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CONFLICTS AND NATURAL DISASTERS AS DRIVERS OF FORCED MIGRATIONS IN A GRAVITY-TYPE APPROACH

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Conflicts and natural disasters as drivers of forced migrations in a gravity-type approach[*]

Luca Buzzanca[°], Caterina Conigliani [×], Valeria Costantini [◊]

Abstract

The literature identifies three main drivers for forced migration, namely conflict, food insecurity, and natural and man-made disasters, although finds no empirical consensus on the association between climate change and migrations. Aim of this study is to identify the different push and pull factors of forced migration in different regions of the world by means of gravity-type models. Particular attention is devoted to determining the effects of climatic factors and conflicts, while controlling for the economic, political and social relationship between the origin and the destination countries. We model both total forced migration, that includes refugees, asylum seekers, internal displacements, and returnees, and cross-border forced migrations. Finally, we consider a full panel data analysis and estimate both fixed effects and random effects model specifications.

Keywords: Forced migration; IDPs; Conflicts; Natural disasters; Climate change; Gravity models

JEL classification: C230, D740, F220, O150, Q540

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1. Introduction

According to the International Organization for Migration (IOM), forced displacement is the movement of persons who have been forced to flee or leave their habitual residence as a result of armed conflict, situations of generalized violence, violations of human rights, natural or human-made disasters.[1] It includes refugees, asylum seekers, and internally displaced persons (IDPs). Refugees, in particular, are persons who, owing to a well-founded fear of persecution for reasons of race, religion, nationality, membership of a particular social group or political opinion, are outside the country of their nationality and are unwilling to avail of the protection of that country; they are defined and protected under international law by the 1951 United Nations Refugee Convention. Instead, asylum seekers are individuals seeking international protection whose claim has not yet been finally decided on by the host country. Finally, IDPs are persons who have been forced to flee or leave their places of habitual residence who have not crossed an internationally recognized State border, so that they remain under the rule of their government, even if that government is the reason for their displacement.

Notice that between 1990 and 2012 the total number of forced migrants worldwide has remained rather stable, because many displaced people were able to repatriate, built permanent homes in their host communities or relocated in third countries. In the last decade, on the other hand, the situation has changed and the number of refugees, asylum seekers and IDPs has substantially increased. As wars and conflicts continued, refugees and IDPs were not able to return home, host countries started setting limits for the number of refugees that they would accept and started refusing to integrate displaced people.

As of mid-2021, the United Nations High Commissioner for Human Rights (UNHCR) estimated that the number of forcibly displaced people worldwide has surpassed 84 million, of which 50 million were IDPs, 21 million refugees and 4,4 million asylum seekers. In particular, due to the Syrian civil war, Syria had the largest refugee population, with 6,7 million refugees hosted by 126 countries. Turkey was the country that hosted the highest number of Syrian refugees (3,7 million), followed by Lebanon (852.000), Jordan (668.000) and Iraq (246.000); in Europe the main host countries were Germany (616.000) and Sweden (115.000). Syria had also an incredibly high number of IDPs (6,8 million), preceded only by Colombia (8,1 million) and followed by the Democratic Republic of the Congo (5,1 million). Instead, the majority of the asylum seekers were from Venezuela (950.000), Iraq (270.000), Afghanistan (230.000), the main host countries being the United States (1,2 million), Peru (540.000), Turkey (320.000) and Germany (230.000).[2]

[1] International Organization for Migration (IOM). International Migration Law: Glossary on Migration. Available at: https://publications.iom.int/system/files/pdf/iml_34_glossary.pdf

[2] UNHCR. Refugee Data Finder. Available at: https://www.unhcr.org/refugee-statistics/

