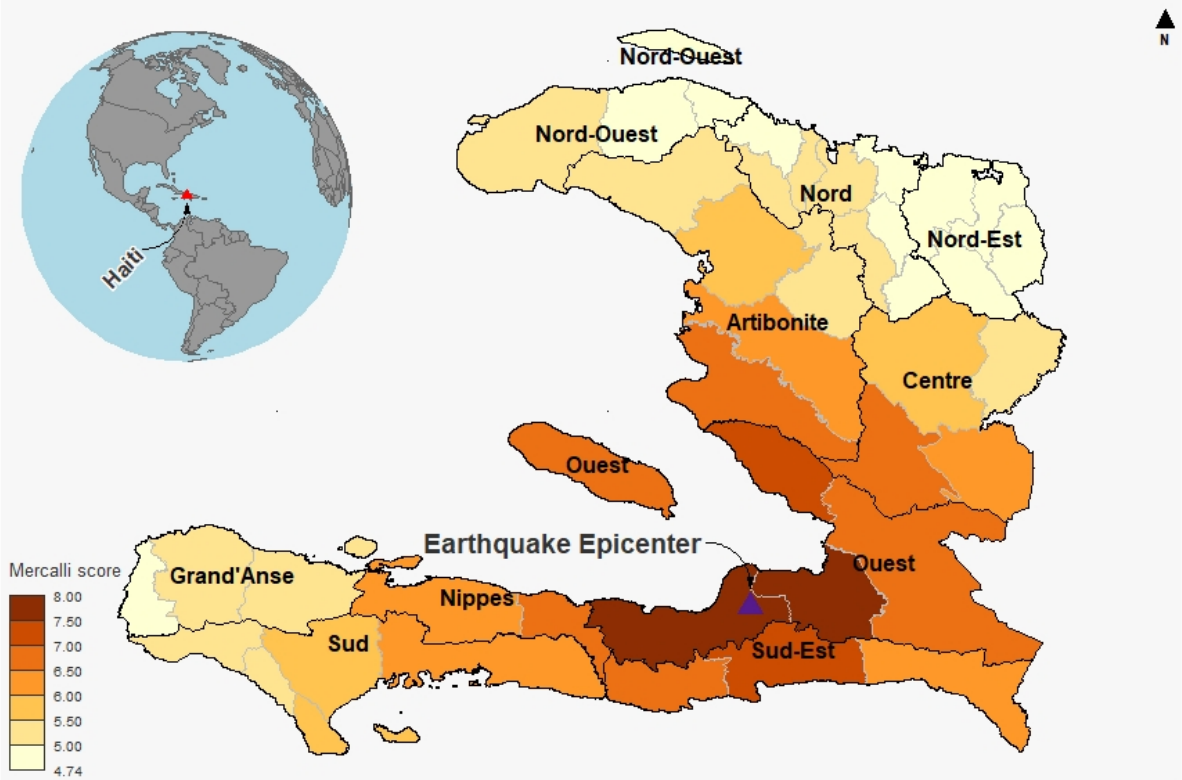
are available from 2013 to 2019 with two existing satellites (F15-F16) using pre-dawn data. Indeed, the first night light data sets were produced by NOAA and can be downloaded from this site : <https://www.ngdc.noaa.gov/eog/dmsp/downloadV4composites.html> from 1992 to 2013. The extension series is available during the period 2013-2019 on this site : <https://eogdata.mines.edu/products/dmsp/>. These new data have the same spatial resolution as the previous raw data and help us to extend the study period.

Land area and Population. To control for the area of the districts in our econometric analysis, we rely on information provided by the Center For International Earth Science Information Network-CIESIN-Columbia University (2018) on the land area raster. The image provides estimates of land area in square kilometers, excluding permanent ice and water, on a per-pixel basis, and was used to calculate population density and weighted nighttime lights that allow a comparison of districts with different structural and socio-demographic characteristics. The data files used were extracted from the global image with a resolution of 30 arc-seconds and were used to control for the area of the districts in the different specifications. Our DMSP-OLS luminosity index is the mean of sum lights times the land area by pixels ($\sum \frac{\text{lights} \times \text{landarea}}{N}$) in district i over the year t . We also used the geocoded population data from WorldPop (2018) and establishment count for each second subnational unit. The data files were produced as global rasters at 30 arc-second resolution.¹⁰

Earthquake intensity. The last data source used in this empirical study is the geocoded map of the 2010 earthquake intensity. We take advantage of the random and exogenous nature of the intensity with which different areas of the country were affected by the earthquake to estimate its impact and produce causal estimates of its effects. The intensity was recorded on the Modified Mercalli Scale (MMI), which is a measure based on the extent of damage observed at a given location on natural objects, industrial facilities and people. This measure, based on a narrative description of damage severity, is used as an indicator of the loss of social capital experienced at the local level as a result of the earthquake (Porcelli and Trezzi, 2018). It is a twelve-point ordinal scale with the following levels : instrumental (I), weak (II), light (III), moderate (IV), rather strong (V), strong (VI), very

10. The units are the number of people per pixel with country totals adjusted to match the corresponding official United Nations population estimates (WorldPop, 2018).

strong (VII), destructive (VIII), ruinous (IX), disastrous (X), very disastrous (XI), catastrophic (XII) (Worden et al., 2012). The lower numbers of the intensity scale generally deal with the manner in which the earthquake is felt by people. The higher numbers of the scale are based on observed structural damage. Structural engineers usually contribute information for assigning intensity values of VIII or above (United States Geological Survey, 2010). It is therefore the best way to evaluate the damage caused by earthquakes and felt by the population (Charles Scawthorn, 2003). We used the continuous value of the earthquake’s intensity.



Notes : Data from the United States Geological Survey (2010). The average intensity by district and associated standard deviations are calculated and presented in Tables 2.1 and 2.12. The brighter the color, the greater the average damage in the district. The triangle indicates the epicenter. Source : Author’s own illustration.

Figure 2.1 – Average intensity of the 2010 earthquake across districts and location map of Haiti

We obtained the average Mercalli Score of each district by merging the earthquake intensity map and the country’s administrative boundaries (GADM), which provides information on subnational administrative regions and their boundaries. Our observation unit

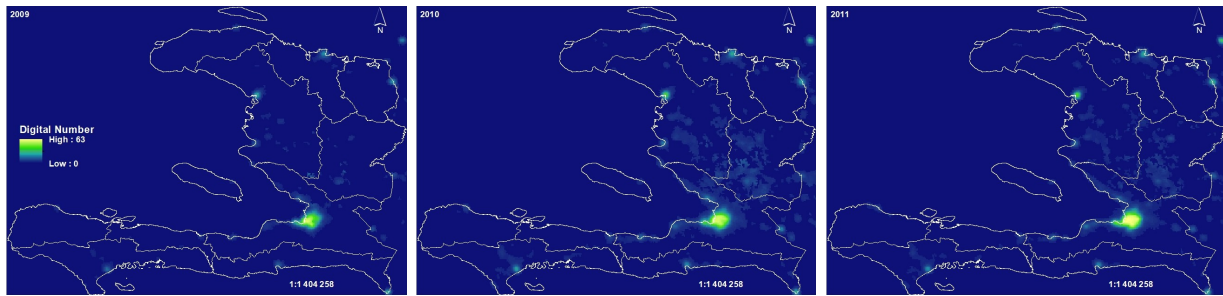
is a district (second administrative structure of the country).¹¹ We consider the districts affected by an intensity ≥ 7 as our treatment group and those that were not strongly affected by the earthquake as the control group (Figure 2.1). We present global descriptive statistics for all above-mentioned variables in Table 2.11.

2.2.1. Descriptive Statistics

We begin by looking descriptively at the pixel-level nighttime light data. Figure ?? is a satellite image of the economic activity of Haiti in 2009, 2010 and 2011 extracted from the global images of those years. Port-au-Prince, the capital located in the West Department, is heavily lit compared to the rest of the country. Around the other densely populated major cities, representing the overall urban areas, the light intensities are increasingly high. The image taken in 2010 appears to be qualitatively brighter than the one taken in 2009 despite the fact that we are in the post-earthquake period. This image is consistent with the reality observed after the earthquake, and the theoretical analyses carried out in addition to the empirical part indeed show that the pixels observed in 2010 are brighter than those observed in 2009. With the departure of many non-governmental organizations (NGOs) and the decrease in international aid over time, international solidarity lessens and the population begins to feel the impact of the earthquake as shown in the image of 2011, which is dimly lit compared to that of 2010. Very little economic activity is observed in the black areas outside the major cities. Although suggestive, these images show that the earthquake negatively affected the distribution of nighttime lights in the country. Table 2.1 gives an idea of the data, describing the distribution of digital numbers across pixels for ten districts representing the overall economic and social situation of the country.

Before discussing our formal empirical analysis, we provide a brief preview. Table 2.1 shows the fraction of pixels assigned to different reading intervals on the 0-63 scale and the summary statistics for all variables used in our analysis for the ten richest districts of

11. Haiti is divided into ten departments. Today, these departments are subdivided into 42 districts, 146 communes and 575 communal sections. We work at the district level for several reasons. Firstly, a district is the second administrative unit in the country. Haitian districts have no representatives, no administration and no elected officials, unlike municipalities, departments or communal sections. Since this structure has no representative, no decision is taken at this level and it can be said that the arrondissements are exogenous to political and economic decisions. Secondly, as shown by Gibson et al. (2021) and Gibson and Boe-Gibson (2021), the NTL data were a more useful proxy for economic activity in densely populated areas.



Notes : Data collected by US Air Force Weather Agency (Earth Observation Group, Payne Institute for Public Policy, Colorado School of Mines, 2020 ; NOAA's National Geophysical Data Center, 2020). Images cover the entire country. Yellow pixels indicate more intense nighttime lights. Source : Author's own illustration.

Figure 2.2 – Change in DMS-OLS Nighttime Lights between 2009, 2010 and 2011 in Haiti

the country, representing the various departmental capitals. In all districts, a high fraction of pixels is unlit. Among the districts in Table 2.1 (and more generally in the sample), there are remarkably few pixels with digital numbers of 1 or 2. Over the twenty-eight years analyzed, the pixels only reach their maximum values in Port-au-Prince, where the political and economic capital of the country is located, in 1992 and 2011, representing 0.05% of top-coded pixels over the entire period.¹² Table 2.1 also shows the mean digital number and the population density per district. The mean ranges from 7.95 in Port-au-Prince to 0.1 in J'érémié and Port-de-Paix. At the district level, intensity levels ranged from 4.74 (Trou-du-Nord) to 7.9 (Léogâne) (see Table 2.12 for more details). Figure 2.1 shows the average level of intensity in the districts. The second map on the left-hand side illustrates the location of Haiti in the world. The districts in red-purple are those that were strongly affected by the earthquake, of intensity between 7 and 7.9, where the potential damage is considerable, visible and felt at all levels (loss of human life, displacement of populations, destruction of houses and roads). Given these descriptive statistics in Table 2.1 and geographical maps in Figures 2.1 and ??, it appears possible that changes in nightlight intensity stem from earthquake intensity.

12. It is important to note that the small fraction of saturated pixels in Port-au-Prince (and more generally in the sample) reinforces the strategy used without intercalibration of the night lights since, in the other localities, the pixels do not reach their maximum values. We have confirmed our results by using the intercalibrated data annually and by satellite.

Table 2.1 – Descriptive Statistics : Nighttime Lights, 1992–2019

Digital Number (DN)	Cap-Haïtien	Cayes	Gonaïves	Hinche	Jacmel	Jérémie	Miragoâne	Ouanaminthe	Port-au-Prince	Port-de-Paix
0	67.9	89.87	93.09	96.24	93.15	97.49	95.46	92.52	58.89	97.7
1-2	5.02	1.55	0.91	0.65	0.99	0.64	1	0.62	1.72	0.41
3-5	12.2	6.38	2.53	2.34	3.34	1.55	3.01	3.06	9.34	1.31
6-10	9.59	1.79	2.08	0.76	1.94	0.32	0.54	2.36	7.28	0.56
11-20	4.86	0.34	1.12	0.01	0.57	0	0	1.18	7.21	0.03
21-62	0.43	0.07	0.26	0	0.01	0	0	0.26	15.53	0
63 (top-coded)	0	0	0	0	0	0	0	0	0.05	0
avg. DN values	2.08	0.47	0.51	0.16	0.38	0.1	0.18	0.55	7.95	0.1
avg. Earthquake Intensity (2010)	4.94	5.66	5.71	5.85	7.3	5.09	6.99	4.94	7.86	4.98
	(0.44)	(0.46)	(0.58)	(0.51)	(0.44)	(0.35)	(0.48)	(0.36)	(0.54)	0.48
Pop. density (per sq. km) (2000–2019)	1236.05	354.52	423.91	172.23	372.18	262.14	302.01	330.89	3408.78	370.5

Notes : The first seven rows following the column names show the fraction (in %) of unlit, unsaturated, and saturated pixels for different reading intervals on a 0-63 scale by district. This is followed by the average of pixels, earthquake intensity, and population density by district. Standard deviations associated with the means are presented in parentheses. *Source* : Author’s calculations based on NOAA’s National Geophysical Data Center, Payne Institute for Public Policy’s Colorado School of Mines, WorldPop, Center For International Earth Science Information Network, United States Geological Survey databases and Global Administrative Areas map data.

2.3. Econometric Models

2.3.1. Difference-in-Differences (DID)

We created a panel data based on all forty-one districts of the country observed from 1992 to 2019 to study the economic development and we estimated a fixed-effects difference-in-differences model. The identification strategy is similar in spirit to the one used in recent works by Heger and Neumayer (2019) and De and Thamarapani (2022). The basic estimation strategy uses the following specification :

$$Light_{jt} = \beta_0 + \beta_1 post_t + \beta_2 mi_j + \beta_3 mi_j(mi_j \times post_t) + X_{jt} + \gamma_j + \gamma_t + \delta_j t + \epsilon_{jt} \quad (2.1)$$

where $Light_{jt}$ is the natural logarithm of the DMSP-OLS nighttime lights in district j over the year t . $post_t = 1$ if the year is ≥ 2010 and 0 otherwise. mi_j is a zero-one dummy variable representing areas affected by an intensity ≥ 7 .¹³ γ_j , γ_t are respectively location and time fixed effects and $\delta_j t$ is a district-specific linear trend. We include district trends in all specifications to control for the potential of preexisting district convergence.¹⁴ Coefficient β_3 in equation 2.1 is the deviation term in the difference in change over time and can be interpreted as the average effect of a one-unit change in the Mercalli Score on the growth of nighttime light intensity across districts. Standard errors are clustered at the district level to account for correlations between and within districts across time.

Due to the limited number of districts, we used the wild cluster bootstrap to overcome the serial correlation problem, as did Cameron et al. (2008), and to correct for errors, since conventional inference methods are unreliable and assumptions about large samples do not hold. Bertrand et al. (2004) showed that below 50 clusters, the pooled standard deviations that are asymptotically correct may be biased downward and the null hypothesis over-rejected. The probabilities associated with the coefficients, calculated according to the Roodman et al. (2019) method, are presented in square brackets and the conventional

13. We report the definition of level VII of the *Modified Mercalli Intensity Scale*. *Damage* : negligible in buildings of good design and construction ; slight to moderate in well-built ordinary structures ; considerable in poorly built or badly designed structures. Some chimneys broken (United States Geological Survey, 2010). Noticed by persons driving motor cars. All details can be found in the paper by Porcelli and Trezzi (2018).

14. In this paper, differences in social and economic capital across districts are captured by the district fixed effect given their persistency over time.

standard deviations are in parentheses (Table 2.2).

2.3.2. Dynamic Model

For causal identification, we predominantly run a difference-in-differences regression. Our work is related to two strands of the literature : The first is the literature on difference-in-differences (Card and Krueger, 1994 ; De and Thamarapani, 2022 ; Heger and Neumayer, 2019). Following the vast literature on the economics of natural disasters mentioned above, we use geographic variation in the destructiveness of the earthquake to conduct a difference-in-differences analysis to evaluate its impact on growth/economic activity. Once the evaluation was done, we performed a set of robustness tests to validate our control groups and, unlike the authors mentioned in Section 2.2, we opted for a dynamic panel data model and impulse response functions in addition to the previous model. These methods, belonging to the second strand of the literature, enabled us to observe how the different areas of the country recovered after the earthquake (Cerra and Saxena, 2008).¹⁵ To do this, we constructed a new dataset, in which the temporal dimension of the lights is a year instead of a satellite-year : the units of observation are the second subnational levels. Our second balanced panel uses 41 districts, covering the period 1992 to 2019.

In this subsection, we present the specification of the dynamic panel data model for our sample. Following the literature, we first studied the stationarity of the nighttime lights variable, and impulse response functions to the earthquake shock were estimated through a panel vector autoregression model in order to examine the economic recovery process (Cerra and Saxena, 2008).¹⁶ In this regard, we estimate the following long-run model :

$$Y_{jt} = Y_{jt-1}A_p + X_{jt}B + e_{jt} \quad (2.2)$$

where Y_{jt} is the vector of the dependent variable ; X_{jt} is a matrix of exogenous covariates including interactions between earthquake intensity and the binary time variable ($post_t$), controls for saturated and undervalued lights, and the growth of nighttime lights ; e_{jt} is a

15. The two models are complementary. The first one allows to validate the previously defined control group and the second one to estimate the response functions.

16. We worked on the undifferentiated series following Cerra and Saxena (2008) given the non-convergence of the results of the stationarity tests. Results are available upon request.

vector of idiosyncratic errors.¹⁷ The matrices A_p and B are parameters to be estimated. This method has the advantage of taking into account the possible endogeneity of the variables by using internal instruments (Abrigo and Love, 2016). The estimated impulse response functions (Figure 2.3) are presented with robust standard deviations taken from a thousand Monte Carlo simulations.

2.4. The Empirical Results

2.4.1. Regression Results

In this section, we present the empirical results. First, we focus on a benchmark regression, before expanding the analysis and testing its robustness in several ways. Next, we turn to a spatially disaggregated analysis of the reactivity of grid cells to earthquake intensity. We probe the limits of the earthquake effects and confirm previous findings. Our results are based on comparisons of economic activity in the least-damaged districts and those most heavily affected by the quake. The results of the long-run analysis from 1992 to 2019 are presented in Tables 2.2 to 2.10. Columns 2-6 contain point estimates of the interaction between the ‘post’ dummy variable and the earthquake intensity in different specifications. The first column refers to the base specification while the other columns report estimation results adding covariates step by step. We see that earthquake intensity diminishes post-treatment economic activity per year relative to the control group.

17. We fit a multivariate panel regression of each dependent variable on lags of itself, lags of all other dependent variables, and lags of exogenous variables using generalized method of moments (GMM).

Table 2.2 – Basic results :
Difference-in-differences effect of the earthquake on Nighttime Lights, 1992–2019

	Dependent variable : Log of weighted lights									
	Satellite-Year FE					Year FE				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Post \times Earthquake Intensity ≥ 7	-0.996***	-1.759***	-1.446***	-1.610***	-1.277***	-0.884***	-1.528***	-1.286***	-1.475***	-1.181***
	(0.323)	(0.467)	(0.473)	(0.553)	(0.470)	(0.246)	(0.421)	(0.384)	(0.496)	(0.416)
	[0.043]	[0.044]	[0.06]	[0.041]	[0.039]	[0.034]	[0.052]	[0.045]	[0.038]	[0.036]
Elasticity	-0.0261	-0.0461	-0.0379	-0.0421	-0.0334	-0.0308	-0.0532	-0.0448	-0.0514	-0.0411
Base covariates										
ln[sum(top-coded +1)]		-0.145**	-0.281***	-0.389***	-0.308***		-0.0852	-0.229***	-0.336***	-0.226**
		(0.0651)	(0.0967)	(0.0996)	(0.101)		(0.0563)	(0.0784)	(0.0858)	(0.0855)
ln[sum(unlit)]		-5.886***	-6.005**	-4.806***	-5.902***		-4.831***	-4.055**	-4.043**	-3.455**
		(2.099)	(2.278)	(1.701)	(1.864)		(1.765)	(1.511)	(1.513)	(1.307)
ln(light _{<i>j,t-1</i>})			0.272***		0.253***		0.265***		0.278***	
			(0.0500)		(0.0642)		(0.0536)		(0.0634)	
ln(population)				-1.151*	-0.801**				-1.663**	-1.192**
				(0.570)	(0.390)				(0.718)	(0.540)
Regression statistics :										
(Within districts) R^2	0.444	0.490	0.507	0.569	0.595	0.506	0.543	0.570	0.602	0.635
Observations	1,681	1,681	1,353	1,189	984	1,148	1,148	1,107	820	820

Notes : All columns contain district fixed effects, and a district-specific linear trend. Columns 1-5 also include satellite-year fixed effects and the unit of observation is a district/satellite-year. In columns 6-10, we include year fixed effects, and the unit of observation is a district/year. Standard errors are clustered at the district level. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels. The two tailed p-values associated with the wild cluster bootstrap-T method appear in square brackets. *Source* : Author's calculations.

Each row of the table provides the DID marginal effect of the earthquake in the affected districts, compared to the unaffected districts. Cluster-robust standard errors appear in parentheses and two tailed p-values associated with the wild cluster bootstrap-T method appear in square brackets. In all cases, both methods indicate statistically significant findings. The fit of the regression is good with an R-squared within districts of approximately 0.5. All coefficients on the interaction terms are in accordance with expectations. Column 1 first investigates the bivariate relationships between earthquake intensity thresholds and nighttime lights. The estimate is negative and significant. The difference in nighttime lights between Léogâne, Port-au-Prince, Jacmel, Baint, Archaie and the rest of the country decreases by about 0.03 percentage point with one unit percent of the Modified Mercalli Intensity value. In column 2, we include control variables for saturated pixels and unlit areas per district. The coefficient estimate on affected areas relative to less affected areas is statistically significant. The differential impact is greater at -82.8% for one unit change in the Mercalli Intensity value.¹⁸ This decrease implies that the GDP gap between highly affected areas and the rest of the country drops by about 24.8% with an additional intensity.¹⁹

Column 3 controls for nighttime lights delayed by one period and the interaction terms are negative and significant. The magnitude of the estimate is smaller and is -1.45, which represents -76.5% in change of lights for one unit change of earthquake intensity. In the last two columns (4-5), data on population have been taken into consideration. Column 5 does not control for lagged lights : the estimate is still negative and significant at the same level. The decrease is about -1.6 and, in terms of percentage change, we can say that when switching from non-earthquake districts to highly affected districts, we expect to see an increase of about -80% in the geometric mean of lights. We additionally examine the relative change in nighttime lights in districts by including all control variables in column 6. We find that the responsiveness of changes in lights associated with a change in the earthquake intensity is -0.04 percentage point. The net marginal effect of interaction terms on lights is -1.27, statistically significant at 1% level. The DID regression coeffi-

18. We run a log-level regression and interpret the regression coefficient estimate results. Technically, the interpretation is the following : $\% \Delta_{lights} = 100 \times (e^{\beta} - 1)$.

19. A one percent increase in GDP in the nighttime lights translates to an increase in GDP of about 0.3% for low and middle-income countries (Henderson et al., 2012).

coefficients represent the change in economic activity corresponding to a one-unit difference in treatment and control groups in the earthquake intensity. The coefficient on interaction terms is remarkably stable in sign and magnitude.