According to literature there are three main reasons that cause forced migration: conflict, food insecurity, and natural and man-made disasters, that interact with each other in a complex way. In fact, as reported in the International Institute for Strategic Studies (IISS) Armed Conflict Survey 2021, the number of conflicts hit a record high in 2020, with more active conflicts than at any time since 1945, especially due to non-state armed groups. Most of the armed conflicts remain internal, although have become increasingly internationalized, with third party interventions and spillovers to neighboring countries.[3] The civilian-military casualty ratio of contemporary conflicts shows a high variability; in some cases, as Cambodia (1975-1979) or Rwanda (1994), it reached a 9:1 ratio, while in other cases, as the civil war in Sri Lanka (1983-2009), conflict led to the deaths of more combatants than civilians (Roberts, 2010). Notice that clearly not all conflicts result in migration; in fact, the relationship between conflicts and migration can be a reverse one, with conflict being an outcome of migration due to competition over natural and economic resources, ethnic and socioeconomic tensions, burden on infrastructure and services (Reuveny, 2007). In any case the evidence in the literature on the conflict-migration linkage suggests that countries that experience violent conflicts tend to have higher migration flows (Lozano-Gracia et al. 2010); it is also plausible that the influence of conflict on migration is indirect, with conflicts affecting factors like income loss or institutional failure, that in turn induce migration (Coniglio and Pesce, 2015). It is also important to recall that, because many conflicts are fought in rural areas and target productive agricultural assets, often people dependent on agriculture are the most affected by them, and food insecurity turns out to be strongly related to both conflict and migration. Indeed, protracted conflicts can cause both forced migrations and food insecurity, that is driven by sudden food price spikes, dispossession, or loss of agricultural assets. On the other hand, food insecurity can lead to forced migrations, can prevent many who had already migrated to return to their homes, and can increase the likelihood and intensity of armed conflicts. But it is also true that forced migrations and food insecurity may disrupt social cohesion in local communities and fuel conflicts, giving rise to a vicious circle for rural population. Notice that the causal relationships among these factors are never straightforward, and the situation is worsened by the fact that conflicts are often compounded by drought, floods and other climate shocks, that also affect rural food security.[4]

Interestingly, climate related migration is one of the most important topics in the disclosure on global warming and its consequences. Indeed, global warming has effects on precipitation, floods, droughts, wildfires, cyclones, and therefore influences substantially the living condition in the

[3] International Institute for Strategic Studies (2021). Armed Conflict Survey. Available at: https://www.iiss.org/publications/armed-conflict-survey/2021/armed-conflict-survey-2021

[4] FAO-IFPRI (2017). Conflict, migration and food security: the role of agriculture and rural development. Available at: https://ebrary.ifpri.org/utils/getfile/collection/p15738coll2/id/131430/filename/131640.pdf

affected regions. However, although IOM now officially considers climate risk one of the major causes of displacement, to the extent that it includes natural disasters explicitly among the determinant of forced displacement in its definition, the rights of people migrating because of climate change are still an open problem, especially with respect to cross-border moves (Hartmann, 2010; Suar, 2013; Bettini, 2017; Wiegel et al., 2019). One consequence of this lack of official status for climate-related migrants is that many of them are IDPs.

The main aim of this study is to identify the different push and pull factors of forced migration in different regions of the world by means of gravity-type models. We are going to employ bilateral data from UNHCR on forced migrations from four different regions (covering the whole of Africa, the Middle East and South and South-East Asia) with worldwide destinations in the time span 1990-2016. Particular attention is devoted to determining the effects of climatic factors and conflicts, while controlling for the economic, political and social relationship between the origin and the destination countries. We also distinguish between total forced migrations and cross-border forced migrations in order to isolate the role of internal displacements, which in some regions represent more than 50% of total forced migrations. This last point is worth a few considerations. In fact, gravity models are designed to handle bilateral data from an origin location i and a destination location j, typically with $j \neq i$. When we model total forced migrations, on the other hand, in some cases we observe internal displacements, that are forced migration flows that stay within their country ($j = i$). If we were modelling IDPs only, we would clearly not need a bilateral model; but given that we are modelling IDPs as well as refugee and asylum seeker flows, then the estimation of a bilateral model is crucial, and the destination of IDPs is just regarded as one of the many possible destinations that the model takes into account. A similar application of gravity models can be found in Levine (2010) in the context of estimating crime trips between different zones.