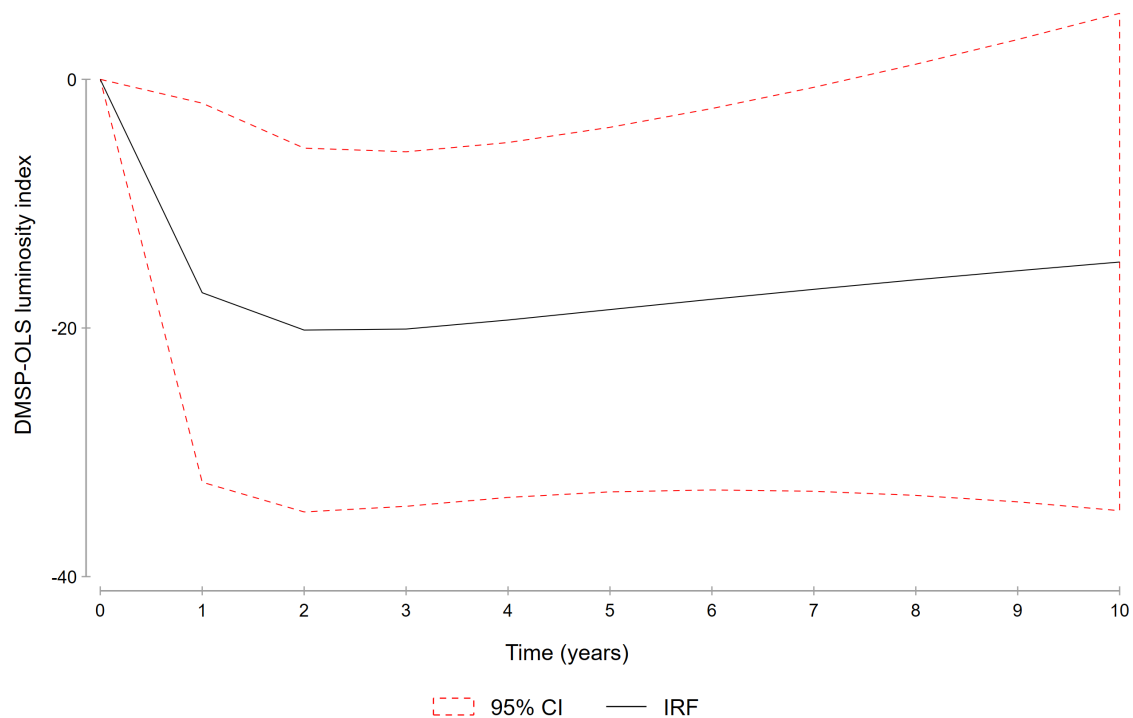
In contrast to previous analyses, we computed the average intensity by calendar year and estimated the regressions of equation 2.1. The estimates reported in columns 6-10 show that the results on intensity and economic disaster are similar to those reported in columns 2-6. All variables keep the same sign and remain statistically significant in all specifications. The estimated decline in economic activity growth is highly significant. This drop is smaller than that estimated in the satellite-year fixed effects models (our preferred model). Overall, the results imply that an increase in earthquake intensity above 7 is associated with a decrease in the difference in nighttime lights between heavily affected areas and the rest of the country. On the Modified Mercalli Intensity value, seismic shaking is considered very strong to extreme and causes moderate to very heavy damage at intensity level VII and above, which is consistent with the regression results.

2.4.2. Impulse Response Functions (IRF)

The average effects of the earthquake on nighttime lights' growth in heavily affected areas were evaluated and analyzed in Table 2.2. In this subsection, we present the impulse response functions from the estimation of the model described in equation 2.2. As six satellites without on-board calibration were used to generate the time series of nighttime lights imagery from 1992 to 2019, these images are inconsistent in digital number (DN) values and cannot be applied to perform a comparative analysis directly (Wu et al., 2013).²⁰ To overcome this problem, in estimating the long-run model, we cannot control for fixed effects directly and estimate the impulse response function. We first estimated the regressions of the nighttime lights on the control variables including year fixed effects and district-specific linear trends. The residuals were recovered and, in the second stage, we evaluated the impact of the earthquake on the annual residuals of light.

We obtained a global picture of the response of the districts over a ten-year period by controlling for no-light and top coded areas. This time frame represents the period requi-

20. DN values of nighttime stable lights were influenced by differences between sensors, differences in crossing time between satellites, and degradation of the sensors (Baugh et al., 2010 ; Elvidge et al., 2009).



Notes : average annual residuals of nighttime lights in treatment and control districts, 1992-2019. The red dashed lines below and above the black line represent a 95% confidence interval. Standard deviations and confidence intervals are based on a thousand Monte Carlo simulations. Source : Author's own illustration.

Figure 2.3 – Impulse responses : Earthquake

red for lights to return to their long-term level. These functions are differential averages between areas affected by intensity ≥ 7 compared to those affected by an intensity below this critical point.

The results are presented in figure 2.3. The earthquake caused a significant loss of lights in the first year. Over a period of 10 years, the earthquake had negative effects on economic growth during all years at the 5 percent level. The earthquake impact is negative and persistent over time. Taken together, the results on light reported in Table 2.2 and figure 2.3 reveal a persistently significant relationship between the average level of earthquake intensity and economic activity in the two groups. In terms of levels, this figure indicates that the earthquake caused a decrease in nighttime light intensity in the country. This result shows the depth and persistence of the earthquake's effect on future economic activities in severely affected areas compared to slightly affected areas. Persistence implies that disasters may have long-lasting negative effects on the economic activity as discussed

by Solomon and Amir (2014), and the destruction of capital is so severe and long-lasting that affected economies never fully recover. We can confirm that in the heavily affected areas, where the damage was considerable, the development dynamics were slowed down by the earthquake and the country was not able to recover from this negative shock for many years. As an additional check, we employ a robust regression analysis using grid cells instead of subnational units of analysis (see Figure 2.4).

2.5. Robustness of the Main Results

In this section, we examine the sensitivity of the main results to a set of robustness checks. We show, as a first step, that the baseline estimates of Table 2.2 are robust to different treatment groups, to an alternative unit of analysis, to different choices of spatial clustering of standard errors when taking into account the spatial dependence of the data and to the use of a spatial model. As a second step, we conduct additional robustness tests with some alternative stable lights to validate the choice of lights used. We present the results of these robustness checks in Tables 2.3-2.10, using variants of equation 2.1.

2.5.1. Sensitivity to Different Earthquake Intensity Levels

In order to assess the robustness of our results, we tested several specifications to explore the relationship between earthquake intensity and economic activity at the district level. Table 2.2 was created using nighttime lights by satellite-year as DMSP data has no in-flight calibration.²¹ In the baseline specification, we considered the districts that were affected by the earthquake intensity ≥ 7 as our treatment group. However, one might be concerned that the treated group was not well constructed. The non-inclusion of districts affected by an intensity level of 6.5, and above or less, in the treatment group may have dampened the estimated economic effect of the earthquake.

To address this issue, we began by dividing the intensity of the earthquake into three groups : moderate to strong for an average intensity below or equal to 6 ; strong if the intensity is greater than 6 and lower than 7 ; very strong if the average Mercalli Score

21. Because de facto sensor settings may vary across satellites and as a satellite ages, Elvidge et al. (2009) perform an “intercalibration” by using the invariant region method. Rather than use the formulas presented in Elvidge et al. (2009) to carry out that specific intercalibration, in statistical work we control for these problems with year fixed effects.

Table 2.3 – DID estimates :
Results using different levels of earthquake damage

	Dependent variable : Log of Weighted lights				
	(1)	(2)	(3)	(4)	(5)
Intensity (Omitted= $mi \leq 6$) :					
Post \times Earthquake Intensity [6 – 7[-0.0823 (0.544)	-0.360 (0.546)	-0.260 (0.420)	-0.465 (0.519)	-0.501 (0.423)
Elasticity	-0.00593	-0.0259	-0.0187	-0.0335	-0.0361
Post \times Earthquake Intensity ≥ 7	-1.021*** (0.360)	-1.880*** (0.516)	-1.533*** (0.527)	-1.772*** (0.607)	-1.449*** (0.517)
Elasticity	-0.0267	-0.0492	-0.0401	-0.0464	-0.0379
Additional covariates :					
$\ln[\text{sum}(\text{top-coded} + 1)]$		-0.145** (0.0658)	-0.282*** (0.0975)	-0.390*** (0.101)	-0.309*** (0.102)
$\ln[\text{sum}(\text{unlit})]$		-5.984*** (2.149)	-6.071** (2.346)	-4.952*** (1.748)	-6.065*** (1.935)
$\ln(\text{light}_{j,t-1})$			0.272*** (0.0509)		0.252*** (0.0640)
$\ln(\text{population})$				-1.083* (0.594)	-0.676 (0.407)
(Within districts) R^2	0.445	0.491	0.508	0.570	0.597
Observations	1,681	1,681	1,353	1,189	984

Notes : All columns include district, satellite-year fixed effects, and district-specific linear trends. Standard errors are clustered at the district level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Source* : Author's calculations.

is above 7. Next, we applied difference-in-differences estimates by comparing changes in districts affected by these intensity levels with changes in other categories. The intensity level below 6 was used as a reference. The estimate is negative but statistically insignificant for intensity levels greater than 6 and smaller than 7. The districts affected by an intensity of at least 7 experienced a significant decrease in nighttime light growth (row 3, columns 1-5, Table 2.3), after the earthquake. In column 1, we estimate fixed effects models without additional controls. Estimations in column 2 contain control variables for saturated pixels and unlit areas. Columns (3) and (5) include nighttime lights delayed by one period and, in the last two columns (4-5), population control has been taken into

consideration. These results are approximately the same as those presented in Table 2.2. However, the magnitude of the coefficients is higher than the baseline model.

Table 2.4 – Specification Checks :

Difference-in-differences estimates of the effect of the Earthquake on Nighttime Lights : 1992–2019

Variables	Dependent variable : Log of weighted lights				
	(1)	(2)	(3)	(4)	(5)
Earthquake Intensity Post × (Continuous)	-0.334* (0.183)	-0.605** (0.254)	-0.483** (0.232)	-0.599** (0.262)	-0.555** (0.225)
Controls		✓	✓	✓	✓
(Within districts) R^2	0.444	0.490	0.507	0.570	0.598
Observations	1,681	1,681	1,353	1,189	984
Post * Earthquake Intensity ≥ 5	-0.310 (0.566)	-0.341 (0.602)	-0.261 (0.469)	-0.313 (0.625)	-0.553 (0.482)
Elasticity	-0.0648	-0.0713	-0.0547	-0.0655	-0.116
Controls		✓	✓	✓	✓
(Within districts) R^2	0.442	0.481	0.500	0.562	0.593
Observations	1,681	1,681	1,353	1,189	984
Post * Earthquake Intensity ≥ 6	-0.333 (0.463)	-0.733 (0.497)	-0.567 (0.402)	-0.783 (0.482)	-0.730* (0.392)
Elasticity	-0.0736	-0.121	-0.0962	-0.135	-0.128
Controls		✓	✓	✓	✓
(Within districts) R^2	0.442	0.485	0.503	0.566	0.595
Observations	1,681	1,681	1,353	1,189	984
Post × Earthquake Intensity ≥ 6.5	-0.565 (0.347)	-1.164** (0.499)	-0.889* (0.444)	-1.138** (0.531)	-0.913* (0.463)
Elasticity	-0.0370	-0.0762	-0.0582	-0.0745	-0.0598
Controls		✓	✓	✓	✓
(Within districts) R^2	0.443	0.490	0.506	0.569	0.596
Observations	1,681	1,681	1,353	1,189	984
Post × Earthquake Intensity ≥ 7	-0.996*** (0.323)	-1.759*** (0.467)	-1.446*** (0.473)	-1.610*** (0.553)	-1.277*** (0.470)
Elasticity	-0.0261	-0.0461	-0.0379	-0.0421	-0.0334
Controls		✓	✓	✓	✓
(Within districts) R^2	0.444	0.490	0.507	0.569	0.595
Observations	1,681	1,681	1,353	1,189	984

Notes : All columns include district, satellite-year fixed effects, and district-specific linear trends. Columns 2-5 control for top-coded and unlit pixels. Columns 3-5 include lagged lights in logs. Columns 4-5 contain population control. Standard errors are clustered at the district level. *, ** and *** denote significance at the 10%, 5%, and 1% levels, respectively. *Source* : Author's calculations.

Table 2.4 reports several specification checks, using the same specification in the previous

Table 2.2 variants of equation 2.1. The treatment group is a binary variable representing areas affected by various intensity levels. The models reported in columns 2-5 also include the same additional control variables as those used in Table 2.2. In the first row of each panel, we consider the earthquake intensity using the continuous measure of the average Mercalli Score for the districts following Callaway et al. (2021). The coefficient on interaction remains negative and statistically significant, and is even smaller than in our main specification. As the intensity level increases, the nighttime light per area decreases in the districts. The interaction between intensity and time periods (DID) is of expected sign and significant at the 5% levels except for the first column. The estimate is negative and narrowly misses significance at the 10% level.

The coefficients associated with the interactions between the year of the earthquake and intensity levels ≥ 5 are not statistically significant. For average levels of more than 6, the effect is negative and insignificant at the 5% levels. For average levels of more than 6 and less than 7, the estimate is negative and not statistically significant (columns 1-5). Although the coefficients associated with the interaction terms are negative and significantly different from zero for intensity levels greater than or equal to 6.5, the coefficient of the interaction is negative and significant at the 5% levels (columns 2 and 4). From level 7 and above, all coefficients are negative and significant as shown in the baseline results (see Table 2.2). The point estimates in columns 1-5 imply that the districts with a higher intensity level exerted a negative impact on economic activity.

Table 2.5 provides estimation results for an alternative specification. We check whether our baseline results are influenced by the way we aggregate the observations at the district level. In our baseline model, the regressions are conducted on lights, weighted by district area (Table 2.2). In this second check, we construct the same variables as in the baseline, but use lights per capita and the total lights per district as dependent variables in Table 2.5.

The dependent variables are respectively the sum of all lights, and lights divided by the total population by district. All columns examine district variations in the different versions of equation 2.1. The coefficients associated with the interactions have the expected

sign and the significance levels of the coefficients remain the same. The estimated decline in economic activity is greater than that computed in the previous specifications (Tables 2.2, 2.3, 2.4). However, our conclusions are robust to the sensitivity analysis, in which we vary the control and treatment group and the dependent variable in the data. The estimated damage decreases significantly with the intensity of the earthquake.

Moreover, we check whether the baseline evidence is influenced by our classification of affected districts. In the absence of clearly defined control areas due to the power of the earthquake and the small size of the country (approximately 27,000 km^2), we created indicator variables to identify the group exposed to the treatment and estimated its causal impact on the growth of nighttime light intensities at the district level. We followed the damage classification scale of Worden et al. (2012) and considered areas affected by intensity levels greater or equal to 5, 5.5, 6, 6.5, and 7 to have been treated ($mi_i=1$). Locations with intensities below these thresholds are the control groups ($mi_i=0$). Table 2.4 reports results of estimating our panel regression by first using a continuous treatment and the defined thresholds above. In all rows we have a semi-log estimation. Because of continuous post-treatment variables, our coefficients on interaction terms can be interpreted as semi elasticity. The results reveal a significant negative relationship between earthquake and economic activity. In column 2, -33.4% is thus the percentage change in growth resulting from a unit change in earthquake intensity at the 10 percent levels. The coefficients associated with the first three groups are not significant at the 1 and 5 percent level. The districts affected by an intensity of at least 7 experienced a significant decrease in nighttime light growth (last rows, columns 1-5, Table 2.4) after the earthquake. These results are approximately the same as those presented in Table 2.2.

Table 2.5 – DID estimates : Results using alternative measures of lights

	Dependent variable							
	Log of total lights by district (1992-2019)				Log of lights per capita by district (2000-2019)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post * Earthquake Intensity ≥ 7	-1.042*** (0.330)	-1.804*** (0.473)	-1.522*** (0.470)	-1.673*** (0.551)	-1.327*** (0.473)	-1.007*** (0.303)	-1.704*** (0.560)	-1.458*** (0.521)
Elasticity	-0.0273	-0.0472	-0.0399	-0.0438	-0.0347	-0.0263	-0.0446	-0.0382
(Within district) R^2	0.434	0.476	0.491	0.554	0.578	0.507	0.538	0.566
Observations	1,681	1,681	1,353	1,189	984	1,189	1,189	943
District and Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Controls		✓	✓	✓	✓		✓	✓

Notes : All columns include district, satellite-year fixed effects, and district-specific linear trends. Columns 2-5 and 7-8 contain exogenous regressors, including the number of unlit and top-coded pixels. Estimations in columns 4 and 5 also include population per district as an additional explanatory variable. In columns 3, 5 and 8, we additionally control for one-year lagged lights. Standard errors are clustered at the district level. ***, **, and * indicate respectively 1%, 5%, and 10% significance levels. FE : Fixed Effects. *Source* : Author's calculations.

2.5.2. Alternative Unit of Analysis

We continue by exploring the sensitivity of our estimates against three alternative specifications. Here, aggregation at the district level is done by taking the unweighted average of lights and using it as a unique dependent variable in all subsequent specifications. Table 2.6 presents the estimates of equation 2.1 by considering a highly disaggregated design which is more appropriate for the analysis of a large earthquake impact. This analysis is based on subnational observation units in the form of cells of 0.083×0.083 degrees latitude and longitude (approximately 10×10 kilometers at the equator). In this part, our unit of analysis is cell/satellite-year or cell/year. We use this level of aggregation in addition to administrative boundaries to ensure that our unit of observation is exogenous to political decisions, power distribution (Berman et al., 2017 ; Besley and Persson, 2011 ; Michalopoulos and Papaioannou, 2013) and development assistance. Hence, by using grid cell units, each geographic unit is comparable in size across the country. Our main dataset uses 451 grid cells for the period 1992-2019 (T=28 years or 41 satellite-years). All models estimated contain exogenous regressors specific to the cell, including the number of unlit and top-coded pixels and population data. We begin by estimating Table 2.6 without taking into account any spatial spillovers. The dependent variable is log transformation of nighttime lights.

Since a substantial portion of the nighttime light intensities is zero, following the literature, we added 0.01 to the calculated mean before the natural log transformation (Hodler and Raschky, 2014b ; Lee, 2018 ; Michalopoulos and Papaioannou, 2013). The addition of the constant allows us to work on the whole sample, but also explains the fact that a zero pixel value does not necessarily imply the absence of economic activities (agricultural, commercial) in a location, but that lights may be too dim to be detected by satellites (Lee, 2018). For example, in 1994, in the Grand'Anse department no light was detected by the satellite F10, while in the Northwest both satellites (F10 and F12) show zero annual average values for all pixels. In Nippes, however, all pixels are zero in 1994 and 2002. Table 2.6 reports the estimation of the system estimated on grid cells. The results are obtained using OLS estimation with the same set of observations as in the benchmark estimation with robust standard errors without addressing the spatial dependence of the data. However, the inclusion of a rich set of fixed effects eliminates most forms of heterogeneity.

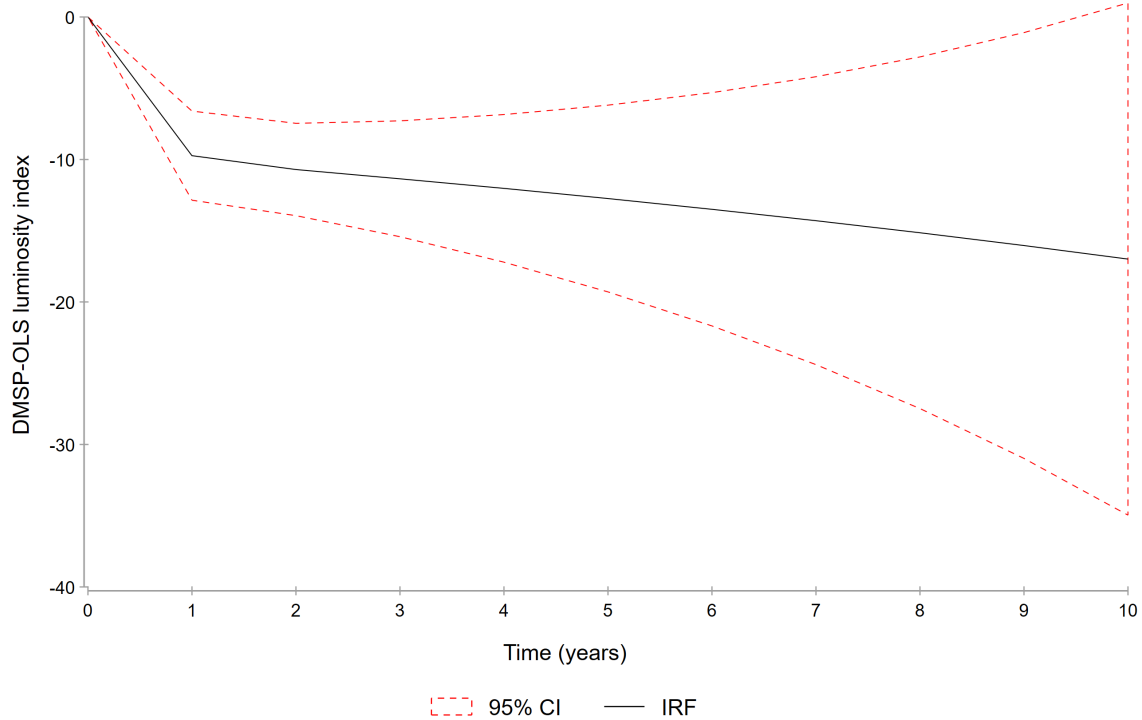
In addition to the cell and year dummies, all models also include the additional control variables used in Table 2. The evidence largely confirms the baseline since coefficients of interaction terms remain highly significant.

Further, we check the robustness of our results by estimating Eq. 2.2 using grid-cell units and controlling for top-coded and unlit areas, grid and year fixed effects, and district-specific linear trends. Fig. 2.4 indicates that lower growth is associated with a higher intensity of affected grid cell within the same year. The differential impact is statistically significant at the 1% level. Given that natural disaster is exogenous, we attribute the low growth to the impact of the 2010 earthquake in Haiti

Table 2.6 – Cell, year and district \times year fixed effect regressions of night lights

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post * Earthquake Intensity ≥ 7	-0.64513 (0.22921)***	-0.54974 (0.14968)***	-0.62648 (0.24556)**	-0.50800 (0.15787)***	-0.70852 (0.30103)**	-0.64531 (0.19724)***	-0.64695 (0.30666)**	-0.55926 (0.19384)***
Elasticity	-0.0219	-0.0187	-0.0213	-0.0173	-0.0241	-0.0219	-0.0220	-0.0288
Root MSE	0.851	0.762	0.882	0.772	0.826	0.746	0.859	0.760
Observations	17,794	14,322	12,441	10,296	17,779	14,305	12,430	10,284
Cell and Year FE	✓	✓	✓	✓	✓	✓	✓	✓
District \times Year FE					✓	✓	✓	✓
District-specific linear trend	✓	✓	✓	✓				

Notes : All columns include controls for top coded and unlit pixels. Lights, top-coded and unlit pixels, population are in log transformations. Columns 2, 6 and 8 contain first order lagged lights. Col. 3, 4, 7 and 8 control for population per grid cell. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. FE : Fixed effects. *Source* : Author's calculations.



Notes : Average annual residuals of nighttime lights in treatment and control groups, 1992-2019. Each observation is a cell/year. The red dashed lines below and above the black line represent a 95% confidence interval. Standard deviations and confidence intervals are based on a thousand Monte Carlo simulations. Source : Author’s own illustration.

Figure 2.4 – Impulse responses of the earthquake using alternative units of analysis

Spatial Econometric Issues

The second part of our empirical analysis integrated control for spatial spillovers associated with the proximity to the earthquake epicenter. In some columns in Tables 2.2 to 2.6 we partially resolve autocorrelation issues by including lagged lights in equation 2.1 and by weighting our dependent variable. In this particular case, it does not make sense to consider the characteristic of neighboring districts when we work at the global administrative unit level (Table 2.2-2.5). This strategy used land area data per pixel to take into account spatial spillover effects following Henderson et al. (2012) as detailed in Section 2.2. Here, we estimate the same model by correcting standard errors *À la* Conley (1999) and Hsiang et al. (2011).

In this paper, first we assigned treatment following geographic boundaries and corrected standard errors at the cell or district level in the spirit of Cameron and Miller (2015) and

Bertrand et al. (2004). However, earthquake effects could cross over borders (districts, cells) and our lights variable could be spatially autocorrelated due to direct contagion. In this particular case, according to Butts (2021), a standard difference-in-differences estimation produces biased estimates for the average treatment effect. As noted by Petersen (2008), Beck and Katz (1995) and Hoechle (2007), estimated standard errors that are robust to heteroscedasticity and autocorrelation can be biased if cross-sectional or spatial dependences are present. In this case, statistical inference based on such standard errors is invalid since economic activity may spill over into contiguous or economically related districts. To address these issues, we used Prais-Winsten estimates with a sandwich-type estimator of the covariance matrix in column 1 through 3 of Table 2.8. The panel-corrected standard errors (PCSE) estimates, for linear cross-sectional time series models developed by Beck and Katz (1995), are robust to very general forms of cross-sectional dependence as well as autocorrelated errors of type AR(1).²² In columns 5-6, we put forward Driscoll and Kraay (1998) standard error estimates. Their covariance matrix estimator produces heteroskedasticity and autocorrelation-consistent standard errors that are robust to general forms of spatial and temporal dependence when the time dimension becomes large, as it does in our case.

Due to the high spatial resolution of data on light density, measured by satellites at night, we estimate equations 2.1 and 2.2 using OLS and a pvar model, respectively in our baseline specifications, by including several dimensions of fixed effects. Note also that we have more than 1600 district \times year fixed effects in most specifications. District \times year fixed effects are included to filter out all district-wide time-varying characteristics affecting lights and economic activity in Haiti, such as political crises in densely populated cities. In Table 2.7, we implement a distance-year fixed effects methodology (columns 5 to 8) in the spirit of Butts (2021). The fixed effects control for all factors that are either time or space invariant. Our measure of distance (measure in kilometers) defined as the distance from the epicenter located in Léogâne (at 25 km to Port-au-Prince) to the grid cell centroid. We create a series of dummy variables for each distance band. Our following

22. In computations, standard errors and variance-covariance estimates, the Prais-Winsten regression assumes that the disturbances are, by default, heteroskedastic and contemporaneously correlated across panels.

bandwidths are : 0–24 km, 25–49 km, 50–99 km, 100–149 km and > 150 km.²³ We take spatial correlation into account since both lights and earthquake intensity are clustered in space. Following Berman et al. (2017) in Table 2.7, standard errors are estimated with a spatial HAC correction allowing for both cross-sectional spatial correlation and location-specific serial correlation, applying the method developed by Conley (1999) and Hsiang et al. (2011).²⁴ In all specifications, we retain a radius of 100 km for the spatial kernel close to the mean (102.265 km) and the median (100.8604 km) internal distance to the earthquake epicenter from the grid cell in our new sample. Finally, we experimented a dynamic, spatially autoregressive Durbin model that we estimated by maximum likelihood following Anselin (1988) using a stata command developed by Belotti et al. (2017). The last three columns in Table 2.8 deal with this full spatially and temporally autoregressive model.

The results for various specifications and the definition of spatial correlation are given in Tables 2.7 and 2.8. We see that in all columns, the interaction term between earthquake intensity ≥ 7 and the ‘post’ dummy variable - our coefficient of interest - is negative and significant at the 1 or 5 percent levels. Thus, earthquake intensity decreases the lights in cells. We estimate equation 2.1 by including year, cell, district \times year, distance \times year, distance \times year fixed effects and a district specific linear time trend. Without including population control, we detect a negative and significant impact at 1 percent level of earthquake intensity on local economic activity (Table 2.8). In columns 2 we replicate the specification of column 1 by additionally controlling for population per grid cell. We find that the coefficient of interest is slightly lower and misses significance at a 1 percent level but has the expected negative sign. Estimations in columns 3 and 4 include cell and district \times year fixed effects. The effect is 0.003 percent higher (column 3) than with the two-way fixed effects models (i.e column 1). Column 4 shows that the results of column 2 are robust to controlling for district-year fixed effects instead of year fixed effects. The last two columns deals with all fixed effects specified, excepting the interaction of time- and district- fixed effects. In both cases, coefficient estimates remain similar with respect to sign, size and statistical significance with the coefficients reported in columns 1 and 2.

23. The maximum distance to the earthquake’s epicenter in our sample is 200 km.

24. The horizon at which serial correlation is assumed to vanish can be up to 12000 years, in which case we deal with 12000 lags.

By controlling for the sets of fixed effects, we capture unobserved heterogeneity for border cells. Overall, on average a 1 percentage point appreciation in the earthquake intensity decreases the economic growth by 0.02 percentage points.

Table 2.7 – Effect of earthquake intensity on night lights : accounting for spatial and temporal correlations

	(1)	(2)	(3)	(4)	(5)	(6)
Post * Earthquake Intensity ≥ 7	-0.64513 (0.24180)***	-0.62648 (0.26050)**	-0.70852 (0.29790)**	-0.64695 (0.30387)**	-0.64513 (0.24180)***	-0.62648 (0.26050)**
Elasticity	-0.0219	-0.0213	-0.0241	-0.0220	-0.0219	-0.0213
Observations	17,794	12,441	17,794	12,441	17,794	12,441
R-squared	0.165	0.176	0.0947	0.0930	0.165	0.176
Year FE	✓	✓			✓	✓
Cell FE	✓	✓	✓	✓	✓	✓
District \times Year FE			✓	✓		
Distance \times Year FE					✓	✓
District-specific linear trend	✓	✓	✓	✓	✓	✓

Notes : All columns include controls for top coded and unlit pixels. Estimations of odd columns include control for population per grid cell. In columns 5 to 8, we control for distance border. Conley (1999) standard errors, in parenthesis, allow for spatial correlation within a 100 km radius. *** p<0.01, ** p<0.05, * p<0.1. FE : Fixed Effects. *Source* : Author's calculations.

Table 2.8 – Contemporaneous impacts of earthquake intensity using spatial models

	PCSE estimates			DK estimates		Spatial Durbin Model			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post * Earthquake Intensity ≥ 7	-0.64513	-0.62648	-0.81884	-0.81459	-0.56332	-0.56213	-0.72344	-0.73944	-0.51002
	(0.10307)***	(0.09832)***	(0.14000)***	(0.13312)***	(0.09345)***	(0.10826)***	(0.32264)**	(0.32673)**	(0.18110)***
(Within model) R^2 R-squared	0.796	0.796	0.793	0.795	(0.320)	(0.334)	(0.335)	(0.356)	(0.469)
Elasticity	-0.0219	-0.0305	-0.0278	-0.0396	-0.0214	-0.0304	-0.0252	-0.0258	-0.0254
Observations	17,794	12,441	17,794	12,441	11,955	8,407	17,360	17,360	12,152
Cell and Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
District-specific linear trend	✓	✓	✓	✓	✓	✓	✓	✓	✓
PSAR(1)			✓	✓					
MA(3)					✓	✓			
ρ							0.40400	0.35975	0.01488
							(0.01987)***	(0.00045)***	(0.00055)***

Notes : Prais-Winsten (PSCE) estimates and fixed effects (within) regression models with Driscoll and Kraay (DK) standard errors. Standard errors are in parentheses. ***, **, and * indicate respectively 1%, 5%, and 10% significance levels. Columns 7 through 10 corrected for clustering at the cell level. PSAR (1) stands for panel specific AR(1)-type autocorrelation. MA(3) denotes autocorrelation of the moving average type with automatic lag length. Estimations in columns 2, 4, 6 include population data. All columns include controls for top coded and unlit pixels. The spatial Durbin Watson Model includes both time lagged and space-time lagged dependent variable in the model. The coefficient ρ associated with the spatial autoregressive term $W \times Y$ indicates how pixel values in the neighborhood affect economic activity in the cells. *Source* : Author's calculations.

Table 2.8 presents the results of the regression analyses for different spatial techniques, allowing to correct for spatial correlation and spillover effects. Each column includes three sets of results from PCSE, DK estimations and a spatial Durbin Watson model. We first estimate equation 2.1 by using a linear regression with panel-corrected standard errors, assuming there is no autocorrelation within panels without population control as shown in columns 1, 3, 7 and 8. We find that increasing earthquake intensity has a contemporaneous negative effect on local economic activity in districts affected by a high earthquake intensity level compared to low level intensity districts. Its impact is, however, highly significant but of lower magnitude compared to previous estimates using administrative units. Moreover, by controlling for a spatial lag of the interaction terms (column 7) and a spatial lag of the dependent variable in columns 8 and 9, the negative growth effect of earthquake intensity is still significant at the same level for all models.

In columns 7 to 9, neighbors are defined according to a first-order row-standardized Queen contiguity spatial weight matrix. Our spatial dependence is defined by W , which is a binary contiguity matrix taking 1 if cells surround the cell of interest within a 100 km distance cutoff and a weight of 0 to other cells. This implies that we consider as neighbors the real number of bordering cells (minimum 0, maximum 8 and mean 6.28 neighbors). For the sake of brevity, we do not show the coefficients of $W \times$ post-treatment variable or our dependent variable. We do not detect any impact on local intensity in neighboring cells. Earthquake spillovers are not significant in space. With respect to lights, the coefficient of the first lag of lights in the cell of interest maintains its positive sign, magnitude and significance level. A one percentage point increase in this variable is associated with a 0.34 percentage point increase in lights likelihood in the subsequent year relative to the grid-cell long-term mean. We also detect an impact on local lights in neighboring cells. The increase of lights by one percentage point in one of the neighbors induces a 0.66% percentage point increase in the cell itself (i.e. 4.14 percentage point increase in the average cell) confirming that lights tend to spill over with spatial decay. Our interpretation of the results in columns 7 through 9 is that economic activity diffuses in space.

We verify our baseline scenario with several alternative specifications. The evidence largely confirms the baseline results since the coefficients remain significantly high. The point

estimates of the coefficients of earthquake intensity and the post dummy variable are lower than the baseline with the same significance level. According to our estimates, one level increase in the average *Mercalli* rank in an affected grid decreases lights by around 40% (more than 12% of GDP). Despite the different spatial schemes, the magnitude and significance of all coefficients are in line with the baseline results.

2.5.3. Results using DMSP-OLS NTL (1992–2013) and DMSP-like Nighttime Lights Derived from VNL (2014–2019)

To ensure that the results are not due to the data used to extend the series, we submit our findings to an additional robustness check. We used recently produced DMSP-like Nighttime Lights Derived from VNL (DVNL) datasets composites generated by Nechaev et al. (2021) and Ghosh et al. (2021) from 2014 to 2019 instead of extension series of DMSP-NTL. A major advantage of this annual dataset - derived from monthly composites in which sunlight, moonlight, and cloudy pixels, background light, aurora, and biomass burning have been eliminated - is that all processing steps and thresholds are identical across the series, thus enhancing the reliability of inter-annual change estimates. VIIRS imagery also improves the spatial resolution of DMSP-OLS because its pixel footprint is 45-fold smaller (Elvidge et al., 2013).

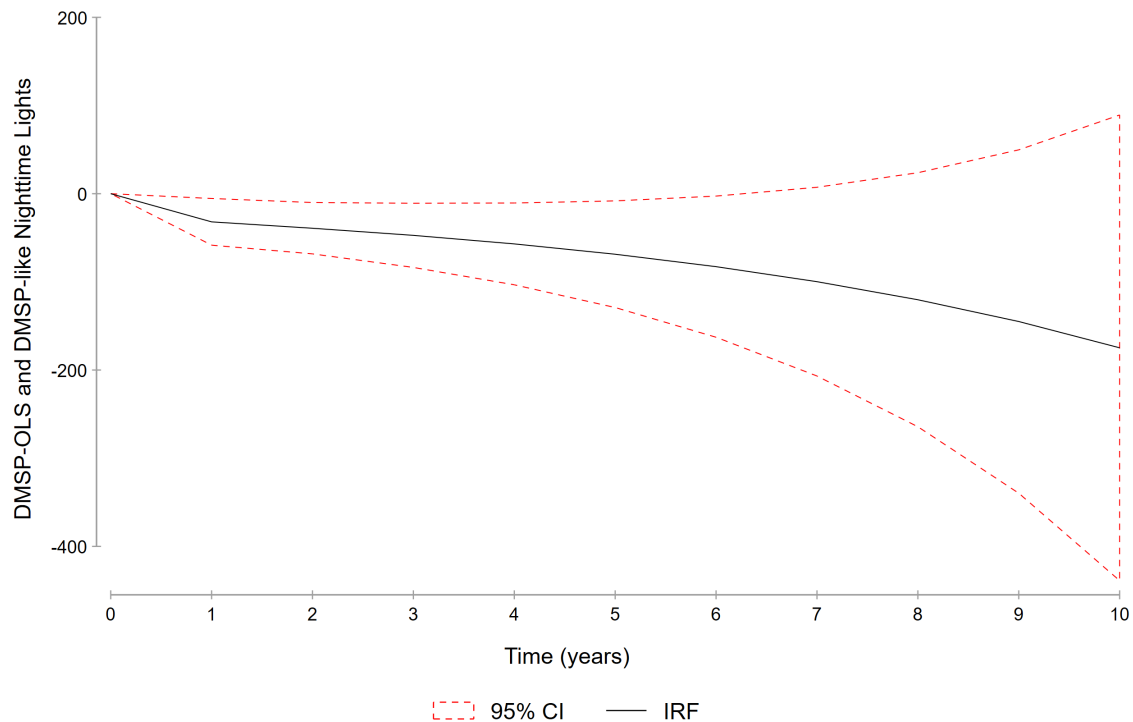
Table 2.9 and Figure 2.5 demonstrate that our main results are robust to this combined sample of DMSP-NTL and DMSP-like Nighttime Lights Derived from VNL data in treated and untreated districts. As Table 2.9 shows, results are very similar and do not depend on the choices made in the construction of our main variables of interest. The only difference is in the magnitude of the coefficients. These coefficients are almost identical to the baseline when using an extension of DMSP (2014-2019). This suggests that, regardless of the type of data used to extend the series, economic activity decreased sharply after the earthquake in heavily affected areas compared to weakly or unaffected districts.

Our results are valid, robust, and consistent with the recent literature reviewed by Gibson and Boe-Gibson (2021) on the comparison of DMSP nighttime lights to VIIRS data, as we worked at the level of the second administrative subdivision of the country.

Table 2.9 – Results using DMSP-OLS and DMSP-like Nighttime Lights Derived from VNL : DID effect of the earthquake, 1992–2019

	Dependent variable : Log of weighted lights									
	Satellite-Year FE					Year FE				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Post * Earthquake Intensity ≥ 7	-0.889	-2.027	-1.597	-1.610	-1.529	-0.789	-1.519	-1.396	-1.259	-1.174
	(0.310)***	(0.612)***	(0.567)***	(0.507)***	(0.546)***	(0.237)***	(0.408)***	(0.395)***	(0.361)***	(0.339)***
Elasticity	-0.0184	-0.0420	-0.0331	-0.0334	-0.0317	-0.0234	-0.0450	-0.0414	-0.0373	-0.0348
(Within districts) R^2	0.453	0.509	0.534	0.629	0.604	0.520	0.592	0.598	0.709	0.712
Observations	1,640	1,640	1,353	902	779	1,148	902	861	574	574
Control		✓	✓	✓	✓		✓	✓	✓	✓

Notes : Data constructed by combining Version 4 DMSP-OLS Nighttime Lights Time Series (1992 -2013) and DMSP-like Nighttime Lights Derived from VNL (2014-2019). All columns contain district fixed effects, and a district-specific linear trend. Columns 1-5 also include satellite-year fixed effects and the unit of observation is a district/satellite-year. In columns 6-10, we include year fixed effects, and the unit of observation is a district/year. The models reported in columns 2-5 and 7-10 include controls for top coded and unlit pixels. Estimations in columns 4, 5, 9 and 10 include population data. Columns 3-5 and 8-10 additionally control for one-year lagged lights. Standard errors are clustered at the district level. *, **, *** indicate statistical significance at the 10%, 5% and 1% level. *Source* : Author's calculations



Notes : Average annual residuals of NTL in treatment and control groups, 1992–2019. Each observation is a district/year. The red dashed lines below and above the black line represent a 95% confidence interval. Standard deviations and confidence intervals are based on a thousand Monte Carlo simulations. Source : Author’s own illustration.

Figure 2.5 – DMSP-NTL and DMSP-like Nighttime Lights Derived from VNL : Impulse responses of the earthquake

2.5.4. Results using Intercalibrated DMSP-OLS Stable Lights

In a previous analysis (Tables 2.2-2.9), we use uncalibrated DMSP-OLS Nighttime Lights and the extension series following (Bluhm and Krause, 2022 ; Heger and Neumayer, 2019 ; Henderson et al., 2012 ; Lee, 2018), and control for location and time fixed effects in all estimations. The use of satellite-year/year fixed effects in this study, combined with control variables for top-coded and unlit areas, overcomes the intercalibration problem and pixel saturation as discussed in the aforementioned papers, respectively.

Several studies have focused on solving the saturation and non-calibration problems of DMSP-OLS nighttime lights or on the integration of NTL observations from the DMSP and VIIRS data by developing various methods (Elvidge et al., 2009 ; Li et al., 2017,2).²⁵

²⁵. As there are many calibration methods, the adjusted DN values are still just an approximation. This is why we used fixed effects in previous tables to assure that DNs are comparable to each other and that our composites across satellites and years are more comparable.

As an additional sensitivity analysis, we run regressions with calibrated night lights, that are more comparable with and without a fixed effect model, controlling for unlit areas and removing the control variable for saturated lights since we have no more top-coded values in the data. As shown in Table 2.1, no fraction of pixels (0 percent), in Port-au-Prince (rich and densely populated areas), are censored. Of all the grid cells over the years, exactly one observation in Port-au-Prince reaches the maximum digital number of 62.95 for Haiti.

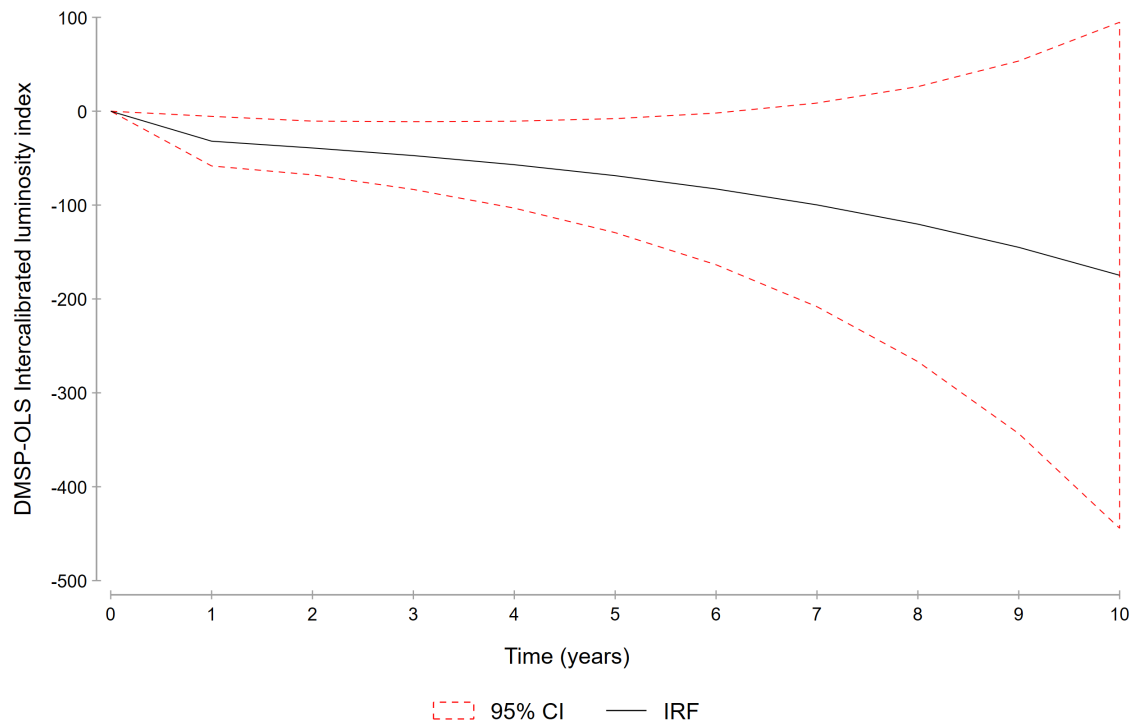
Given that intercalibrated stable lights are available from 1992 to 2013, we run the models described in Section 2.3 with various specifications. For reasons of space, we do not show the distribution of pixel values at the cell level before aggregating them by district-year as shown and discussed in Subsection 3.1 for uncalibrated DMSP Night Lights.²⁶ As can be seen, each line in Table 2.10 corresponds to the same specification as in the previous Table 2.2. In columns 2-5 and 7-10, we control for unlit areas, population and lagged lights. The results are similar to that of Table 2.2, both statistically and qualitatively.