Clearly our data set, that will be illustrated in detail in Section 3, includes a large number of zeroes for the response variable, corresponding to all forced migration routes that have not been travelled. This data characteristic involves some difficulties, as the response variable cannot be treated as a continuous variable. In fact, notice that zeroes could be interpreted as flows too small to report, in which case it would be legitimate to drop them from estimation, or they could be seen as generated from meaningful selection, in which case OLS estimation without accounting for selection would be biased (Anderson, 2011). One solution to deal with the zeroes without automatically discarding them could be to estimate the gravity model in a multiplicative form and to apply the Poisson Pseudo Maximum Likelihood (PPML) estimator; this approach has been advocated for instance in Santos Silva and Tenreyro (2006, 2011) in the context of international trade data and has been applied for modelling migration flows in Beine and Parsons (2015). Another possibility could be to estimate a model in two stages: first, we could fit a model for the probability that the migration flow is not zero and then, conditionally on this event, we could fit a model for positive migration flows. The present work falls within this second approach, although involves only the description and estimation of models to predict the intensity of the flow on a migration route, on condition that the route has been travelled. The main reason for this lies in the very nature of forced migrations. In fact, UNHCR data on forced migrations report only official forced displacements, that clearly underestimate the real phenomenon; in this context it is quite likely that the zeroes are not true zeroes, but represent routes that did not lead to asylum applications and for which we have no data. For this reason, rather than trying to understand why forced migrants go to some places and not to others, in what follows we will take the aforementioned conditional approach and will focus on models that can identify the characteristics of the origin, of the destination, of the origin-destination pair that explain why certain routes were travelled by larger flows of forced migrants while other routes had much smaller numbers.

The rest of the paper is organized as follows. We first briefly describe gravity models and their main applications in the literature in Section 2. Section 3 describes the bilateral dataset we have obtained by merging data from different sources. Section 4 presents the model and the main results for total forced migrations and cross-border forced migrations. We conclude with final remarks and policy implications in Section 5.

2. Gravity models and migrations

Decisions about migration and forced migration depend on a number of economic, political, social, cultural factors, that can be formalized by an appropriate statistical model. In particular, gravity models allow taking into account the determinants of migration at its origin and destination. Gravity models derive from Newton's law of universal gravitation that in its simplest form states that bodies with mass attract each other with a force that is a direct function of the product of their masses and an inverse function of the square of the distance between them; in formulae:

$$F_{ij} = G\frac{M_i M_j}{D_{ij}^2}$$

where F_{ij} represents the gravitational force between objects i and j, M_i (M_j) represents the mass of object i (j), D_{ij} is the distance between i and j, and G is a gravitational constant.

Notice that since the work of Tinbergen (1962), gravity models have been employed for modelling trade between two countries as a function of the attractive mass of the two economies and of the distance between them. Given the multiplicative nature of the gravity equation, they are often log-linearized and expanded with an additive error term. Another possibility relies on the Poisson Pseudo-Maximum Likelihood approach (Santos Silva and Tenreyro, 2006, 2011). Despite their simplicity, gravity models have revealed interesting predictive power; moreover, in the context of trade, their use has been justified by generating gravity equations from a general equilibrium framework (Bergstrand, 1985).

Another setting in which gravity models are increasingly applied is that of modelling migration flows (Lee, 1966; Todaro, 1969; Lewer and Van den Berg, 2008; Letouzé et al., 2009; Reuveny and Moore, 2009; Anderson, 2011; Coniglio and Pesce, 2011; Arif, 2020; Freeman and Lewis, 2021). The first suggestion in this sense goes back to the work of Ravenstein (1889) for studying migration patterns in United Kingdom. In the simplest formulation, migration between location *i* and location *j* is a direct function of the two population sizes, and an inverse function of the distance between *i* and *j*. Since the work of Stouffer (1940), that extended gravity models by introducing the notion of intervening opportunities, many increasingly complex migration models have been suggested in the literature in order to explain migration behavior, both from the point of view of aggregate migration flows and individual migration decision. However, most of these studies concern voluntary migration, rather than forced migration. Even the structural model of migration set out in Anderson (2011), that aims at building a theoretical foundation for it similarly to what has been done in the context of trade, refers to voluntary migration.

One paper that considers a gravity model approach in the context of forced migration is that by Abel et al. (2019), that aims at empirically establish the causal relationship between climate change, conflicts and cross-border migration simultaneously. In fact, the majority of the literature on this subject takes into account the relationship only between any two of these three phenomena, and in particular finds no empirical consensus on the association between climate change and migrations. According to Abel et al. (2019), this lack of consensus is partly due to the complexity of migration processes, that makes climatic impacts on migration be indirectly mediated through social, demographic, economic, political and environmental factors (Black et al. 2011). This remark led the authors to conclude that when studying the relationship between climate and migration, it is fundamental to take into account the complex interactions among migration drivers. Thus, using bilateral refugee flows data between 2006 to 2015 for 157 countries, Abel et al. (2019) employ sample selection methods for gravity-type models to estimate first the impact of climate on conflicts and then the impact of conflicts on asylum seeking applications. Their results suggest that climatic conditions, by affecting the likelihood of armed conflicts, have a significant effect for explaining forced migrations only for countries that were affected by the Arab Spring.