26. Table is available upon request.

Table 2.10 – Results using intercalibrated DMSP-OLS Nighttime Lights : DID effect of the earthquake, 1992–2013

Variables	Dependent variable : Log of weighted lights									
	Satellite-Year FE					Year FE				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Post * Earthquake Intensity ≥ 7	-1.162 (0.328)*** [0.0931]	-1.855 (0.446)*** [0.1131]	-1.641 (0.462)*** [0.1031]	-1.314 (0.389)*** [0.1041]	-1.262 (0.364)*** [0.1131]	-1.292 (0.260)*** [0.0871]	-1.596 (0.346)*** [0.0941]	-1.400 (0.348)*** [0.1071]	-1.078 (0.310)*** [0.0901]	-1.027 (0.306)*** [0.0971]
Elasticity	-0.0100	-0.0160	-0.0141	-0.0113	-0.0109	-0.0172	-0.0212	-0.0186	-0.0143	-0.0137
$\ln[\text{sum}(\text{unlit})]$		-5.786 (2.361)**	-5.439 (2.343)**	-4.521 (1.727)**	-4.608 (1.901)**		-2.677 (1.982)	-2.587 (1.847)	-2.527 (1.573)	-2.572 (1.550)
$\ln(\text{light}_{j,t-1})$			0.173 (0.051)***		0.081 (0.075)			0.152 (0.056)**		0.065 (0.071)
$\ln(\text{population})$				2.294 (1.039)**	2.198 (1.214)*				2.344 (1.005)**	2.155 (0.975)**
(Within districts) R^2	0.442	0.467	0.452	0.577	0.559	0.538	0.543	0.553	0.669	0.670
Observations	1,394	1,394	1,148	902	779	902	902	861	574	574

Notes : All columns contain district fixed effects, and a district-specific linear trend. Columns 1-5 also include satellite-year fixed effects and the unit of observation is a district/satellite-year. In columns 6-10, we include year fixed effects, and the unit of observation is a district/year. Standard errors are clustered at the district level. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels. The two tailed p-values associated with the wild cluster bootstrap-T method appear in square brackets. *Source* : Author's calculations



Notes : Average annual residual of intercalibrated stable lights in treatment and control groups. Each observation is a district/year. The red dashed lines below and above the black line represent a 95% confidence interval. Standard deviations and confidence intervals are based on a thousand Monte Carlo simulations. Source : Author’s own illustration.

Figure 2.6 – Intercalibrated Stable Lights : Impulse responses of the earthquake, 1992 – 2013

In Figure 2.6, we replicate the baseline impulse response function (see Figure 2.3) since the definition of the dummy earthquake remains the same. All coefficients remain significantly different from zero and, in the dynamic model estimates, the sign is always negative. Overall, the evidence largely confirms the baseline results.²⁷ The regression results are not sensitive to which DMSP-OLS Stable Lights data we used in fixed effects models. Despite the two types of data used in our fixed-effect models, the magnitude and significance of all coefficients is comparable to the baseline. The use of uncalibrated lights in a fixed year effect model had no impact on the results found and is in line with the literature.

2.6. Discussion

Using a difference-in-differences estimation framework as well as impulse response func-

²⁷. It is important to note that we also replicate Tables 2.4 and 2.5 by re-estimating our robustness specifications using the intercalibrated light dataset. The effect of the earthquake on economic activity remains large, negative, and highly significant. To avoid overloading the paper with too many additional tables and to save space, we do not show these tables. However, they are available upon request.

tions, and controlling for observed and unobserved heterogeneity, we find that the 2010 Haitian earthquake highly depresses economic growth. We also show that the effects are persistent and are not compensated within 10 years from the event. Our estimates provide new evidence on the short- and long-term economic growth effects of large natural disasters. Combining short- and long-run models poses a number of challenges for estimation and constitutes an original contribution to the empirical economic disasters literature. This approach allows us to produce two novel sets of results : first, the evaluation of the causal average effect of natural disasters given their strictly exogenous nature ; and second, the assessment of the effects' persistence.

Our findings suggest that earthquakes and, more broadly, natural disasters are setbacks for economic growth, as evidenced by Robert J. and Xavier (2003) and Raddatz (2009). Such an empirical result, as well, has been shown in many other studies conducted in Haiti and around the world. For instance, in an attempt of investigating the causal effect of environmental catastrophe on long-run economic growth, Solomon and Amir (2014) concluded that affected countries are permanently relegated to a lower growth path. Similarly, Heger et al. (2008) focused on all the Caribbean islands and found that as growth collapses in the aftermath of climatic events, the fiscal and external balances both deteriorate and the island economies of the region find it difficult to rebound. A negative effect of disasters on growth was also reported in numerous other studies Berlemann and Wenzel (2018) ; Felbermayr and Gröschl (2014) ; Hazem et al. (2021) ; Noy (2009) ; Rasmussen (2004), as did Cavallo et al. (2013,1) for the 2010 earthquake in Haiti.

On the other hand, Loayza et al. (2012) and Cavallo and Noy (2011) found positive economic effects in the aftermath of disasters, in particular under certain circumstances, such as a high level of development in the country, insured losses and, most importantly, only moderately destructive disasters. In the case of Haiti, a low-income country with small exports highly concentrated in assembly industries, generally under-industrialized, in which informal activity predominates, the insurance system is underdeveloped despite the occurrence of natural disasters. These and other factors have probably exacerbated the negative impacts of the earthquake on the country's short- and long-term economic growth.

When it comes to disaster recovery, Heger and Neumayer (2019) analyzed the largest aid and reconstruction effort in Aceh's flooded districts, compared to counterfactuals, and found positive growth impacts of such interventions following the 2004 Indian Ocean tsunami. In Haiti, a country well known for its environmental catastrophes as opposed to the Indonesian province of Aceh, the response and recovery plans have been conceived quickly, right after the earthquake, with different international approaches that led to an astonishing inefficiency. Moreover, the pledges of aid have not fully translated into additional funds to help rebuild the country, and information on the exact amount of aid disbursed in the wake of the earthquake is not available, as some aid has been managed by nongovernmental organizations without any oversight or accountability. Furthermore, neither the precise areas to be considered as damaged and to be targeted by relief measures nor the amount and guidelines for the assignment of the funds allocated to this purpose were defined by the government shortly after the quake. Therefore, we were unable to capture such relationships.

Given the earthquake-related interventions were mainly concentrated in heavily affected districts, future research may want to closely analyse whether quake-induced relief measures and reconstruction aid dampens the effects of disaster exposure on other aspects of economic and social life, in particular the reduction of social conflicts and the distribution of income at the local level. Our own analysis has not been able to quantify any channels through which the earthquake can directly influence economic growth, which could include local appropriate disaster policies including mitigation, economic and institutional capabilities, and international aid. Another potential direction would be to consider how human choice, political willingness, political uncertainty, effective management of foreign aid, or other structural and institutional details may worsen or mitigate this negative impact.

Further, recent research suggests that disasters have an indirect impact on various aspects of economic development (Becchetti et al., 2017 ; Chowdhury et al., 2021 ; Juan et al., 2020 ; Paudel and Ryu, 2018 ; Pleninger, 2022). De and Thamarapani (2022) found that the diminished levels of wellbeing in individuals exposed to the 2006 Yogyakarta earth-

quake in Indonesia persisted for 8 years after the disaster. Arouri et al. (2015) and Karim (2018) showed that disasters such as storms, floods, and droughts have negative effects on household income and expenditure. Nevertheless, institutional quality and international openness could mitigate the negative effects (Felbermayr and Gröschl, 2014). Due to the lack of information on socioeconomic characteristic of households before the earthquake in the country, such potentially interesting outcomes cannot be examined with night lights data. These are valuable research questions which would deserve to be considered in future studies.

Disasters may increase the accumulation of the government debt in their aftermath (Klomp and Valckx, 2014 ; Melecky and Raddatz, 2011). Although the international community cancelled Haiti's debt as a contribution to reconstruction in the middle of 2010, this indirect aid did not really restore the country's level of growth prior to the earthquake, as our results show. Nel and Righarts (2008) suggest that natural disasters may not only have economic, but also political consequences. It is believed that large natural disaster impacts on countries, regions, economic sector or low-income households could be higher, especially through education, health and income effects. Answers to these research questions will emerge as additional data on socio-economic activity become available as further are collected.

Our study showed that natural disasters lead to lower income growth. Our data allowed us to decompose the short- and long-term effects initially across administrative subdivisions such as districts and grid cells as subnational units, so that the mechanisms are better understood. This is the first study of this nature for the country. Regarding Haiti's political situation since the earthquake, it is not surprising to observe this persistent negative effect. New data collection and research efforts should take this aspect into account.

2.6.1. Policy Implications

Our results have significant implications for both Haiti and the rest of the world. This is especially the case in developing countries that face natural disasters and are particularly vulnerable because of the fragility of their economies and their often equally poor or poorer populations, with limited resources to rebound. The January 12, 2010 Haiti

earthquake resulted in some of the most significant social impacts of an earthquake in recent decades. To start with, the persistence of negative results shows the ineffectiveness of government action to revive economic activity and improve the living conditions of the local population after the earthquake. The Haitian government did not take advantage of international solidarity, following the earthquake, to revive local economic activity, whether through national saving, official development assistance or foreign capital to finance the country's recovery.

From our results, it can be deduced that governments and their development partners need to put in place state structures to ensure harmonization and alignment of aid with well-designed local initiatives. Meanwhile, they must ensure greater accountability of local structures and make certain that the aid received is invested in the most productive sectors, in which the district (more generally the country) has a comparative advantage. They should also reduce the duplication of public development aid actions by non-governmental organizations (NGO) in carrying out small projects without significant impact.

Another implication of these results is that the majority of the country's formal and informal businesses are located in the capital region (Port-au-Prince), which was the most affected by the earthquake and is by far the most populous in the country, with nearly one-third of the total population. Due to the high risk of natural disasters, climate change and rapid population growth in the country, a generalized decentralization and a deconcentration of economic activities through the territories less at risk could help reduce significant socio-economic consequences, and human losses due to natural disasters in the short and long term.

Disasters, such as the Haiti earthquake, impact local economies by damaging capital stock, degrading marketplace infrastructure, and killing or injuring a population. These impacts can result in declines and shifts in local output that may amplify pre-disaster trends and contribute to economic instability and de-investment according to Benson and Clay (2004). The government must therefore implement policies to encourage long-term investment by developing a new infrastructure that is more resource-efficient and less polluting, especially in the energy and transportation sectors. It should also promote earthquake-

resistant construction to reduce risks in the event of natural disasters and protect the country's economy from the hazards of nature.

These estimates are useful to put this event in perspective. They also serve to inform the international community that the country has not recovered 10 years following this experience and that the population continues to feel the effects of the earthquake. This is necessary in order to put forward the enormity of the challenge, i.e. the task of recovery, which the Haitian economy is faced with. It should also encourage productive investment in key sectors of the economy to revive growth and rebuild the country sustainably.

These findings also have implications for developing countries, which must strengthen themselves in the face of future disasters by preparing for immediate post-disaster needs and adapting their long-term responses to country-specific needs through long-term sustainable development programs. Finally, the frequency of natural disasters in developing countries, the extent of the damage and the inability of governments to reduce human and economic losses are all factors that drive people to seek refuge in countries where the risk of natural disasters is lower. This also impacts developed countries, hence the need for joint efforts to reduce the average global losses from these disasters by building back stronger, faster, and more inclusively, and helping affected countries to recover socially, economically, politically and sustainably.

2.6.2. Limitations

Despite the extensive discussions in the literature, the quantitative assessment of natural disasters is still a challenge due to the lack of continuously collected empirical data before, during and after disasters occur in developing countries. Here we assess the plausibility of several threats. A potential concern regards our results derived from the DMSP-OLS stable lights data, which could be a poor proxy for GDP outside of cities according to Gibson et al. (2021). We are dealing with this issue in two ways. First, we look at the level of infrastructure in the country before and after the earthquake using the World Bank's Global Infrastructure Map (World Bank, 2021b). Given that the spatial and qualitative analyses conducted in addition to the empirical part show an increase in the level of infrastructure in the country after the earthquake and the partial or total reconstruction of

almost all destroyed public administration buildings. We believe that the negative causal effect observed and proven in this article is solely the result of the decrease in local economic activity in the country.

Second, our research design relies on the fact that the second sub-national level in Haiti is highly populated and urbanized (Table 2.1). Gibson and Boe-Gibson (2021) argue that using more spatially aggregated data improves the performance of DMSP in predicting economic activity (relative to what VIIRS does). Given there are no GDP data for Haiti's sub-districts, DMPS can be used to assess economic consequences of disasters in weakly disaggregated design, which is the case in our strategy. Moreover, estimation of economic activity from the nighttime lights helps to overcome many of the problems associated with data collected through surveys, as the nighttime lights dataset are easily available and can be frequently updated. In addition, there are several challenges to the collection of high quality GDP data at the global or local level in developing countries such as Haiti, including the absence of standardized national income accounting methods, different bureaucratic capacity of states, lack of consistent methodology in data collection, low levels of efficiency of surveyors, the subjective response of the responders in ground surveys, and the varying political and economic situation between countries (Henderson et al., 2012 ; Tilottama et al., 2010).

We recognize that our results are very context-specific since we have no economic or statistical and social spatially-disaggregated data, even at the lowest level of disaggregation (department) to support our results.²⁸ We cannot compare our luminosity index to the true Gross Domestic Product (GDP) directly since Henderson et al. (2012) find that nighttime lights are correlated with GDP with an elasticity of about 0.3 as discussed in Section 2.4.1, and show, like Bruederle and Hodler (2018), that nighttime lights are a good proxy for economic output when subnational data are not available. Our paper is part of this literature. We were unable to assess the direct impact of the earthquake on the determinants of economic growth at the regional or district level (labor, capital,

28. Haiti is a data-scarce environment : the national censuses are too far apart, and the Demographic and Health Surveys (DHS) datasets contain few or no observations on socioeconomic characteristics of household or economic measures such as income, expenditure, asset holdings, employment, savings and debt. They only comprise socio-economic indicators such as health conditions, and no other panel data is available for the country.

land, debt, labor rates, credit to the economy, import and export levels, aid, climatic and meteorological hazards, social protection program prior to the earthquake or some discontinuity in the aid response). Future works could check how much trade or migration links prior to the earthquake matter in the ability of districts to bounce back after being hit by an earthquake.

We acknowledge that we lack socio-economic data to be able to explain the whole situation of Haiti following the earthquake since activities that are not well-lit do not appear in night lights and the Haitian economy is highly informal. However, we believe that night lights data are particularly helpful in places lacking in transparency or accurate statistics, such as Haiti, and give an idea of the long-term consequences of the earthquake at the district level.

Our belief is that the consistent results across a variety of data sources and a short (Difference-in-Differences) and long run model constitutes a convincing case for negative impacts of earthquake intensity. We provide district-level results to link to the previous literature. It bears mentioning that our results show only average effects. This average is likely to mask important heterogeneity across districts in the country. In particular, we quantify the average impact of the earthquake and model the recovery process. However, with the available data, we are not in a position to explain why some regions are more or less affected by controlling for the intensity of the earthquake or the distance to the epicenter; or why some districts recover faster than others. Therefore, this analysis could be repeated for other countries with better data as an avenue for future research.

2.7. Conclusion

In this paper, we examined the economic impact of the 2010 earthquake in Haiti by conducting a disaggregated empirical analysis at the district level from 1992 to 2019. We combined data on district variations in nighttime light intensities with an indicator for earthquake damage to evaluate its impact and analyse the economic recovery. By using a DID regression framework, we found that the earthquake was associated with a decrease in nighttime light growth in strongly impacted zones relatively to neighboring districts. In addition, IRFs showed the persistence of the negative effects over time. Our findings

are robust to a series of sensitivity analyses. Employing spatial econometric techniques across grid cell units, as opposed to the subnational administrative boundaries used in the baseline specification, DMSP intercalibrated stable lights, or lights derived from the Visible Infrared Imaging Radiometer Suite (VIIRS), and controlling for spatial spillovers, produce fairly similar results on the short- and long-run economic growth. This paper provides evidence of causality and contributes to the outgoing debate on the effects of natural disasters on economic growth via the so-called continuous Modified Mercalli Scale.

Given the shortcomings of national statistics with no panel data available over the years from 1992 to the present day, and the steady evolution of informal economic activity in the country over the past few decades, models derived from nighttime lights proved useful in assessing the dynamics of local development after the earthquake. This can help economists and policy makers better understand the economic situation in developing countries and undertake constructive development policies following a major negative shock, such as health and natural disasters. We believe that our approach of combining panel data on lights at the subnational level with information about the quake opens a promising avenue for future research projects on economic growth and recovery following natural disasters.

2.8. Appendix A : Descriptive Statistics

Table 2.11 – Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max	Count
Panel A : DMSP-OLS Nighttime Lights						
ln(light)	1,681	-2.79	1.88	-4.60	2.55	1,681
ln(top-coded)	1,681	0.0026	0.076	0	2.56	17
ln(unlit)	1,681	6.46	0.65	4.50	7.79	1,681
Population	1,189	16.16×10^4	31.20×10^4	0	265.26×10^4	1,189
Earthquake Intensity	1,681	5.79	0.86	4.74	7.90	1,681
Earthquake Intensity ≥ 7	1,681	0.097	0.30	0	1	164
$Post_t=1$ for year ≥ 2010	1,681	0.27	0.44	0	1	1,681
Panel B : Intercalibrated Stable Lights						
ln(light)	1,394	-3.45	2.57	-7.21	2.56	1,394
ln(unlit)	1,394	6.47	0.64	4.74	7.79	1,394
Population	902	22.14×10^4	33.38×10^4	5.09×10^4	251.34×10^4	902
Earthquake Intensity	1,394	5.79	0.86	4.74	7.90	1,394
Earthquake Intensity ≥ 7	1,394	0.07	0.26	0	1	102
$Post_t=1$ for year ≥ 2010	1,394	0.12	0.32	0	1	1,394

Source : Author's calculations based on NOAA's National Geophysical Data Center, Payne Institute for Public Policy's Colorado School of Mines, WorldPop, Center For International Earth Science Information Network, United States Geological Survey databases and Global Administrative Areas map data.

Table 2.12 – Average Mercalli Score by District

District	Mean	Std	Min	Max
Trou-du-Nord	4.74	0.39	3.8	5.6
Saint-Louis-du-Nord	4.75	0.34	4.4	5.6
Ouanaminthe	4.94	0.36	4.4	5.6
Cap-Haïtien	4.94	0.44	4	5.8
Borgne	4.95	0.34	4.4	5.8
Vallières	4.96	0.37	4.4	5.6
Grande-Rivière-du-Nord	4.96	0.35	4.4	5.6
Anse-d’Hainault	4.97	0.23	4.6	5.4
Port-de-Paix	4.98	0.48	4.2	6.2
Fort-Liberté	5.03	0.43	4.2	5.8
Jérémie	5.09	0.35	4.6	5.8
Limbe	5.14	0.37	4.6	5.8
Plaisance	5.19	0.37	4.6	6
Acul-du-Nord	5.19	0.42	4.4	6
Saint-Raphaël	5.19	0.39	4.4	6
Chardonnières	5.27	0.35	4.8	6
Môle-Saint-Nicolas	5.29	0.44	4.4	6.4
Gros-Morne	5.38	0.48	4.6	6.8
Côteaux	5.39	0.38	4.8	6.2
Corail	5.43	0.43	4.6	6.4
Cerca-La-Source	5.44	0.54	4.6	6.4
Marmelade	5.5	0.43	4.8	6.4
Cayes	5.66	0.46	4.8	6.6
Gonaïves	5.71	0.58	4.8	7
Hinche	5.85	0.51	4.4	6.8
Port-Salut	5.89	0.30	5.2	6.4
Lascahobas	6.02	0.45	4.8	6.8
Belle-Anse	6.1	0.44	5.2	7
Aquin	6.18	0.56	5.4	7.8
Dessalines	6.23	0.57	4.8	7.6
Anse-à-Veau	6.26	0.53	4.8	7.4
Mirebalais	6.61	0.46	5.6	7.4
Saint-Marc	6.71	0.39	6	7.6
Gonave	6.74	0.50	5.8	8
Croix-des-Bouquets	6.77	0.61	5.2	8
Miragoâne	6.99	0.48	6.2	8
Arcahaie	7	0.45	6.2	8
Bainet	7	0.28	6.4	7.6
Jacmel	7.3	0.43	6.2	8.2
Port-au-Prince	7.86	0.54	6.6	9
Léogâne	7.9	0.56	6.6	9

Notes : Mercalli scores are assigned by plotting the Global Administrative Areas (GADM) onto a map of the earthquake intensity provided by the United States Geological Survey (2010). Earthquake intensity is then averaged across district.

2.9. Appendix B : Data Sources

Data Availability Statement : The DMSP stable lights annual composites are available at <http://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html>, accessed on 02 October 2020. The annual DMSP Nighttime Lights Extension data used in this study are available for download from the Earth Observation Group of the Colorado School of Mines at <https://eogdata.mines.edu/dmsp/downloadV4composites.html>, accessed on 30 April 2021 and the DMSP-like Nighttime Lights Derived from VNL (DVNL) data are at https://eogdata.mines.edu/wwwdata/viirs_products/dvnl/, accessed on 26 March 2022. The population data are available from the WorldPop at <https://www.worldpop.org/geodata/listing?id=75>, accessed on 02 October 2020. The geocoded earthquake intensity data are from the United States Geological Survey (USGS) available at <https://earthquake.usgs.gov/earthquakes/eventpage/usp000h60h/shakemap/intensity>, accessed on 30 September 2019. Land and Water Area data are from the Center for International Earth Science Information Network (CIESIN). The data can be download from <https://sedac.ciesin.columbia.edu/data/set/gpw-v4-land-water-area-rev11/data-download>. Accessed 02 November 2020.

The economic impact of refugees in Africa

Résumé : Nous étudions l'impact des camps de réfugiés sur l'activité économique locale en Afrique. Nous combinons des données géoréférencées sur les camps de réfugiés de 2000 à 2016 avec les données de la série chronologique DMSP-OLS Nighttime Lights. En traitant la localisation endogène des camps de réfugiés sur la base de caractéristiques observées et non observées, augmentée d'une approche par variable instrumentale, nous trouvons que la présence de réfugiés est associée à une baisse significative de l'activité économique locale dans les zones proches des camps de personnes déplacées de force. L'effet moyen est néanmoins économiquement négligeable et dépend largement de la capacité d'absorption, c'est-à-dire de la politique d'asile en vigueur dans les pays d'accueil. Cette hétérogénéité met en lumière les options politiques permettant de transformer la présence des réfugiés en une opportunité de développement.

Mots clés : Réfugiés, personnes déplacées de force, lumières émises la nuit et captées par satellite, Afrique.

JEL Codes : O12, O15 ; R12, R23.

Abstract : We investigate the impact of refugee camps on local economic activity in Africa. We combine georeferenced data on refugee camps from 2000 to 2016 with DMSP-OLS Nighttime Lights Time Series data. While dealing with the endogenous location of refugee camps based on observed and unobserved characteristics, augmented with an Instrumental Variable approach, we find that the presence of refugees is associated with a significant decline in local economic activity in areas near camps of forcibly displaced people. The average effect is nonetheless economically negligible and largely depends on the absorption capacity, i.e., the Asylum Policy of the hosting country. Such heterogeneity sheds light on policy options for turning the presence of refugees into an developmental opportunity.

Key words : Refugees, forcibly displaced people, nighttime lights, Africa

JEL Codes : O12, O15 ; R12, R23.

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3.1. Introduction

The number of people fleeing war, conflict, violence, human rights violations, persecution, abuse or events seriously disturbing public order reached 89.3 million, the highest level ever recorded in the world, in 2021, which is twice higher than ten years previously, according to UNHCR (2021b).⁴ Among these displaced people, 27.1 million were recognized as refugees, more than half of whom were under 18 (UNHCR, 2021b). Despite the coronavirus pandemic, the number of displaced people has continued to rise and is expected to increase significantly in the coming years. Although media coverage and political concerns often focus on the transit of refugees to Western countries, particularly in Europe and the United States, more than 83% of forcibly displaced people worldwide were hosted in developing countries in regions that often face developmental challenges. By the end of 2021,

4. This included people who were forcibly displaced (refugees, asylum-seekers, and internally displaced people) and those who found a durable solution (returnees), as well as stateless persons, most of whom have never been forcibly displaced. Forcibly displaced people and asylum-seekers increased by 8 percent in 2021 from 82.4 million in 2020 (UNHCR, 2021b). Forced displacement is a different phenomenon from economic migration (EM). Forced displacement is less of a choice and less voluntary than economic migration, although there is ultimately always a choice behind most (but not all) migration decisions. According to Verme and Schuettler (2021) forced displacement is a decision that is taken quickly following a sudden shock as opposed to EM, which is more often a carefully planned move. Forced migrants typically carry some small savings with them but little else because of the sudden nature of the shock, whereas economic migrants tend to carry savings and assets, or transfer these in advance of the move. Economic migrants tend to rely on extended networks in the place of origin and destination and plan their move in accordance with these networks. Forced migrants are inclined to move to destinations based on proximity and security criteria rather than personal networks, although networks can occasionally play a role.

approximately 72% of uprooted people were hosted in neighboring countries (UNHCR, 2021b).⁵

In Africa, the number of refugees has increased from close to 3.7 million to about 7.3 million over the past decade (UNHCR, 2021b). The host populations are often as poor or poorer than the displaced, and resources to support the new arrivals are limited or non-existent. In 2020, 40% of forcibly displaced people lived in camps where they received humanitarian assistance. In this context, it is not surprising that a large number of academic studies have been devoted to identifying and quantifying the impact of refugees on several outcomes, with a special focus on Africa (Maystadt et al., 2019 ; Ruiz and Vargas-Silva, 2013 ; Verme and Schuettler, 2021), including economic activities (Alix-Garcia et al., 2018), prices and assets (Alix-Garcia et al., 2012 ; Alix-Garcia and Saah, 2009), consumption and labor market outcomes (d’Errico et al., 2022 ; Maystadt and Verwimp, 2014 ; Ruiz and Vargas-Silva, 2015,1 ; Taylor et al., 2016), the of local public goods (Kreibaum, 2016 ; Maystadt et al., 2019), and health (Baez, 2011 ; Dagnelie et al., ming). However, due to data availability, the literature has focused on a few case studies, namely in Kenya, Tanzania, Rwanda, and Uganda. The generalizable nature of the results has been further hindered by the various outcomes used in extant studies, each capturing distinct economic dimensions (Verme and Schuettler, 2021). In this paper, we offer a more general perspective by covering 40 countries in Africa.⁶ Similarly to Alix-Garcia et al. (2018) for Kenya, we also use an aggregated proxy for local economic activity using nighttime lights (Donaldson and Storeygard, 2016 ; Henderson et al., 2012 ; Joseph, 2022).

To assess the impact of forced displacement on economic activity, we exploit a unique georeferenced data on 417 refugee camps and their composition between 2000 and 2016. By exploiting yearly variations in the proximity and size of refugee camps within fine-grained cells and an instrumental variable approach, we find a negative elasticity of the presence of refugees with respect to nighttime lights. However, such elasticity is estima-

5. Up to date at time of writing.

6. Other studies have offered such an Africa-wide perspective but have focused on more specific developmental dimensions, such as vegetation and deforestation (Maystadt et al., 2020 ; Salemi, 2021), health (Dagnelie et al., ming), and conflict (Beine et al., 2021 ; Coniglio et al., 2021 ; Zhou and Shaver, 2021). These cross-country studies give a more negative picture – or at least, suggest no effect – of the consequences of hosting refugees on local communities. We cannot exclude the possibility that data availability in accessible case studies leads to a streetlight effect in refugee research in Africa (Hendrix, 2017).

ted to be economically negligible. The near-zero average effect certainly hides important heterogeneity across refugee-hosting communities. We then exploit existing conditions in terms of absorption capacity, asylum policy, to potentially reconcile the mixed nature of existing evidence across case studies. In particular, our results demonstrate that refugees are more likely to contribute to the local economy when the hosting countries have sufficient resources to host displaced people and implement a less restrictive asylum policy, including with respect to the right to work, land and property.⁷

The rest of the paper proceeds as follows. In Section 3.2, we provide a description of all variables used in our estimation. Then, we introduce our identification strategy in Section 3.3. In Section 3.4, we report the results and discuss major identification threats and offer robustness checks. Section 3.4.1 presents a heterogeneous analysis. Finally, Section 3.5 concludes by summarizing results, providing a brief policy discussion and indicating areas for future research.

3.2. Data

We construct a dataset by creating a 150 km buffer area around 417 refugee camps based on their geographic coordinates. The analysis is based on cells of 0.083 degree latitude \times 0.083 longitude (approximately 10 \times 10 kilometers at the equator). Our analysis is at the cell-year level. We use this level of aggregation, rather than administrative boundaries, because the reported numbers of refugees are limited to those residing in camps, and also to ensure that our unit of observation is exogenous to political decisions, power distribution and conflict events (Berman et al., 2017 ; Besley and Persson, 2011 ; Michalopoulos and Papaioannou, 2016). Hence, by using grid-cell units, each geographic unit is comparable in size across countries. We create a measure of distance (measured in kilometers) defined as distance to the nearest refugee camp from each grid cell.⁸ Our main dataset uses 97,556 10 km \times 10 km grid cells, covering 40 African countries between 2000 and 2016. Below, we further describe the high-frequency georeferenced data we use. The

7. Refugees often face restrictions to their right to work and freedom of movement and settlement, which influences whether and how they are actually able to enter the labor market. Even if granted the right to work, notably in high income countries, refugees often need to wait for status recognition before they can access the labor market, which in turn delays the labor market impact (Verme and Schuettler, 2021).

8. Grid cells are merged with African administrative boundaries using Geographic Information System (GIS) software to identify the country of each grid cell.

data originates from UNHCR refugee data, conflict data from the Uppsala Conflict Data Program (UCDP) (Ralph and Erik, 2013), climatic data from the Berkeley Earth and the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS), DMSP-OLS Nighttime Lights Time Series from Colorado School of Mines' Payne Institute for Public Policy (Earth Observation Group).

UNHCR Refugee Data. To study the impact of refugee camps on economic activity in Africa, we use georeferenced data on 417 refugee camps in Africa and their number of residents. Data on refugee camps are provided by the United Nations High Commissioner for Refugees (UNHCR) over the period 2000-2016 covering 40 African countries. This database has been used previously by Maystadt et al. (2020). It provides information on camp locations (latitude, longitude), year of creation and dissolution, the numbers of refugees living in camps, the country of origin and asylum, accommodation and population type, composition of the camps (age range, number of males and females). We only keep camps hosting refugees.

One of the limits of the refugee data is due to missing geographic coordinates for a few camps.⁹ Out of 417 camps, 37 have the same geographical coordinates as the other camps within the same country. These camps are mainly located in Cameroon (8 camps), Democratic Republic of the Congo (18 camps), Sudan (2 camps), Ethiopia (4 camps), Guinea (2 camps), Cote d'Ivoire (3 camps). As can be seen from Figure 3.2 (a), the georeferenced camps still offer a wide coverage across the African continent. Figure 3.2 (a) indeed displays the location of all camps used for the analysis. Refugee camps are mainly located near country borders. Another drawback is that we only capture refugees residing in UNHCR monitored camps. We may therefore underestimate the total number of refugees and its economic consequences.

Figure 3.1 depicts the evolution of the total number of refugees by plotting camp refugee data aggregated at the yearly level and the UNHCR official statistics on refugees at

9. Serious issues are detected in the location of the camps and out of the 417 retained in our database, 3 camps (two located in Niger and one in Algeria) have country names different from their location (Cameroon and Democratic Republic of the Congo respectively), which can distort the results. However, to make sure that these errors do not affect our results, we performed various robustness tests described in Section 3.4 where we removed these camps. The coefficients associated with the refugee index remain negative and highly significant (see Table 3.5, Panel G).

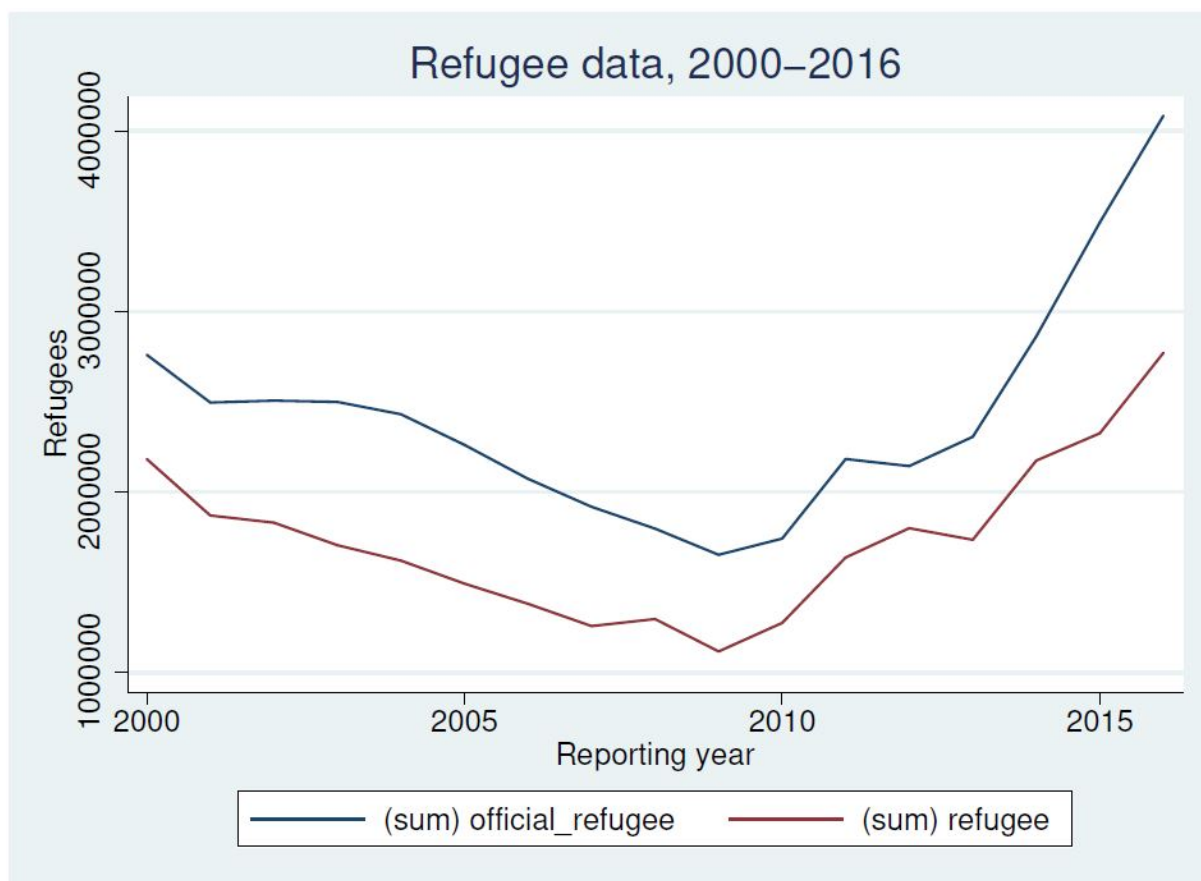
the country level (UNHCR, 2021c). Both lines show a similar upward trend over time. Although overall trends match, our constructed dataset underestimates the true refugee population in Africa since our camp-specific data do not contain dispersed refugees (not in camps) as discussed by Dagnelie et al. (ming). This figure clearly shows the reliability of the database used in this paper since the overall trends match. By cleaning all the aforementioned errors, we believe that UNHCR's internal data is a relatively accurate account of camp locations and years of operation.

Nighttime light data. In the absence of systematic subnational statistics, we use nighttime light to proxy for local economic activity. Nighttime lights (NTL), calculated from weather satellite recordings, are increasingly used by social scientists as a proxy for economic activity or economic development in subnational regions of developing countries where disaggregated data from statistical offices are not available (Bruederle and Hodler, 2018 ; Donaldson and Storeygard, 2016 ; Henderson et al., 2012). The data come from the National Oceanic and Atmospheric Administration using the Defense Meteorological Satellite Program (DMSP), and Colorado School of Mines' Payne Institute for Public Policy.¹⁰

The original data product is gridded in 30 arc-second by 30 arc-second pixels (approximately 1km × 1km at the equator), spans -180° to 180° longitude and 65° to 75° latitude, and is available for the years since 1992. Six different satellites have collected the light data, with some overlap across years. Annual values were then constructed on the daily grid values, and are available from 1992 to 2019.¹¹ In the annual composites for each satellite, the Digital Number (DN) value of each pixel was the average of the visible-band DN values of lights from cities, towns, and other sites with persistent lighting. After obtaining global images of Nighttime light data for 2000-2016, light intensities were extracted

10. The DMSP program is designed to capture information about global weather and weather systems. The DMSP satellites collect images around the globe twice per day, which are then archived and processed by the National Geophysical Data Center. Data processing involves various tasks, such as adjustment for cloud covers, glares, fires, stray light, lightning, lunar illumination, etc., and only keep the lights produced by human activities. For instance, DMSP has no in-flight calibration and the DMSP products have saturation (DN=63) on bright lights. We exclude cells with gas flares from the analysis using shapefiles available here : http://ngdc.noaa.gov/eog/interest/gas_flares_countries_shapefiles.html. Gas flares are not considered as proxies for economic activity.

11. We combine Version 4 DMSP-OLS Nighttime Lights Time Series available from 1992 to 2013 and DMSP Nighttime Lights Extension from 2014 to 2019.



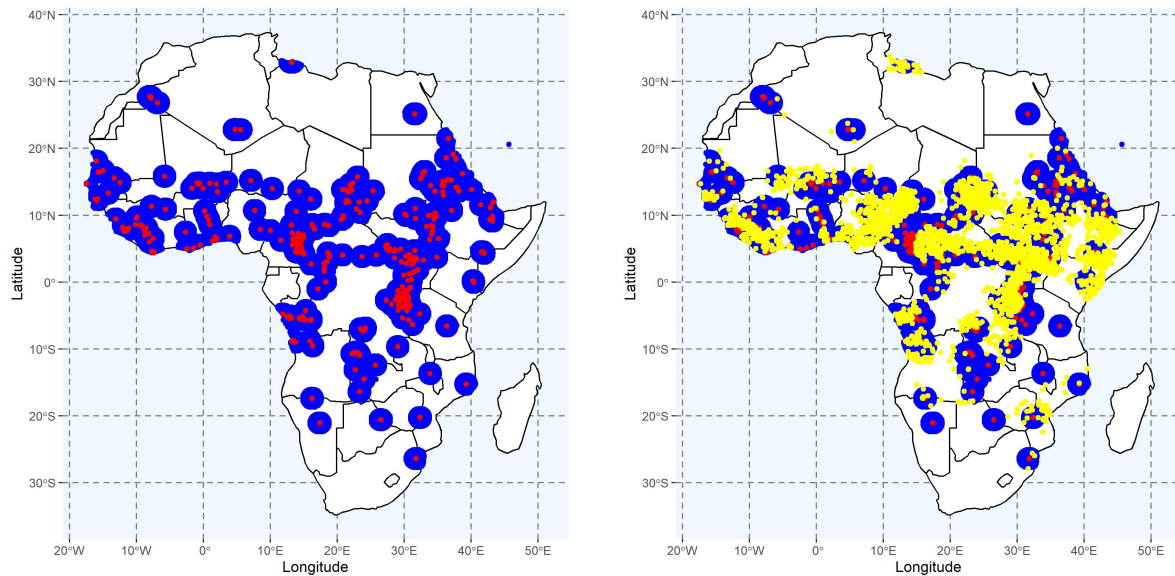
Note : Number of refugees between 2000 and 2016. Source : Created based on Dagnelie et al. (ming) using United Nations High Commissioner for Refugees data from <https://www.unhcr.org/refugee-statistics/download/?url=E1ZxP4>. Map is for illustration purposes only.

Figure 3.1 – Comparing UNHCR aggregated statistics with camp-specific information

according to the African gridded buffer within 150 kilometers from camp refugees. We end up with 97,556 cells located within 150 km from a refugee camp that was active at some point in time between 2000 and 2016. Figure 3.3 plots the distribution of nighttime light intensities of the African countries in 2000 and 2016. The light intensities range from 0 to 63 for each pixel, with higher numbers implying brighter nighttime lights.¹²

Conflict Event data. Refugee camps are often located in conflict-prone areas. While the causal impact of refugees on the likelihood of violence is a contentious one (Beine

12. One may be concerned about the predictive power of night light data as a proxy for GDP at the local level. Chen and Nordhaus (2015) argued that NTL data are a weaker proxy for economic activity in low density areas, given the predominance of agriculture in such places. NTL data are a less useful proxy for fluctuations in overall economic activity in places where agriculture is more important (Gibson and Boe-Gibson, 2021). We believe that this is not an issue in this paper for two reasons. First, we have worked on 10×10 km cells that can be similar to large administrative structures. As a further robustness check, we used cells of 27.5×27.5 kilometers at the equator (See Table 3.7).



(a) Camp refugees within 150 km

(b) Camp + Conflicts within 150 km

Note : 150 km buffers from any camps. The sized of each cell is approximately 10×10 kilometers at the equator. Each red dot represents a refugee camp (2000-2016). Yellow dots are conflicts. Source : Authors' illustration.

Figure 3.2 – Spatial distribution of UNHCR camps and conflicts in Africa between 2000 and 2016.

et al., 2021 ; Coniglio et al., 2021 ; Salehyan and Gleditsch, 2006 ; Zhou and Shaver, 2021), conflict itself and conflict spillovers are known to have detrimental impacts on local economic activities (Blattman and Miguel, 2010 ; de Groot et al., 2022). To take into account this complex co-founding effect, we add to our dataset conflict shocks that occur within a buffer of a 150 kilometer radius around the cell centroids. Figure 3.2 (b) maps cells experiencing at least one conflict event during 2000 through 2016. Data on conflict include the total number of reported annual conflict events, battle deaths, type of violence, etc. Conflict event data is taken from the Georeferenced Event Dataset provided by the Uppsala Conflict Data Program. The basic unit of analysis for the UCDP GED dataset is the 'event'. UCDP codes the latitude, longitude, including several types of violence like state-based conflict, non-state conflict, one-sided violence resulting of civil conflict, ethnic violence, and violence against civilians occurring at a given time and resulting in at least 1 direct death at a specific location and a specific date, etc. Each event is georeferenced as precisely as possible. According to Figure 3.2 (b), conflicts are mainly located in Western, Central and Eastern Africa camps and their proximity to refugee camps reinforces our concerns about their potential co-founding role.

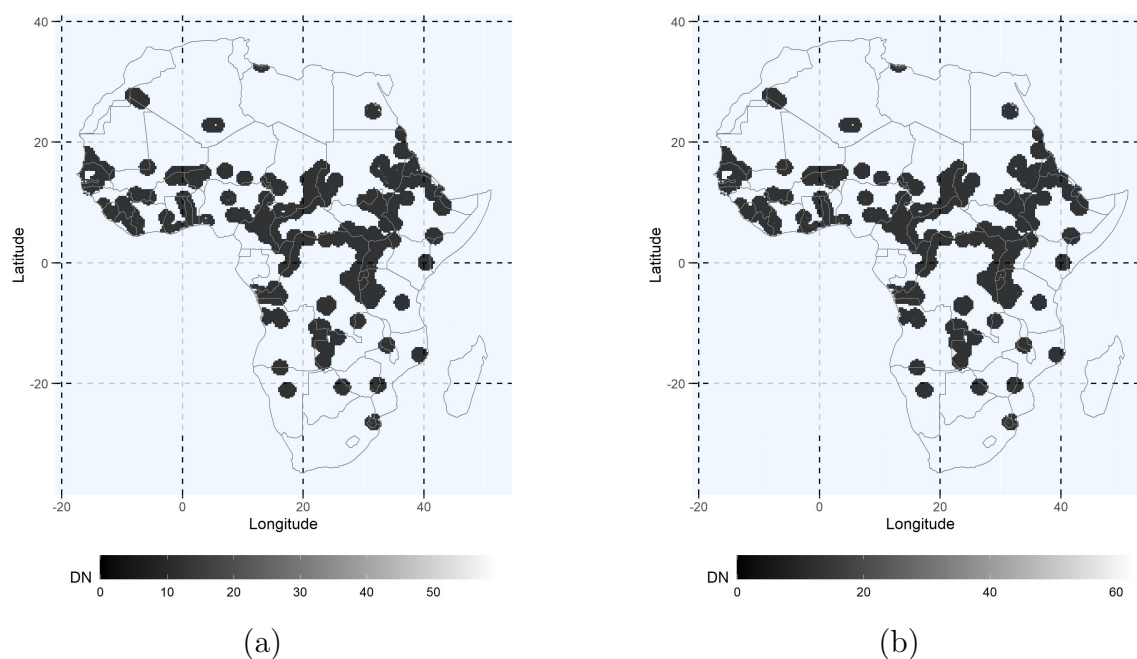


Figure 3.3 – Map of satellite-based night lights digital number (DN) (a) in 2000 and at (b) in 2016 in Africa. Source : Authors’ illustration.

Climate Data. Similarly to conflict events (Burke et al., 2015 ; Harari and Ferrara, 2018 ; Hsiang et al., 2011 ; Mach et al., 2019), weather shocks are likely to affect local economic activity (Barrios et al., 2010 ; Burke et al., 2015 ; Kotz et al., 2022 ; Niang et al., 2014). To capture weather shocks, we use Rainfall Estimates from Rain Gauge and Satellite Observations taken from Berkeley Earth (measured in millimeters per month) and temperature (measured in accumulated degrees per month) data from CHIRPS (Climate Hazards Group InfraRed Precipitation with Station). This data has a long period of records and high spatial resolution (i.e, 0.05 latitude \times 0.05 degree longitude approximately 5.5 \times 5.5 kilometers at the equator). We use local accumulated rainfall anomaly in millimeters and mean temperature anomaly in degrees C as our key climate indicators, for each corresponding grid location and time. Anomaly is measured as the standardized deviation from the long-term mean. We select anomaly to capture abnormal weather variations that may affect local economic activity. We then calculate annual averages of the anomaly at the global scale, with a 0.05 degree spatial resolution. Anomaly has been found to be a relevant transformation to capture time-varying economic risks at a large geographical scale and has been mainly used to capture weather shocks (Barrios et al., 2010 ; Hodler and Raschky, 2014a ; Maystadt et al., 2020 ; Nicholson, 1993).

3.3. Identification Strategy

The aim of the analysis is to quantify the relationship between the presence of refugees and local economic activity. Our main specification is estimated with an Ordinary Least Squares (OLS) method and can be represented as follows :

$$light_{ct} = \delta_t + \delta_c + \beta Refugees_{ct} + \gamma X_{ct} + \psi + \epsilon_{ct}. \quad (3.1)$$

where $light_{ct}$ is the DMSP-OLS Nighttime lights defined at the cell, subscript with c and year, subscript with t . Since a substantial share of the digital numbers is zero in Africa, similar to Alix-Garcia et al. (2018), we apply an inverse Hyperbolic Sine transformation to our dependent variable.¹³ This transformation allows for estimations on the full sample, including lights too feeble to be detected by satellites. The low level of lights in Africa is reflected in the low mean value (0.18) observed in Table 3.1. $Refugees_{ct}$ designates the presence of refugees. This main variable of interest is an index equal to the sum of refugees weighted by the distance between the considered grid cell and all refugee camps within a 150 km buffer. Such an index is standard (Maystadt et al., 2020 ; Maystadt and Verwimp, 2014) and can be formalized as $\sum_{c,k} \frac{Refugee_{ct}}{dist_{c,k}}$. To allow for an interpretation in terms of elasticity, we also apply an inverse Hyperbolic Sine transformation to our main variable of interest. Standard errors are clustered at the grid-cell level.