Notice that our approach differs from that of Abel et al. (2019) in three different ways. First, as explained in the Introduction, because of the nature of UNHCR data on forced migration, we take a conditional approach and consider a gravity-type model that predicts the intensity of the flow on a migration route, on condition that the route has been travelled. For this reason, with respect to the three simultaneous equations in Abel et al. (2019), we estimate a single-equation model; this allows estimating the effect on forced migration of each of its possible drivers (economic, political, demographic, social, environmental) controlling for the others.

Second, while Abel et al. (2019) model solely asylum-seeking flows, since in their opinion refugee figures are prone to be strongly affected by country-specific policies in granting a refugee status, we consider all forced migrations, including IDPs. In fact, by introducing in our model both origin-specific and destination-specific fixed effects, country-specific policies in granting a refugee status (as well as any other country-specific characteristics) are in any case controlled for. Moreover, given that the 1951 Refugee Convention does not recognize environmental factors as criteria to define a refugee, in order to be able to estimate in particular the effect of natural disasters on migration, we find essential to include in the analysis also IDPs.

Third, given the nature of our data, we consider a full panel data analysis and estimate both fixed effects and random effects model specifications. The former offers interesting insights when looking at the most significant country pair (origin-destination) fixed effects; after controlling for natural disasters, conflicts, economic and political factors, these represents the migration routes whose intrinsic characteristics are most relevant for explaining forced migrations. The latter, on the other hand, allows estimating also the effect of time-constant bilateral predictors such as the distance between country of origin and country of destination, the fact that countries share a common language or have a colonial relation, that are controlled for in the fixed effects model without explicitly quantifying their effect.

3. Data

This paper aims at analyzing forced migrations in the time span 1990-2016 for 88 countries divided into four regions, namely South and Southeast Asia, the Middle East and North Africa (MENA), East and Southern Africa, West and Central Africa. For the African regions, in particular, we have used the African Development Bank country subdivisions, and each of them includes two subregions belonging to the same climate zone.[5] MENA, in particular, is a diverse region, affected by economic and political transformations; it benefits from a privileged geographic location with access to large markets, but is particularly vulnerable to natural hazards due to water scarcity, increasing climate variability and a fast-growing population, which is progressively concentrating in urban areas (Banerjee et al., 2014). Since the Second World War, the MENA region has experienced an incredible level of conflict, particularly civil wars; the reasons are diverse, but many of these conflicts have their roots either in the creation of the State of Israel in 1948, or in the revolution in Iran in 1979, that

[5] The African Development Bank country subdivisions is available at https://www.afdb.org/en/countries

reinforced sectarianism between Sunni and Shia Muslims, or in the siege of Mecca in 1979.[6] East and Southern Africa is a geographically, culturally and economically diverse region boasting some of the world's richest natural resources; South Africa, in particular, is the region's largest economy and is one of the most unequal countries in the world. Grave violations against civilians including conflict-related sexual violence continue to be committed in the region, that has been impacted by below-average rainy seasons and is experiencing a major food insecurity crisis.[7] West and Central Africa is a vast and diverse region that has been experiencing an exceptional population growth and an accelerated urbanization as well as political instability, conflicts, violence, extreme poverty, weak governance, and food insecurity. Climate change has been compounding these issues, with frequent severe droughts and irregular and unpredictable rainfall.[8] Finally, South and Southeast Asia are home to one-third of the world's population, and are characterized by a vast cultural diversity in terms of religion and ethnicity; all the countries of this region, with the exceptions of Thailand, Nepal, Afghanistan and Bhutan, have been under the control of European colonial powers in the nineteenth and early twentieth centuries. Unresolved tensions of colonialism, contested border demarcations, contestation over natural resources have been causing many regional conflicts (Avis, 2020); the whole region is also severely affected by climate-related natural disasters.

For each region, we estimate two different gravity-type models, one for total forced migration, that includes the number of refugees, asylum seekers, IDPs, as well as returned refugees and IDPs, and one for cross-border forced migration, that does not take into account IDPs. For both models we assume a fixed effects specification, and when appropriate also a random effects specification.

The response variable of both models consists in the number of forced migrants that in year t moved from origin i to destination j. Bilateral data on forced migration are sourced from the UNHCR database.[9] Notice that this data are provided to UNHCR by host governments or, in least developed countries, by UNHCR field offices and other NGOs.