Our main identification concern relates to the non-random location of refugee camps. From Figure 3.2, there is little doubt that camps are mainly located near international borders. It is likely that peripheral areas, where refugee camps are established, are different from other areas. We therefore control for observed and unobserved heterogeneity. First, we control for unobserved time-constant characteristics using cell (δ_c) and year fixed effects (δ_t). Since we are concerned about national policies or factors that might change the development path, we further control for country-specific time trends (ψ). Second, we control for time-varying factors (X_{ct}) likely to correlate with both our dependent and treatment variables. More specifically, we control for rainfall and temperature anomalies. As can be seen in Table 3.1, the mean of temperature anomaly is 0.95 and indicates a general

13. Inverse hyperbolic sine transformation is similar to a logarithm, and allows to retain zero-value observations (Bellemare and Wichman, 2019).

warming between 2000 and 2016 in our sample. The reverse is observed for precipitation anomalies with a mean value of 0.01. We also increase the baseline specification with the number of conflict events occurring within cell c at time t . The variable is transformed into inverse Hyperbolic Sine. Conflict in Africa is certainly a major determinant of local economic activity and may be linked to the presence of refugees. However, we cannot exclude that such a variable may act as “bad control” (Angrist and Pischke, 2009,1). We will therefore present our main results with and without these control variables.

Despite the use of fixed effects and time-varying controls, we cannot exclude that the source of non-random location of refugee camps is time-varying. We should first stress that the fine-grained nature of the cells helps to reduce the risk of confounding trends between treated and untreated cells. Nonetheless, we assess the sensitivity to the OLS estimates with the application of an Instrumental Variable Approach. In the refugee quantitative literature, we follow Maystadt et al. (2020) by adapting a shift-share instrumental variable, standard in the migration literature since Card’s seminal paper (Amior, 2018 ; Card, 2009 ; Jaeger et al., 2018).

$$IV_{c(D)k(O)t} = \sum_{k \neq c} Refugee_{ODt} \times \left(\frac{1}{Distance_{ck}} \right) \times Q_{kt} \quad (3.2)$$

$Refugee_{ODt}$ denotes the number of refugees moving from country O to country D at year t . The UNHCR Population Statistics Database contains yearly data on the number of refugees going from a country of origin to a country of asylum (UNHCR, 2021c). The second and third terms serve to exogenously allocate a greater number of refugees from a given origin to destinations based on existing pull and push factors. The number of conflict events, capturing the push factor occurring at location k in origin country O , is weighted by the distance between the grid cell centroids c and location k .

The instrument belongs to the Shift-Share family (or Bartik) (Borusyak et al., 2021 ; Goldsmith-Pinkham et al., 2020). The IV is based on a Refugee Shifter. The shock will shift the presence of refugees in cells but is assumed not to shift directly the economic activity at destination. A valid instrumental variable requires two properties : relevance and exogeneity. We follow Borusyak et al. (2021) and assume that exogeneity in share is not necessary and that exogeneity in the shifter. Our instrument is consistent by control-

ling for observables with the set of fixed effects that we included in all specifications. The relevance is assessed statistically using the Kleibergen-Paap F-stat.¹⁴

Figure 3.2 shows the correlation between the proportion of camps and the number of conflicts within a 150 kilometers radius of the camps from 2010 to 2016 for Africa. Indeed, as the graph shows the distribution of both variables, we can see that there is more observation around camp locations, meaning refugees decide to migrate to other countries in Africa, usually close to their country of origin. For graphs of lights in 2000 and 2016, we cannot see any significant correlation between concentration of lights, number of conflicts and camp locations given that the majority of the pixels are null or near zero (Fig. 3.3).

The exclusion restriction requires that shifts are orthogonal to unobservable. In all models, the direct effect of the conflict in cells on a destination country D is captured by the cell and year fixed effects. A major threat for the exclusion restriction may come from conflict spillovers. Indeed, conflict occurring in origin country may directly impact local economic activities through the disruption of factor mobility, such as trade and migration. To minimize such a threat, we first control for spatial correlation and cross-cell spillovers between control and treatment units by using a row-standardized Queen contiguity weight matrix W , in which a weight of 1 is assigned to cells surrounding the cell of interest, within a 150 km distance cutoff, and a weight of 0 to other cells (Harari and Ferrara, 2018 ; Laville, 2021).¹⁵ We construct and add the spatial treatment variable ($W \times \text{Refugee}_{ct}$) to control for refugees in neighboring cells. Second, we enrich the main specification with a proxy for conflict spillovers.

14. Borusyak et al. (2021) argue that exogeneity in shares is not necessary if we can assume that exogeneity in the shifter. However, here, we need a sufficiently large number of elements k , such that the shares are based on, in their case, large numbers of industries; in our case, large numbers of countries.

15. Row-standardized takes the binary zero-one weights and divides them by the row sum.

Table 3.1 – Summary statistics in absolute and ihs values : dependent variable and covariates

Variable	0-30 km.			30-60 km.			60-90 km.			90-120 km.			120-150km.		
	N	Mean	SD	N	Mean	SD	N	Mean	SD	N	Mean	SD	N	Mean	SD
Distance border															
Nighttime Lights	1485089	0.24	2.42	25335	0.22	2.02	36651	0.18	1.86	45711	0.18	1.87	57366	0.18	2.07
Nighttime Lights (IHS)	1485089	0.08	0.41	25335	0.08	0.40	36651	0.07	0.37	45711	0.07	0.36	57366	0.06	0.35
Refugee Index (150km)	1485089	5.57	182.99	25335	285.87	686.44	36651	167.30	431.12	45711	107.30	290.77	57366	64.48	191.91
Refugee Index (IHS, max. 150km)	1485089	0.04	0.48	25335	4.09	2.59	36651	3.53	2.49	45711	3.08	2.39	57366	2.63	2.25
Temperature anomaly	1485089	0.95	0.30	25335	1.06	0.29	36651	1.06	0.29	45711	1.05	0.29	57366	1.05	0.30
Precipitation anomaly	1485089	0.00	0.94	25335	0.07	0.94	36651	0.06	0.95	45711	0.05	0.96	57366	0.05	0.96
Number of conflicts (max. 150km)	1485089	2.21	9.44	25335	6.67	15.87	36651	6.52	16.38	45711	5.94	15.99	57366	5.09	15.04
Number of conflicts (IHS, max. 150km)	1485089	0.55	1.07	25335	1.25	1.51	36651	1.19	1.50	45711	1.12	1.47	57366	0.99	1.40
Distance-weighted-conflict	1485089	0.03	0.19	25335	0.10	0.28	36651	0.09	0.30	45711	0.08	0.27	57366	0.07	0.26
Distance-weighted-conflict (IHS)	1485089	0.03	0.11	25335	0.09	0.21	36651	0.08	0.21	45711	0.07	0.20	57366	0.06	0.18
Distance-weighted-conflict IV (IHS)	1485089	6.99	4.44	25335	9.10	5.11	36651	8.96	5.07	45711	8.78	4.98	57366	8.48	4.97
Distance-weighted-conflict _{t-1} IV (IHS)	1485089	6.92	4.51	25335	9.12	5.15	36651	8.98	5.11	45711	8.78	5.04	57366	8.47	5.04
Number of treated cells 2000-2016	1485089	0.01	0.08	25335	1.00	0.00	36651	1.00	0.00	45711	1.00	0.00	57366	1.00	0.00

Notes : Authors' calculations using UNHCR data, CHIRPS, Berkeley Earth, UCDP and DMSP-OLS Nighttime lights data. Each observation is a cell/year. We exploit data on 417 UNHCR refugee camps in 40 African countries. Refugees includes people in refugee-like situations, 2000 - 2016.

3.4. Results

Table 3.2 provides the main results. The even columns contain the various control variables discussed in section 3.2. In the odd columns, we initially ignore all covariates. To save space, Table 3.2 only reports the coefficients and statistics of interest.¹⁶ As can be seen from column (1), refugees have a negative and significant effect on economic activity. In the remaining columns of Table 3.2, where temperature anomaly, precipitation and the number of conflicts per cell units were included, the presence of refugees still has a negative and significant impact on local economic growth. Columns 2 and 4 include a country-specific time trend and the results are unaltered. Columns (5) to (8) present the results using two-stage least squares (2SLS). The first-stage Kleibergen-Paap F-statistic is large (well above > 10). The coefficient of the instrument in the first stage is large, positive and statistically significant at the one percent level. The resulting coefficient moves towards zero suggesting a negative selection bias. However, despite being precisely estimated, this negative impact is close to zero in magnitude.¹⁷ Indeed, doubling the presence of refugees would only decrease economic growth by 0.5 percent.

Over the time period that we examine, local economic growth in Africa experienced a long-term decline. A concern for our analysis is that potential inconsistency of OLS estimates (columns (1) through (4) of Table 3.2) comes from the possible correlation between conflict and the presence of refugees. To prevent such a problem, it might be desirable to instrument conflicts using instruments correlated with the size of the total conflict but uncorrelated to migration flows between 2000 and 2016 (columns (5)-(8) of Table 3.2). The use of such an instrument enhances the quality of adjustment of the first stage regression in the IV procedure with respect to the use of $refugee_{ODt}$ as a single instrument. For the sake of robustness, we provide the estimation of equation 3.2 using alternative IV in Table 3.5. The second econometric issue is related to the exclusion restriction. As discussed in Section 3.2, the instrument must be relevant. To assess this relevance we can refer to the first stage results in Table 3.2. As expected, the sign of the instrument in the first stage is

16. We provide a detailed Table in the appendix (Table 3.4).

17. We realize that the finding of a zero impact can be suspicious. One could get a negative result if the experiment were poorly designed. In this paper, the high quality nature of the data minimizes the possibility that our results are due to errors in our data. Our robustness checks also support the fact that we are indeed measuring the impact of refugees on local growth accurately.

positive. Recall that the increase in the number of conflicts on the African continent, or another, is expected to increase the flow of refugees in neighboring countries, hence the positive sign. Several factors, that might question the validity of the exclusion restriction, are tested in Table 3.5.

We address concerns over the exclusion restriction by using square of Distance in IV (panel A), square-root of Distance in IV (Panel B), including a lagged IV (Panel C) or one-year lagged conflicts (Panel D), controlling for refugee (Panel E) and conflict spillovers (Panel F) in the second stage regression of our IV specification.^{18, 19} After adjusting for these factors, the effect remains statistically significant in all specifications. As with other robustness checks, the night light effects are also uninfluenced by whether we exclude camps with country name errors (Panel G). The coefficient on Refugees Index (IHS, 150 km) is remarkably stable in sign and magnitude. Finally, in Panel H, we additionally control for refugee squared term. This control leaves the sign unaffected and coefficient estimates are significant at the 5 or 10 percent levels. The similarity of the results to the full sample in First-and Second-stage estimates reduces concern about selective camps and conflict location. This instrument is relevant and exogenous. First-stage statistics confirm the significant and positive correlation between the two endogenous variables and the instruments, i.e, the F stats exceed the critical value of 10, meaning that the instrument is not weak.

Another concern for our 2SLS estimates is that IV models using some form of distance to the border need to take into account potential correlations between distance to the shock and economic conditions that violate the exclusion restriction (Verme and Schuetler, 2021). Within a country, there might be spillovers from violence in affected cells to cells nearby. As expected, temporal spillovers are greatly attenuated once we include cell fixed effects, as some of the persistence is attributed to unobserved cell-level long-run characteristics. To deal with this threat, in the appendix Tables 3.6 and 3.7, we explore the sensitivity of our estimates by replicating Table 3.2 and additionally controlling for

18. Formally, the coefficient on the Refugee Index (IHS, 150km) is estimated from the following instrument : $IV_{c(D)k(O)t} = \sum_{k \neq c} Refugee_{ODt} \times \left(\frac{1}{Distance_{ck}} \right) \times Q_{kt-1}$.

19. The negative sign of the refugee effects remains statistically highly significant when using inverse distance weight matrices with different distance cutoffs.

spatial and temporal correlations. The reported results in Table 3.6 suggest that columns (1) through (4) of Table 3.2 are well-specified with respect to autocorrelation.²⁰ Moreover, controlling for country-specific time trends yields refugee effects on economic growth of equivalent magnitude to our baseline regressions.²¹ Further, in Table 3.7, we consider a lower-resolution 0.25×0.25 degree grid. In all estimations, standard errors are calculated with a spatial HAC correction allowing for both cross-sectional spatial correlation and location-specific serial correlation, applying the method developed by Conley (1999) and Hsiang et al. (2011).²² The effects of refugees remain highly significant. The point estimates and significance levels are very similar to our main regression. They are robust to a large battery of sensitivity checks. Having established the robustness of the baseline findings, finally, we complement our empirical analysis using the more detailed specification in column (7) of Table 3.2 to investigate whether the effects of the refugees on local growth vary based on the specific features outlined in Section 3.1 and discussed in Section 3.4.1.

20. Due to the large number of observations, we cannot replicate the results of the 2SLS models reported in columns (5) to (8) of Table 3.2, and present Conley (1999) standard errors as for the OLS models (columns (1)-(4)). For this reason, lower resolution grid cells were used in Table 3.7.

21. Conley (1999) standard errors corrected for spatial correlation up to 25, 50 and 100 km, i.e., covering the neighboring cells and time dependency up to 2 years in Table 3.6, or infinite serial correlation (i.e., 100,000 years) in Table 3.7.

22. Because of the high number of observations, Conley (1999) standard deviations cannot be calculated in the 2SLS models with a country-specific time (Table 3.7, columns (6) and (8)).

Table 3.2 – Night Lights and Refugees in Africa, 2000–2016 : OLS and 2SLS estimates

	<i>Dependent variable : DMSP-OLS Nighttime Lights</i>							
	OLS estimates				2SLS second stage estimates			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Refugees Index (IHS, 150km)	-0.00091 (0.00008)***	-0.00032 (0.00007)***	-0.00084 (0.00008)***	-0.00025 (0.00007)***	-0.00802 (0.00152)***	-0.00506 (0.00164)***	-0.00733 (0.00150)***	-0.00433 (0.00162)***
Observations	1,650,152	1,650,152	1,648,197	1,648,197	1,650,152	1,650,152	1,648,197	1,648,197
Root MSE	0.111	0.110	0.111	0.110	0.108	0.108	0.108	0.108
Controls			✓	✓			✓	✓
Country-specific time trend		✓		✓		✓		✓
Kleibergen-Paap rk Wald F					5890	4659	5910	4742
					<i>Dependent variable : Number of refugees</i>			
					2SLS first stage estimates			
Distance-conflict-weighted (IHS, 150km)					0.03260 (0.00042)***	0.00981 (0.00042)***	0.03302 (0.00043)***	0.01037 (0.00042)***
Observations					1,650,152	1,650,152	1,648,197	1,648,197
Root MSE					1.194	1.174	1.191	1.172
Controls							✓	✓
Country-specific time trend						✓		✓

Notes : All regressions include cell and year fixed effects. Values of robust standard errors clustered at the cell level appear in parenthesis. The outcome variable is the *Inverse Hyperbolic Sine* of the DMS-OLS luminosity index. Columns (3)-(4) and (5)-(6) include conflict, temperature, and rainfall as explanatory variables. ***, ** and * denote significance at 1, 5 and 10 percent levels respectively.

3.4.1. Heterogeneity Analysis

Previous research on the impact of refugees on economic activity has already been done, drawing attention to and describing key aspects of the economy of refugee camps and urban areas (Jacobsen, 2005 ; Werker, 2007). For instance, Betts et al. (2017) showed how the relationship between refugees and development was conceived. They also examined how attempts to promote self-reliance were developed, and explored the factors that led to success or failure. Other studies have investigated a range of such questions, namely what explains variations in migrants' incomes, what justifies their selection of alternative geographical locations, and what explains the differences in impact of migrants on natives (Abramitzky et al., 2012 ; Borjas, 2014).

Overall, we find that the presence of refugees is associated with a significant near-zero decline on local economic activities. It certainly rejects the claim that refugees would systematically constitute a burden for hosting communities in Africa. However, it somehow contrasts with specific case studies in Kenya (Alix-Garcia et al., 2018), Tanzania (Alix-Garcia and Saah, 2009), Rwanda (Loschmann et al., 2019), and Uganda (d'Errico et al., 2022). In these last cases, the impact is generally quantified as economically positive on the local economy, albeit with non-trivial redistributive effects. In a way, our paper downplays the external validity of these studies. However, it also invites us to investigate the conditions that could lead to the positive or negative economic consequences of hosting refugees.

Indeed, the character and stringency of immigration policies have been shown to be crucial in determining the impact on receiving economies (Beine et al., 2015 ; Mayda, 2006). In developing countries, restrictive policies have often been favored in economies with weak labor markets, limited formal employment and poor adaptive capacity. Even host countries have (or are supposed to have, according to international refugee law) national refugee legislation. In many host countries, the right of refugees to be economically active is ignored, overruled, or at best applied inconsistently (Jacobsen, 2005).²³ However, unlike in the Global North, forced displacement policies in the Global South have become more liberal over time (Blair et al., 2021).

23. A key problem in developing countries is that many host countries do not have specific laws pertaining to refugees, nor do they have a clearly articulated refugee policy (Jacobsen, 2005).

To explore the above hypothesized favorable conditions for hosting refugees, we construct dummy variables for income classifications, refugee policy, refugee-host proximity. Since the literature has often highlighted the transversal nature of gender issues in refugee-hosting contexts, we further stratify our sample between male and female refugees. These classifications were made to keep enough observations in cells while grouping observations with similar characteristics. Here, we extend our Instrumental Variables (IV) identification strategy to allow for country-specific treatment effects.

In order to isolate the impact of refugees on economic growth, it is important to rely on a theoretical framework taking into account the migration decision and the choice of destination country of each type of refugees. The mechanisms through which refugees could affect local economic activity can also be examined in light of heterogeneous effects. In this part, we start with the same model in which we introduce the gender dimension (Table 3.9). We separately estimate the DID effect of the refugees by dividing our sample on the basis of various characteristics of the cells in the destination country. We conduct separate regressions for income level and refugee policy in the developing world. We separately analyze the effect of refugees on economic activity in each subgroup and present the results in Figures 3.4-3.5 and appendix Tables 3.9 through 3.11.²⁴

Country heterogeneity We first conduct separate regressions by region (Western, Southern, Central, East, North Africa) and present the results in columns 1-5 of Table 3.9 that reports the two-stage least squares estimates. We find that countries in Middle Africa experienced a 0.007 percentage point increase in the annual rate of economic activity, while the rate of Eastern and Northern Africa are -0.018 and -0.041 percentage point, respectively. In Southern Africa, we find no significant effect of refugees on economic activity. After close examination, we show no significant evidence of the coefficient of interest for some selected countries, such as Kenya, Uganda, Rwanda and Tanzania.

24. We additionally create 95% confidence intervals of the estimated coefficients, computed from the second stage estimates reported in column (7) of Table 3.2 in Figures 3.4 and 3.5.

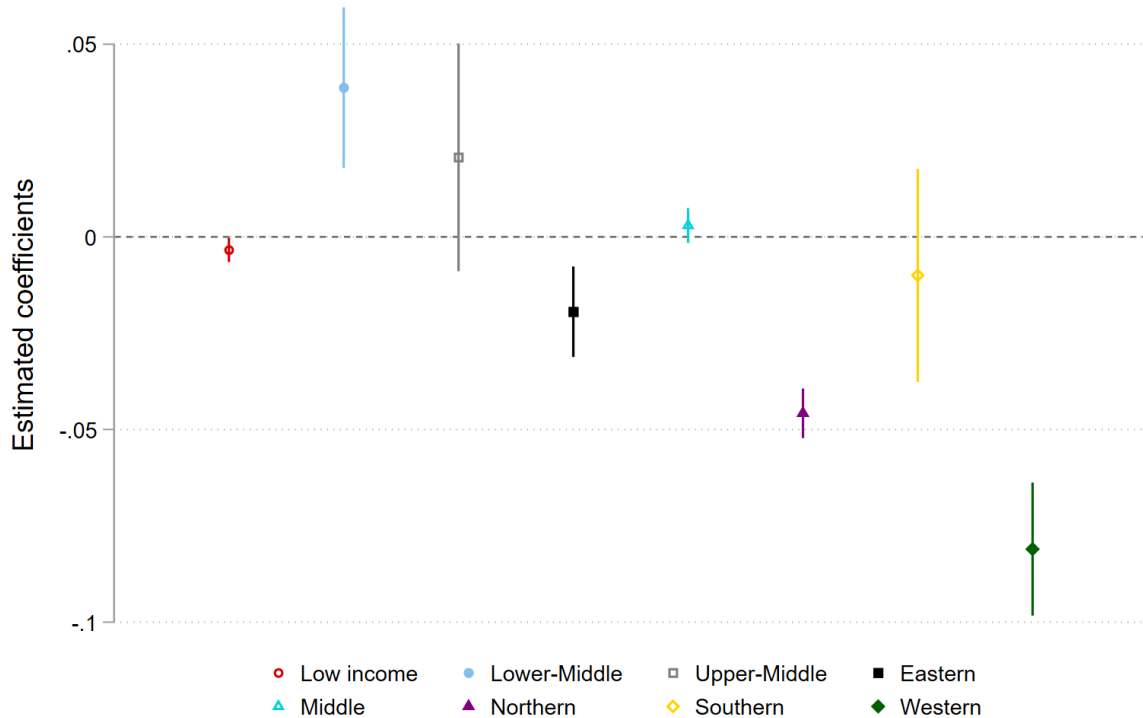


Figure 3.4 – 95% confidence intervals of refugee elasticities differentiated by income level and African regions

Note : 95% confidence intervals of refugee elasticities calculated from the second stage estimates presented in Tables 3.8 and 3.9. Results for selected subgroup countries by World Bank income classification level (Low-Income, Low-middle Income, Upper-middle Income) and African subregions (Eastern, Middle, Northern, Southern, Western).

Sample of Low- and Middle-Income Countries. Second, we also disaggregate the results based on World Bank classifications of 2000.²⁵ The countries are split into three income groups : low income (per capita real GDP less than or equal to 785 dollars), lower middle income (per capita real GDP between 786 and 3125 dollars), upper middle income (per capita real GDP over 3126 dollars) (Fantom and Serajuddin, 2016).²⁶ We separately analyze the effect of refugees on Night Lights as can be seen in the first four columns of Table 3.8. We find that cells in low-middle income experienced a 0.04 percentage points rise in the global annual rate of economic activity, while the rate for low-income was reduced by 0.0034 percentage points (column (1) of Table 3.8). We find no significant evidence for upper-middle income countries. As for the refugee workforce, in particular

25. We use GNI per capita, Atlas method (current US\$) from the World Bank's World Development Indicators (WDI). This dataset contains the largest sample of countries.

26. See Table 3.12 for the list of countries.

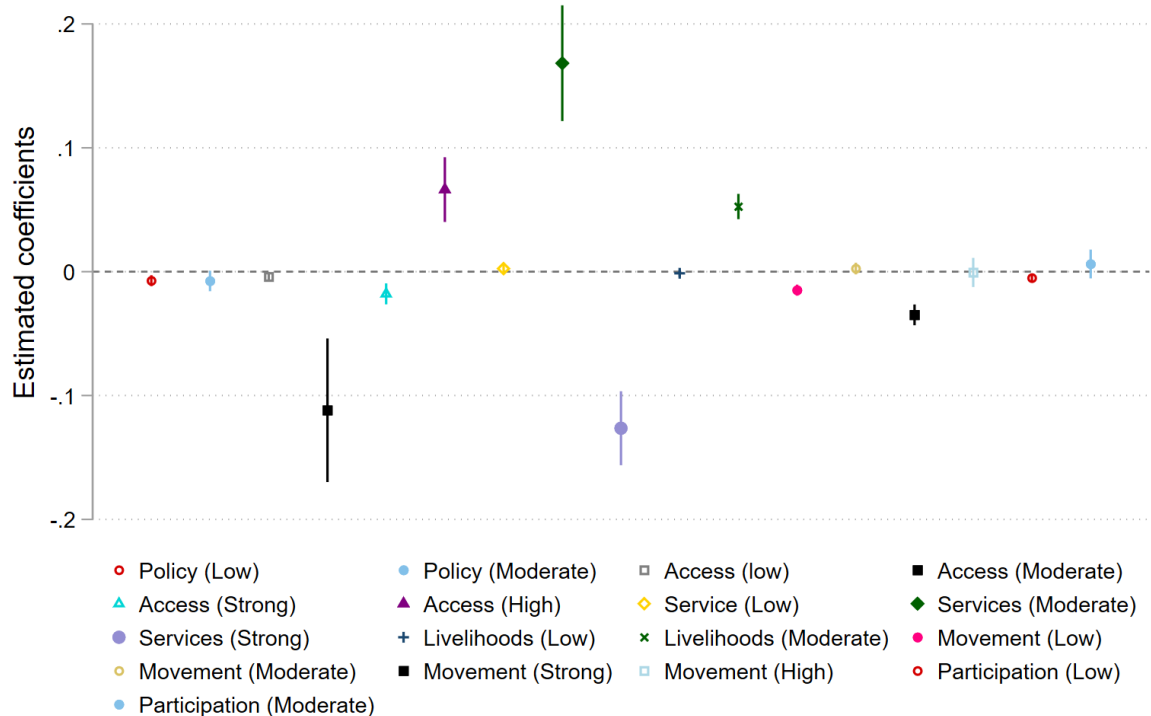


Figure 3.5 – 95% confidence intervals of refugee elasticities differentiated by refugee policy

Note : 95% confidence intervals of refugee elasticities calculated from the second stage estimates presented in Table 3.10. Results by refugee policy index in Africa. We exploit five dimensions of policies like access, services, livelihoods, movement and participation (Blair et al., 2021). This figure plots the impact of refugees on economic growth. Each point is a separate estimate. The figure represents the estimated coefficient for each category. All models include year and cell fixed effects and the full vector of control variables from column (3) of Table 3.2. Robust Standard errors are clustered on cells.

the proportion of men and women in low- and middle-income countries, the estimate on the refugee index is negative at the one and five percent levels, respectively, while in upper-middle income countries, we find no significant effects. The regressions in columns (4) through (6) and (7) through (9) are fairly similar in sign and significance.

Sample of Asylum Policy in the Developing World. Refugees, in general, receive different treatment from nationals in the country of asylum. To see differential impacts of refugees on economic activity considering immigration policies, we use the Developing World Refugee and Asylum Policy (DWRAP) dataset from Blair et al. (2021). This dataset is an original dataset of all national laws pertinent to forcefully displaced populations in a sample of 92 African, Middle Eastern, and South Asian countries between 1951 and 2017. In total, the Developing World Refugee and Asylum Policy (DWRAP) dataset in-

cludes 229 unique, national-level migration laws. This dataset conceptualized refugee and asylum policy as a combination of policy 's regulating five core dimensions : (1) access : the ease of entrance and security of status ; (2) services : ' of public services and welfare ; (3) livelihoods : the ability to work and own property ; (4) movement : encampment policies ; and (5) participation : citizenship and political rights.

The policy over time score in 2000 is used to quantify the intensity of asylum policy in different countries. The unique policy measure we introduce is a dummy variable for the level of restriction in a destination country D . We measure policy score across countries, which varies from 0 (low-level) to 0.63 (the maximum value in Africa), and implement an ordinal version of the index obtained by dividing the countries into four groups. High score (g_1) comprises countries where the policy index and/or its components was very strong (≥ 0.75), strong score (g_2) includes countries where score was strong ($[0.50 - 0.75[$), and moderate score (g_3) contains countries where the index was $[0.25 - 0.5[$ and g_4 where the policy score < 0.25 .

Using these different subgroups for our policy score over time in 2000, Table 3.10 reports results for each subgroup. In the first two columns, we use the average policy index score divided into low and moderate groups. Column (1), showing countries with restricted asylum policy measures, exhibits a negative and significant effect of refugee presence in Africa. For countries with a moderate policy index score, the estimate is negative and just misses significance at the 5% level. Policy liberalization has been especially pronounced with respect to access and movement domains in the developing world (Blair et al., 2021). In this line, we exploit five dimensions of asylum policies like access, services, livelihoods, movement and participation.²⁷ The IV estimates in columns (3) to (5) show statistically significant negative coefficients for the refugee index. In countries with high access, we detect a highly significant increase in the economic growth. When it comes to services (columns (7) through (9)), the effect on the refugee index has been mixed except for low score countries for which we see no significant effects.

27. These policy dimensions, including rights to work and own property, citizenship rights, and rights to political participation are critical for refugee integration, but are also politically sensitive, often sparking native opposition (Blair et al., 2021 ; Gathmann and Keller, 2017).

With respect to access to refugees' livelihoods (property, land, employment), we see, in countries with a moderate score, a rise in the economic activity of 0.053 percentage point. As to restrictions on movement, a negative and statistically significant effect was detected only for countries with strong access, which is counterintuitive. One possible explanation is that, as shown in column (2) of Table 3.9, if countries with no movement restrictions on refugees are in the low-income group, the negative effect may be justified. However, further checks, such as a principal component analysis (PCA) combining both absorption capacity and asylum policies, are needed to better explain these mechanisms.²⁸ Finally, the estimation reported in column (16) reveals that the effect is negative and significant in countries with a low score on participation (citizens and rights). But no significant effect in countries with a moderate score. One can also, as an additional form of analysis, check interactions with policy measures or the level of development in the host-country. To reinforce our conclusions, in Table 3.11 we report estimation results after having additionally controlled for interaction of our 'Refugee Index and GNI per capita' (column (1)) or policy index (column (2)) and its components (columns (3) through (7)). We confirm that absorption capacity as well as livelihoods are positive and significant pathways through which local economic activity raises in and around the refugee camps. Thus, we can state that heterogeneity in policy components definitely affects the impact of refugees in Africa.

In all tables (except for columns (6) through (8) of Table 3.9), the Kleibergen and Paap (2006) test statistic reveals that the null hypothesis of zero correlation between instruments and endogenous variables can be rejected at conventional levels of significance, suggesting that under-identification is not a problem. The value of the Kleibergen-Paap *rk Wald F* statistic indicates that the null of a weak correlation of instruments and endogenous variables should also be rejected. The IV estimates on the refugee index reported in columns (5)-(8) appear to be similar to the results presented in Table 3.5. The coefficients of refugees are negative, statistically significant, and similar in size, suggesting that the detected effect of refugees on economic growth is not a mere reflection of reverse causality. The results either measure absolute effects or relative effects for certain groups compared to other groups.

28. Restrictions on movement hinder the economic activity of refugees by : (1) preventing them from participating in more lucrative markets, (2) increasing uncertainty for participation in outside markets and (3) increasing the time costs of participating in outside markets (Werker, 2007).

3.5. Discussion and Conclusion

Using data from numerous sources, we examined the impact of refugees on local economic growth rates in Africa. Employing both standard OLS and IV methods, with or without covariates, we found that refugee inflows have, on average, a robustly significant negative impact on economic activity, close to zero. Next, we empirically evaluated the various channels through which forced displacement people might affect local economic activity in host communities in Africa, focusing mostly on the role of the host country's absorption capacity and asylum policies towards refugees. Results reveal that there is a lot of heterogeneity between countries depending on their characteristics (absorption capacity and asylum policy dimensions, see Table 3.12 for more details).²⁹ In middle-income countries, or countries that have moderate access laws (i.e., accepting asylum-seekers, applying no penalty for unlawful entry, extending status to family) or moderate livelihood laws (access to property, land and employment), economic growth rose between 2000 and 2016. The net effect on economic activity is not obvious when we consider subregions of African countries (Table 3.4).

Our approach offers a robust identification of the impact of refugees on night lights (Tables 3.5 through 3.7). Our methodology, based on difference-in-difference estimations or quasi-experiments, is able to eliminate several confounding factors and address endogeneity issues. The results strongly support the theoretical analysis suggesting that refugee inflows may have negative effects on host communities (Maystadt et al., 2019 ; Verme and Schuettler, 2021). Furthermore, they support the theoretical analysis indicating that asylum policies, as well as absorption capacity, determine the sign and magnitude of the relationship between refugees and economic growth. On the other hand, our results seem to be in contrast to the findings of Alix-Garcia et al. (2018), Alix-Garcia and Saah (2009), Loschmann et al. (2019) and d'Errico et al. (2022) who found that there are benefits for local citizens from living near refugee camps. However, their conclusions are based on the analysis of only one country (Kenya, Tanzania, Rwanda, and Uganda respectively), or in most cases one refugee camp.

29. Economic inclusion refers to refugees' legal right to work as well as their actual ability to access and participate in the labor market (Center for Global Development, 2022).

These findings have important policy implications. Refugee economic outcomes are influenced by the institutional environment which itself is determined by host-country refugee policies and absorption capacity. To make the presence of refugees more beneficial, policies that improve the refugees' freedom to work and move, increase the returns on investment, lessen the risk of expropriation, extend the size of the market and reduce bureaucratic costs and delays should be implemented by governments and their partners. Decreasing the barriers to entry and exit of people and goods, or lobbying for new camps to be placed nearer to urban centers should, in most situations, result in an institutional environment more conducive to economic prosperity in Africa. Refugee-hosting countries should ensure that domestic laws grant refugees the right to work and freedom of movement, and that these rights are upheld in practice. Refugees should be included as constituents in work rights policy-making and accountability mechanisms, as suggested by the Center for Global Development (2022). In this regard, Aksoy and Ginn (2022) found no evidence that host communities pay an economic penalty or experience social or political backlash in response to increased refugee economic inclusion. Numerous other papers reveal a positive economic effect of increased integration of refugees (Alix-Garcia et al., 2018 ; Laurence et al., 2019 ; Sanghi et al., 2016). Further research needs an interdisciplinary approach to help understand the mechanisms through which the influx of forced migrants determines impacts on outcomes. Microeconomists could explore whether and how absorption capacity or asylum policies have played a part in this process. One could especially investigate the impact of access to the labor market outside the camps, as illegal immigrants are often excluded from many jobs.³⁰ Other channels, such as acceptance towards refugees by citizens of the host country or informal practices of discrimination deserve to be evaluated in future research.

At the same time, our results also highlight the limitations of the refugee effects on night lights as a proxy for economic activity. Although NTL has been used extensively in the literature, as a substitute for economic activity, some caveat about the limitations of this data is worth mentioning. Even though they do not bias the estimations, nighttime light intensity measures using DMSP-OLS data have their limitations (see Elvidge et al. (2007)), as discussed in Section 3.3. For instance, brightness in urban centers is saturated

30. These policies include the mobility of forced migrants as well as the general business and investment climate.

at 63 with an excess illumination across surrounding pixels and heterogeneity in brightness levels depending on the various economic activities. Furthermore, NTL data is not intercalibrated across time or satellites. To overcome these issues, we follow Henderson et al. (2012), Storeygard (2016) and Joseph (2022) and control for year fixed effects in all specifications. Nevertheless, our paper addresses the central question of endogeneity and unobserved heterogeneity. Finally, we consider a lower-resolution 0.25×0.25 degree grid in Table 3.7 given that night light data have a higher predictive power for subnational Gross Domestic Products (GDP) when working with more aggregated spatial units (Gibson and Boe-Gibson, 2021 ; Gibson et al., 2021). Furthermore, luminosity data do not allow for reliable estimates of low-output-density regions for countries with the worst statistical systems (Chen and Nordhaus, 2011).

In conclusion, we show that refugee camps have an average negative effect close to zero and that this effect varies across host country groups to the extent that these groups differ in terms of immigration policies and absorption capacity. Therefore, our results provide additional empirical evidence in support of refugee-hosting countries and donors that would turn the presence of refugees into a developmental opportunity. In doing so, this paper partly reconciles the results from previous literature by emphasizing the role of absorption capacity and economic inclusion in determining the nature of the relationship between refugee camps and local economic activity. Future research could analyze the extent to which the economic integration of refugees would increase the incomes of surrounding host communities. It could also help to pinpoint when displaced people living in camps are finally counted as part of the local population and can actually contribute to the development of their communities.

Author Contributions :

Iverson-Love Joseph : conceptualization and methodology, literature review, data curation, graphics, remote sensing and GIS analysis, statistical and econometric analysis, paper writing. Olivier Dagnelie : conceptualization, methodology, validation, editing. Jean-François Maystadt : conceptualization and methodology, literature review, validation, editing.

3.6. Appendix A : Descriptive Statistics

Table 3.3 – Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Max
Night Lights	1650152	0.24	2.38	0.00	63.00
Night Lights (IHS)	1650152	0.07	0.40	0.00	4.84
Refugee Index, 150km	1650152	18.33	217.14	0.00	60448.32
Refugee Index (IHS, 150km)	1650152	0.35	1.30	0.00	11.70
Temperature anomaly	1648197	0.96	0.30	-0.34	2.57
Precipitation anomaly	1650152	0.01	0.94	-3.49	4.30
Number of conflicts (IHS, 150km)	1650152	0.61	1.13	0.00	6.15
Distance-weighted-conflic (150km)	1650152	0.03	0.12	0.00	5.52
Distance-weighted-conflict IV (IHS)	1650152	7.17	4.54	0.00	18.42
Distance to the cell	1650152	10.17	31.94	0.00	150.00
Distance to conflict event	1650152	24.67	43.62	0.00	150.00
Number of treated cells	1650152	0.11	0.31	0.00	1.00
Number of UNHCR camp locations	417	-	-	-	-
Number of gridded countries	46	-	-	-	-

Note : IHS : Inverse Hyperbolic Sine transformation ; IV : Instrumental Variable.

Table 3.4 – Night Lights and Refugees in Africa, 2000–2016 : OLS and 2SLS estimates, showing all control variables

<i>Dependent variable : DMSP-OLS Nighttime Lights</i>								
	OLS estimates				2SLS second stage estimates			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Refugees Index (IHS, 150km)	-0.00091 (0.00008)***	-0.00032 (0.00007)***	-0.00084 (0.00008)***	-0.00025 (0.00007)***	-0.00802 (0.00152)***	-0.00506 (0.00164)***	-0.00733 (0.00150)***	-0.00433 (0.00162)***
Temperature anomaly			0.00024 (0.00056)	0.00119 (0.00048)**			-0.00050 (0.00060)	-0.00005 (0.00058)
Precipitation anomaly			-0.00167 (0.00012)***	-0.00108 (0.00011)***			-0.00147 (0.00012)***	-0.00143 (0.00012)***
Distance-weighted-conflict (IHS)			-0.00618 (0.00168)***	-0.00937 (0.00176)***			-0.00197 (0.00196)	-0.00469 (0.00197)**
Observations	1,650,152	1,650,152	1,648,197	1,648,197	1,650,152	1,650,152	1,648,197	1,648,197
Root MSE	0.111	0.110	0.111	0.110	0.108	0.108	0.108	0.108
Kleibergen-Paap rk Wald F					5890	4659	5910	4742
<i>Dependent variable : Number of refugees</i>								
					2SLS first stage estimates			
Distance-conflict-weighted (IHS, 150km)					0.03260 (0.00042)***	0.00981 (0.00042)***	0.03302 (0.00043)***	0.01037 (0.00042)***
Observations					1,650,152	1,650,152	1,648,197	1,648,197
Root MSE					1.194	1.174	1.191	1.172

Notes : All regressions include cell and year fixed effects. Values of robust standard errors clustered at the cell level appear in parenthesis. The outcome variable is the *Inverse Hyperbolic Sine* of the DMS-OLS luminosity index. Columns (3)-(4) and (5)-(6) include conflict, temperature, and rainfall as explanatory variables. ***, ** and * denote significance at 1, 5 and 10 percent levels respectively.

3.7. Appendix B : Tables of the Sensitivity Analysis

Table 3.5 – Sensitivity analysis

Dependent Variable	Number of Refugees				Nighttime Lights			
	2SLS first stage estimates				2SLS second stage estimates			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Distance-conflict-weighted IV, $\alpha = 2$								
Distance-conflict-weighted (IHS)	0.06280 (0.00073)***	0.02879 (0.00073)***	0.06192 (0.00074)***	0.02785 (0.00073)***				
Refugees Index (IHS, 150km)					-0.01034 (0.00125)***	-0.00760 (0.00130)***	-0.00976 (0.00128)***	-0.00688 (0.00133)***
Observations	1,650,152	1,650,152	1,648,197	1,648,197	1,650,152	1,650,152	1,648,197	1,648,197
Root MSE	1.192	1.173	1.190	1.172	0.108	0.108	0.108	0.108
Kleibergen-Paap rk Wald F					7402	6443	6941	6058
B. Distance-conflict-weighted IV, $\alpha = 0.5$								
Distance-conflict-weighted (IHS)	0.02790 (0.00037)***	0.00902 (0.00036)***	0.02840 (0.00037)***	0.00972 (0.00036)***				
Refugees Index (IHS, 150km)					-0.00880 (0.00157)***	-0.00630 (0.00172)***	-0.00807 (0.00154)***	-0.00554 (0.00168)***
Observations	1,650,152	1,650,152	1,648,197	1,648,197	1,650,152	1,650,152	1,648,197	1,648,197
Root MSE	1.194	1.174	1.192	1.172	0.108	0.108	0.108	0.108
Kleibergen-Paap rk Wald F					5805	4538	5958	4740
C. Distance-conflict-weighted IV and lagged IV								
Distance-conflict-weighted (IHS)	0.01885 (0.00045)***	0.00915 (0.00046)***	0.01988 (0.00045)***	0.01014 (0.00046)***				
Distance-conflict-weighted (IHS, t-1)	0.02057	0.00387	0.02093	0.00407				

Table 3.5 (Continued) Sensitivity analysis

	(0.00042)***	(0.00039)***	(0.00042)***	(0.00040)***				
Refugees Index (IHS, 150km)					-0.01114	-0.00888	-0.01035	-0.00814
					(0.00165)***	(0.00177)***	(0.00160)***	(0.00172)***
Observations	1,553,082	1,553,082	1,551,242	1,551,242	1,553,082	1,553,082	1,551,242	1,551,242
Root MSE	1.181	1.160	1.180	1.159	0.108	0.107	0.108	0.107
Kleibergen-Paap rk Wald F					3368	2808	3470	2933
D. Distance-conflict-weighted IV (Conflict_{t-1})								
Distance-weighted (IHS)	0.03545	0.01298	0.03664	0.01395				
	(0.00044)***	(0.00046)***	(0.00044)***	(0.00045)***				
Refugees Index (IHS, 150km)					-0.01081	-0.00846	-0.00999	-0.00772
					(0.00158)***	(0.00167)***	(0.00153)***	(0.00161)***
Observations	1,553,084	1,553,084	1,551,244	1,551,244	1,553,084	1,553,084	1,551,244	1,551,244
Root MSE	1.181	1.160	1.180	1.159	0.108	0.107	0.108	0.107
Kleibergen-Paap rk Wald F					6590	5512	6862	5820
E. Control for Conflict spillovers								
Refugees Index (IHS, 150km)					-0.12734	-0.06806	-0.11443	-0.05677
					(0.02685)***	(0.02548)***	(0.02604)***	(0.02469)**
Distance-conflict-weighted (IHS)	0.00185	0.00169	0.00190	0.00173				
	(0.00009)***	(0.00010)***	(0.00009)***	(0.00010)***				
Conflict spillovers	1.52257	1.52184	1.52264	1.52188	0.19259	0.10249	0.17305	0.08541
	(0.00077)***	(0.00076)***	(0.00077)***	(0.00076)***	(0.04086)***	(0.03877)***	(0.03963)***	(0.03758)**
Observations	1,650,152	1,650,152	1,648,197	1,648,197	1,650,152	1,650,152	1,648,197	1,648,197
Root MSE	0.256	0.254	0.256	0.254	0.112	0.109	0.111	0.108

Table 3.5 (Continued) Sensitivity analysis

Kleibergen-Paap rk Wald F					452.1	437.8	471.6	462.3
F. Control for Refugee spillovers								
Distance-conflict-weighted (IHS)	0.03208	0.00971	0.03290	0.01039				
	(0.00043)***	(0.00042)***	(0.00043)***	(0.00042)***				
Refugees Index (IHS, 150km)					-0.00782	-0.00478	-0.00746	-0.00443
					(0.00154)***	(0.00167)***	(0.00150)***	(0.00163)***
Refugee spillovers	2.41740	1.68962	-4.98518	-3.76987	-0.03146	-0.04346	-0.16781	-0.15366
	(0.11988)***	(0.09986)***	(0.45461)***	(0.35984)***	(0.01098)***	(0.01096)***	(0.02878)***	(0.02875)***
Observations	1,650,152	1,650,152	1,648,197	1,648,197	1,650,152	1,650,152	1,648,197	1,648,197
Root MSE	1.193	1.173	1.191	1.172	0.108	0.108	0.108	0.108
Kleibergen-Paap rk Wald F					5683	4511	5879	4720
G. Excluding 3 camps with incorrect destination country								
Distance-conflict-weighted (IHS)	0.03649	0.01445	0.03780	0.01549				
	(0.00044)***	(0.00046)***	(0.00044)***	(0.00046)***				
Refugees Index (IHS, 150km)					-0.00986	-0.00745	-0.00905	-0.00673
					(0.00155)***	(0.00163)***	(0.00150)***	(0.00157)***
Observations	1,532,956	1,532,956	1,531,116	1,531,116	1,532,956	1,532,956	1,531,116	1,531,116
Root MSE	1.182	1.163	1.180	1.161	0.108	0.108	0.108	0.108
Kleibergen-Paap rk Wald F					6916	5840	7230	6189
H. Alternative treatment variables (including refugee squared term)								
Distance-conflict-weighted (IHS)	-0.00051	-0.00512	0.00031	-0.00459				
	(0.00036)	(0.00038)***	(0.00036)	(0.00038)***				

Table 3.5 (Continued) Sensitivity analysis

Square Distance-conflict-weighted	0.02477 (0.00064)***	0.02258 (0.00067)***	0.02376 (0.00065)***	0.02198 (0.00067)***				
Refugees Index (IHS, 150km)					-0.21544 (0.10734)**	-0.21183 (0.11597)*	-0.15909 (0.06459)**	-0.13606 (0.05840)**
Square Refugees Index					0.79883 (0.41761)*	0.81548 (0.46290)*	0.58753 (0.25344)**	0.52231 (0.23571)**
Observations	1,650,152	1,650,152	1,648,197	1,648,197	1,650,152	1,650,152	1,648,197	1,648,197
Root MSE	0.696	0.691	0.696	0.691	0.212	0.215	0.172	0.161
Kleibergen-Paap rk Wald F					3.081	2.512	6.034	6.116

Notes : All regressions include cell and year fixed effects. Standard errors are clustered at the cell level. Columns (3)-(4) and (7)-(8) include conflict, temperature, and rainfall as explanatory variables and country-specific trends as additional controls. The weight matrix is a first order Queen contiguity matrix. ***, ** and * denote significance at 1, 5 and 10 percent levels respectively.

Table 3.6 – Refugee effects from main specification : OLS and 2SLS estimates

	Dependent Variable : Nighttime Lights			
	OLS estimates		2SLS second stage estimates	
	(1)	(2)	(3)	(4)
Refugees Index (IHS, 150km)	-0.00091	-0.00084	-0.00802	-0.00733
(Clustered SE)	(0.00008)***	(0.00008)***	(0.00152)***	(0.00150)***
(Conley-25km)	(0.00012)***	(0.00012)***	(0.00203)***	(0.00202)***
(Conley-50km)	(0.00018)***	(0.00018)***	(0.00292)***	(0.00290)**
(Conley-100km)	0.00026)***	(0.00026)***	(0.00419)*	(0.00417)*
Observations	1,650,152	1,648,197	1,650,152	1,648,197
Root MSE	0.111	0.111	0.108	0.108
Kleibergen-Paap rk Wald F			5890	5910

Notes : All regressions include cell and year fixed effects. Columns (1), (2), (3), and (4) replicate columns (1), (3), (4), and (7) of Table 3.2, respectively. Standard errors are clustered at the cell level. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 25, 50, and 100 km radius and for serial correlation up to 2 years. The outcome variable is the *Inverse Hyperbolic Sine* of the DMS-OLS luminosity index. Columns (3) and (4) include conflict, temperature, and rainfall as explanatory variables as additional controls. ***, ** and * denote significance at 1, 5 and 10 percent levels respectively.

Table 3.7 – Night Lights and Refugees in Africa : OLS and 2SLS estimates using 0.25×0.25 degree-cells and accounting for spatial and temporal correlations

	Dependent variable : DMSP-OLS Nighttime Lights							
	OLS estimates				2SLS second stage estimates			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Refugees	-0.00130	-0.00058	-0.00119	-0.00049	-0.01544	-0.01413	-0.01413	-0.01243
(Clustered SE)	(0.00020)***	(0.00018)***	(0.00020)***	(0.00018)***	(0.00389)***	(0.00433)***	(0.00428)***	(0.00481)***
(Conley-25km)	(0.00020)***	(0.00018)***	(0.00020)***	(0.00018)***	(0.00393)***		(0.00433)***	
(Conley-50km)	(0.00025)***	(0.00023)**	(0.00025)***	(0.00023)**	(0.00462)***		(0.00508)***	
(Conley-100km)	(0.00032)***	(0.00030)*	(0.00032)***	(0.00030)*	(0.00586)***		(0.00642)**	
Observations	198,764	198,764	198,407	198,407	198,764	198,764	198,407	198,407
Root MSE	0.0966	0.0955	0.0966	0.0955	0.0952	0.0947	0.0950	0.0944
Controls			✓	✓			✓	✓
Country-specific time trend		✓		✓		✓		✓
Kleibergen-Paap rk Wald F					795.5	635.9	654.8	516.3

Notes : This analysis is based on sub-national observation units in the form of cells of approximately 27.5×27.5 kilometers at the equator. All regressions include cell and year fixed effects. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 25, 50, and 100 km radius and for infinite serial correlation. The outcome variable is the *Inverse Hyperbolic Sine* of the DMS-OLS luminosity index. Columns (3)-(4) and (5)-(6) include conflict, temperature, and rainfall as explanatory variables. ***, ** and * denote significance at 1, 5 and 10 percent levels respectively.

Table 3.8 – Heterogeneous effects by host-country absorption capacity

	Income classification								
	Working populaton								
	All			Male			Female		
	Low	Lower-middle	Upper-middle	Low	Lower-middle	Upper-middle	Low	Lower-middle	Upper-middle
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
Refugees	-0.00339	0.03874	0.02064	-0.00796	-0.16216	0.03065	-0.00724	-0.15983	0.03732
	(0.00161)**	(0.01063)***	(0.01508)	(0.00380)**	(0.04571)***	(0.02240)	(0.00345)**	(0.04500)***	(0.02729)
Observations	1,492,647	86,513	21,165	1,492,647	86,513	21,165	1,492,647	86,513	21,165
Kleibergen-Paap rk Wald F	4768	896.7	532.2	2024	273.7	529.5	2232	288.3	519.1
Root MSE	0.105	0.119	0.175	0.105	0.149	0.175	0.105	0.147	0.175

Notes : Djibouti, Eritrea, Libya, Somalia, South Sudan and Western Sahara were not included in the estimates as data on GNI per capita in 2000 are not available. All regressions include temperature, and rainfall as explanatory variables and cell and year fixed effects. Standard errors are clustered at the cell level. ***, ** and * denote significance at 1, 5 and 10 percent levels respectively.

Table 3.9 – Heterogeneous effects by Regions Of Africa and selected countries

	Region of Africa					Selected countries			
	Eastern (1)	Middle (2)	Northern (3)	Southern (4)	Western (5)	Kenya (6)	Rwanda (7)	Tanzania (8)	Uganda (9)
Refugees	-0.01859 (0.00714)***	0.00740 (0.00281)***	-0.04072 (0.00322)***	-0.01384 (0.01347)	-0.12701 (0.01346)***	-0.07763 (0.17420)	-0.10138 (0.35455)	0.00887 (0.01968)	0.00300 (0.06222)
Observations	455,464	512,104	216,325	48,178	416,126	23,824	4,544	52,672	30,656
Kleibergen-Paap rk Wald F	129.4	826.3	5959	711.9	276.8	0.298	0.915	6.703	2.090
Root MSE	0.0895	0.0846	0.134	0.150	0.191	0.0844	0.223	0.0739	0.0792

Notes : All regressions include temperature, and rainfall as explanatory variables and cell and year fixed effects. Standard errors are clustered at the cell level. ***, ** and * denote significance at 1, 5 and 10 percent levels respectively.

Table 3.10 – Heterogeneous effects by Refugee Policy in Africa

	Policy Index		Access				Services		
	Low (1)	Moderate (2)	Low (3)	Moderate (4)	Strong (5)	High (6)	Low (7)	Moderate (8)	Strong (9)
Refugees	-0.00727 (0.00224)***	-0.00750 (0.00422)*	-0.00409 (0.00189)**	-0.11187 (0.02958)***	-0.01793 (0.00432)***	0.06625 (0.01333)***	0.00245 (0.00191)	0.16830 (0.02384)***	-0.12640 (0.01523)***
Observations	1,229,861	418,336	959,680	285,379	288,677	114,461	1,131,618	483,514	33,065
Kleibergen-Paap rk Wald F	2347	1108	2698	37.75	1837	131.4	3788	88.17	175.3
Root MSE	0.0937	0.141	0.0829	0.162	0.146	0.159	0.0973	0.209	0.163
	Livelihoods		Movement			Participation			
	Low (10)	Moderate (11)	Low (12)	Moderate (13)	Strong (14)	High (15)	Low (16)	Moderate (17)	
Refugees	-0.00128 (0.00144)	0.05259 (0.00520)***	-0.01492 (0.00227)***	0.00253 (0.00240)	-0.03487 (0.00428)***	-0.00062 (0.00599)	-0.00503 (0.00169)***	0.00619 (0.00594)	
Observations	1,331,198	316,999	246,666	784,159	477,581	139,791	1,592,233	55,964	
Kleibergen-Paap rk Wald F	6255	1252	3059	2640	1210	193	4405	263.2	
Root MSE	0.100	0.141	0.0899	0.0941	0.143	0.0816	0.109	0.0734	

Notes : All regressions include temperature, and rainfall as explanatory variables and cell and year fixed effects. Standard errors are clustered at the cell level. ***, ** and * denote significance at 1, 5 and 10 percent levels respectively.

Table 3.11 – Refugees and Night Lights, controlling for GNI per capita and Asylum policy in Africa

	Asylum Policy in Africa						
	GNI per capita	Policy Index	Access Index	Services Index	Livelihoods Index	Movement Index	Participation Index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Refugees	0.00567 (0.00210)***	-0.00654 (0.00186)***	-0.01139 (0.00198)***	-0.00050 (0.00158)	0.01433 (0.00135)***	-0.00717 (0.00162)***	-0.00726 (0.00165)***
Refugees × Index score	-0.00003 (0.00001)***	0.01924 (0.01400)	0.03504 (0.00882)***	-0.04866 (0.00722)***	-0.24939 (0.02275)***	0.00844 (0.00257)***	0.09593 (0.01286)***
Observations	1,600,325	1,648,197	1,648,197	1,648,197	1,648,197	1,648,197	1,648,197
Kleibergen-Paap rk Wald F	172	690.2	427.2	1111	391	1360	2328
Root MSE	0.107	0.108	0.108	0.108	0.114	0.108	0.108

Notes : Djibouti, Eritrea, Libya, Somalia, South Sudan and Western Sahara were not included in the estimates as data on GNI per capita in 2000 are not available. All regressions include temperature, and rainfall as explanatory variables and cell and year fixed effects. Standard errors are clustered at the cell level. ***, ** and * denote significance at 1, 5 and 10 percent levels respectively.

3.8. Appendix C : Countries' List

Table 3.12 – World Bank country classifications by income level, and Blair et al. (2021) refugee policy index in 2000

Sample of Low-Middle Income			Policy Index score		Access Index score				Service Index score			Livelihoods Index score		Movement Index score			Participation Index score		
Low Income	Low-Middle Income	Upper-Middle Income	Low	Moderate	Low	Moderate	Strong	High	Low	Moderate	Strong	Low	Moderate	Low	Moderate	Strong	High	Low	Moderate
Angola	Algeria	Botswana	Benin	Algeria	Benin	Burkina Faso	Algeria	Ghana	Benin	Algeria	Senegal	Algeria	Angola	Botswana	Congo	Algeria	Burkina Faso	Algeria	United Rep. of Tanzania
Benin	Egypt	South Africa	Botswana	Angola	Botswana	Cameroon	Angola	Liberia	Botswana	Algeria	Angola	Benin	Guinea	Central African Rep.	Cote D'Ivoire	Algeria	Ethiopia	Angola	
Burkina Faso	Gabon		Cameroon	Burkina Faso	Central African Rep.	Congo	Burundi	Mozambique	Cameroon	Burkina Faso		Botswana	Mali	Chad	Dem. Rep. of the Congo	Benin	Gabon	Benin	
Burundi	Morocco		Central African Rep.	Burundi	Chad	Cote D'Ivoire	Egypt	Namibia	Central African Rep.	Burundi	Burkina Faso	Namibia	Guinea-Bissau	Djibouti	Burundi	Togo	Botswana		
Cameroon	Namibia		Chad	Egypt	Dem. Rep. of the Congo	Lilya	Gabon	Togo	Chad	Gabon	Burundi	Niger	Lilya	Gambia	Cameroon	Burkina Faso			
Central African Rep.	Swaziland		Congo	Gabon	Djibouti	Niger	Guinea		Congo	Ghana	Cameroon	Nigeria	Sierra Leone	Guinea	Egypt	Burundi			
Chad			Cote D'Ivoire	Ghana	Eritrea	Rwanda	Malawi		Cote D'Ivoire	Guinea		Central African Rep.	South Africa	Somalia	Kenya	Eritrea			
Congo			Dem. Rep. of the Congo	Liberia	Ethiopia	South Africa	Morocco		Dem. Rep. of the Congo	Mali		Chad	Zimbabwe	Swaziland	Malawi	Ghana	Central African Rep.		
Cote D'Ivoire			Djibouti	Morocco	Gambia	United Rep. of Tanzania	Nigeria		Djibouti	Morocco		Congo		Uganda	Mauritania	Liberia	Chad		
Dem. Rep. of the Congo			Eritrea	Namibia	Guinea-Bissau		Senegal		Egypt	Namibia		Cote D'Ivoire		Western Sahara	Namibia	Mali	Congo		
Eritrea			Ethiopia	Nigeria	Kenya		Zimbabwe		Eritrea	Niger		Dem. Rep. of the Congo			Niger	Morocco	Cote D'Ivoire		
Ethiopia			Gambia	Senegal	Mali				Ethiopia	Nigeria		Djibouti			Rwanda	Mozambique	Dem. Rep. of the Congo		
Gambia			Guinea	Togo	Mauritania				Gambia	Togo		Egypt			South Sudan	Nigeria	Djibouti		
Ghana			Guinea-Bissau	United Rep. of Tanzania	Sierra Leone				Guinea-Bissau	United Rep. of Tanzania		Eritrea			Sudan	Senegal	Egypt		
Guinea			Kenya	Zimbabwe	Somalia				Kenya	Zimbabwe		Ethiopia			United Rep. of Tanzania	South Africa	Eritrea		
Guinea-Bissau			Libya		Sudan				Liberia			Gabon			Zambia		Ethiopia		
Kenya			Malawi		Sudan				Libya			Gambia			Zimbabwe		Gabon		
Malawi			Mali		Swaziland				Malawi			Ghana					Gambia		
Mali			Mauritania		Uganda				Mauritania			Guinea-Bissau					Ghana		
Mauritania			Mozambique		Western Sahara				Mozambique			Kenya					Guinea		
Mozambique			Niger		Zambia				Rwanda			Liberia					Guinea-Bissau		
Niger			Rwanda						Sierra Leone			Libya					Kenya		
Nigeria			Sierra Leone						Somalia			Malawi					Liberia		
Rwanda			Somalia						South Africa			Mauritania					Libya		
Senegal			South Africa						South Sudan			Morocco					Malawi		
Sierra Leone			South Sudan						Sudan			Mozambique					Mali		
South Sudan			Sudan						Swaziland			Rwanda					Mauritania		
Sudan			Swaziland						Uganda			Senegal					Morocco		
Togo			Uganda						Western Sahara			Sierra Leone					Mozambique		
Uganda			Western Sahara						Zambia			Somalia					Namibia		
United Rep. of Tanzania			Zambia									South Sudan					Niger		
Zambia												Sudan					Nigeria		
Zimbabwe												Swaziland					Rwanda		
												Togo					Senegal		
												Uganda					Sierra Leone		
												United Rep. of Tanzania					Somalia		
												Western Sahara					South Africa		
												Zambia					South Sudan		
																	Sudan		
																	Swaziland		
																	Togo		
																	Uganda		
																	Western Sahara		
																	Zambia		
																	Zimbabwe		

3.9. Appendix D : Data Sources

Data Availability Statement : The DMSP stable lights annual composites are available at <http://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html>., accessed on 2 October 2020. The annual DMSP Nighttime Lights Extension data used in this study are available for download from the Earth Observation Group of the Colorado School of Mines at <https://eogdata.mines.edu/dmsp/downloadV4composites.html>, accessed on 30 April 2021. Data on climate come from Berkeley Earth and are available on <http://berkeleyearth.org/data/>, accessed on 21 October 2021 and precipitation data from Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) can be downloaded from <https://www.chc.ucsb.edu/data/chirps>. Conflict event data is taken from the Georeferenced Event Dataset, provided by the Uppsala Conflict Data Program (UCDP) available at <https://ucdp.uu.se/downloads/>. Accessed on 21 October 2021. The geo-referenced data on 810 refugee camps in Africa and their number of residents are provided by the United Nations High Commissioner for Refugees (UNHCR) over the period of 2000–2016. Time-series population statistics on the number of refugees in a destination country in a given year from a particular origin country also come from UNHCR. We created a replication dataset and code appendix that will be made available.

✧ Conclusion Générale ✧

L'objectif de cette thèse était d'analyser, de manière quantitative les conséquences démographiques et économiques du tremblement de terre de 2010 en Haïti ainsi que l'impact des camps de réfugiés sur l'activité économique locale en Afrique. Avec le réchauffement climatique qui semble augmenter la fréquence et la force des catastrophes liées au climat et la multiplication de leurs conséquences sociales, démographiques, et économiques, la capacité à modéliser, analyser et évaluer leurs répercussions sur des paramètres de la vie réelle déterminant comment les pays touchés peuvent se redresser suite à ces chocs négatifs est plus importante que jamais. Plus loin, avec l'accroissement du nombre de personnes déplacées de force dans le monde en raison de ces dérèglements, des violences et des conflits, examiner empiriquement l'impact des réfugiés sur la croissance économique est une contribution importante à la littérature.

Dans le **premier chapitre** nous avons analysé la dynamique démographique à la suite du séisme en se basant sur trois paramètres clés tels que la fertilité, les mortalités néonatale et infantile. Les résultats de cette recherche peuvent être résumés en deux principales contributions. Premièrement, ce chapitre éclaire notre compréhension de l'évolution des processus démographiques dans le pays en construisant une base de données mensuelle de 2005 à 2015 et en tenant compte de la migration interne. Ensuite, elle contribue à la littérature sur les effets démographiques des catastrophes naturelles en évaluant les conséquences du séisme à très court terme (1 à 27 mois après). Nous constatons que le tremblement de terre a augmenté les taux de natalité et mortalité infantiles dans les camps de déplacés. Il est bien documenté que la mortalité néonatale et infantile est un facteur du sous-développement. Étant donné que le tremblement de terre a entraîné la destruction massive des infrastructures et le cadre de vie de la population des zones fortement touchées, la mise en place des politiques de gestion post-catastrophes, la construction des infrastructures sociales, sanitaires, économiques durables et la lutte contre la mortalité néonatale et infantile devraient être une priorité absolue du gouvernement et des agences

de développement internationales.

Dans le **Chapitre II**, nous avons analysé les conséquences du séisme sur la croissance et le redressement économique. La contribution principale de ce travail est l'utilisation des lumières de nuit comme une approximation de l'activité économique dans les endroits où d'autres données ne sont pas disponibles afin d'évaluer les conséquences du tremblement de terre en combinant un modèle de différences de différences à effets fixes et un modèle de panel dynamique. Ce chapitre a démontré que l'effet négatif moyen observé persiste plus de dix ans après la catastrophe. Il contient une discussion approfondie sur les mesures à mettre en place pour relancer la croissance économique et promouvoir un développement local, équitable et durable à travers des investissements productifs à long terme. Les résultats montrent également la nécessité de mettre en œuvre des politiques publiques de reconstruction adaptées aux réalités locales par les États touchés et les organisations internationales afin d'améliorer le bien-être des populations affectées, particulièrement dans les pays en développement. Des recommandations pratiques pour le ciblage des aides et pour le redressement économique du pays ont été formulées. Plus généralement, le pays est situé dans une zone où le risque sismique, climatique (cyclone/inondation, sécheresse), sanitaire est élevé, d'autres recommandations visant à réduire la vulnérabilité du pays aux catastrophes naturelles, augmenter l'efficacité des aides à la reconstruction et au développement, et améliorer les conditions de vie de la population ont été discutées et suggérées.

Contrairement aux chapitres précédents, le **troisième chapitre** était consacré à l'évaluation de l'impact des camps de réfugiés dans les communautés d'accueil en Afrique. Dans ce dernier, nous offrons une perspective plus large de l'impact économique des réfugiés, à l'opposé de la littérature antérieure sur cette question, qui se focalise généralement sur un seul pays ou un seul camp de réfugiés en raison de la non disponibilité des données. Ce travail aide à comprendre les conditions dans lesquelles les réfugiés contribuent au développement économique des pays qui les accueillent. Les analyses empiriques révèlent que la présence des réfugiés dans les camps de déplacés est associée à une baisse de la croissance économique locale – négligeable d'un point de vue économique. Les résultats indiquent que les décideurs politiques doivent mettre en œuvre des politiques favorisant l'intégration économique des réfugiés afin qu'ils puissent participer pleinement au déve-

loppement de leurs communautés. En utilisant les données sur le revenu national brut par tête, en plus de la politique d'asile dans les pays d'accueil, ce chapitre souligne également l'obligation pour les pays en développement qui sont parfois pauvres et qui doivent accueillir des millions de personnes déplacées de force incluant des réfugiés, d'améliorer le niveau de vie de leurs concitoyens et des migrants.

La construction des bases de données désagrégées au niveau infra-national en Haïti, et en Afrique incluant des données spatiales, et des enquêtes officielles est novatrice et apporte de nouvelles connaissances à la problématique des catastrophes et réfugiés. Cependant, comme toute recherche empirique, cette thèse comporte des limites. Les données sur la migration externe à la suite du séisme n'ont pas été prises en compte dans les estimations empiriques du Chapitre I en raison de l'inexistence de ces informations. Dans le deuxième chapitre, des données spatiales ont été exclusivement utilisées pour pallier l'absence des enquêtes socio-économiques dans le pays après séisme. En ce qui concerne le Chapitre III, les réfugiés dispersés dans les pays d'accueil n'ont pas été intégrés dans l'analyse empirique. Ce choix s'explique cependant par l'inexistence d'une base de données socio-économiques au niveau régional ou national sur les réfugiés dispersés dans les pays d'accueil, et par l'impossibilité d'analyser leurs impacts du fait de leur éparpillement. Malgré ces limites, cette thèse offre de nouvelles connaissances sur les catastrophes naturelles, sur les réfugiés, et ouvre de nouvelles perspectives de recherches.

Par l'étude systématique des différentes dimensions affectées par le séisme de 2010, cette thèse a permis d'améliorer la connaissance scientifique sur Haïti, pays sous-étudié dans le champ de l'économie. Les thématiques étudiées dans cette thèse sont des problématiques actuelles suscitant un intérêt croissant. Dans une perspective de généralisation des résultats du premier chapitre, il serait intéressant d'étendre l'analyse des conséquences démographiques à d'autres paramètres, notamment les accouchements prématurés, l'intervalle entre les naissances, le poids à la naissance des enfants, la mortalité, la morbidité, la migration après le séisme. En ce qui concerne le Chapitre II, il serait aussi intéressant d'examiner les impacts à long terme des cyclones tropicaux, des ouragans et des inondations fluviales sur la croissance économique en Haïti ou dans d'autres régions du monde, et d'apporter des preuves empiriques des canaux de transmission à différents niveaux de

désagrégation administratifs. Pour ce qui du troisième chapitre, afin d'approfondir les résultats, il serait en outre pertinent d'analyser l'impact d'autres mécanismes pouvant influencer sur la baisse ou la hausse d'activité économique locale telle que l'acceptation envers les réfugiés et des pratiques de discrimination dans les pays d'accueil, l'ethnicité des réfugiés, ou la proximité avec les pays d'origine.

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