Similarly to Abel et al. (2019), the main predictors of our gravity-type models concern climatic factors and conflicts. In fact, different kind of climate variables have been considered in the literature for studying the climate change-migration linkage (Beine and Jeusette, 2021); these include both slow onset events, that capture long-run climatic factors measured as levels, deviations, variability of precipitation and temperature, and fast onset events that typically capture natural disasters. Notice that while the decision to migrate as an adaptation strategy could equally depend on short or long-

[6] Tackling Intersecting Conflicts in the MENA region. Available at: https://www.crisisgroup.org/middle-east-north-africa/tackling-intersecting-conflicts-mena-region

[7] Global Humanitarian Overview (2022). Southern and East Africa. Available at: https://gho.unocha.org/appeals/southern-and-east-africa

[8] Global Humanitarian Overview (2022). West and Central Africa. Available at: https://gho.unocha.org/appeals/west-and-central-africa

[9] UNHCR Data. Available at: https://www.unhcr.org/data.html

term changes, the magnitude of the migration flow and its duration are substantially affected by the type of events. More precisely, while long-term changes in living conditions leads to constant flows, sudden disruptions might induce massive flows immediately after the event (Vallejo and Mullan, 2017). For this reason, given the nature of forced migrations, here we are focusing on natural disasters, both those that are climate-related (such as drought, floods, storms) and those that are not (such as earthquakes and volcanic eruptions); this is another difference with Abel et al. (2019), that measure climatic factors, and in particular the duration and magnitude of drought conditions with respect to normal conditions, using the Standardised Precipitation-Evapotranspiration Index (SPEI). More specifically, we are including into our models both the number of natural disasters occurred yearly in each origin country and the number of individuals directly affected by them; the former is a measure of hazard's risk, while the latter is a measure of the intensity of exposure (Neumayer et al., 2014). Both predictors are sourced from the Centre for Research on the Epidemiology of Disaster's (CRED) International Disaster Database (EM-DAT)[10], and for both of them we take into account both their simultaneous and their lagged values.

Instead, data on conflicts are sourced from the Uppsala Conflict Data Program (UCDP) Georeferenced Event Dataset (GED) Global version 21.1 (Sundberg and Melander, 2013; Pettersson et al. 2021).[11] In particular, we used the unique numeric ID identifying each event in the database to compute the number of conflicts occurred yearly in each origin country and the corresponding number of fatalities; the former is a measure of the frequency of the conflicts, while the latter is a measure of their intensity. Notice that in the models for both predictors we take into account their simultaneous and their lagged values. Moreover, we also include the (simultaneous) number of conflicts occurred yearly in each destination country, in order to establish if forced migration flows head towards safer places.

The remaining predictors of our models include standard variables previously used in the literature for modelling migrations with gravity-type models (Backhaus et al., 2015; Beine and Parsons, 2015; Abel et al, 2019); they capture bilateral and country-specific push and pull factors and are obtained from a number of sources. In particular, from the CEPII database we obtained the distance between the capital cities of the origin and the destination countries, as well as three dummy variables indicating whether the two countries share a common language, have had a colonial relationship, are contiguous.[12] The remaining predictors pick up either socio-economic or political characteristics of the origin, of the destination, or of both the origin and the destination; as general controls we included the population sizes of the origin and of the destination (in hundreds of

[10] Available at: https://www.emdat.be/database

[11] H. Stina (2021). *UCDP GED Codebook version 21.1.* Department of Peace and Conflict Research, UPPSALA University.

[12] Available at: http://www.cepii.fr/CEPII/en/bdd_modele/presentation.asp?id=6

thousands of individuals) and a dummy variable indicating migration flows representing IDPs in the model for total forced migration.

Starting from the socio-economic factors, the first controls that we included in the model concern the economic performance of the origin and of the destination countries as approximated by the GDP per capita, that is sourced from the World Development Indicators (WDI) database from World Bank.[13] In particular, the World Bank classifies all countries according to their GDP per capita as *Under the poverty line* (if the GDP per capita is lower than 825$), *Middle-lower income* (if the GDP per capita is between 826$ and 3255$), *Middle-higher income* (if the GDP per capita is between 3256$ and 10065$), *Higher income* (if the GDP per capita is higher than 10066$). Starting from this classification, we focused on the threshold 3255$, and for both the origin and the destination, we created a time-varying indicator that is equal to 1 if in year *t* the country was classified as under the poverty line or as a middle-lower income, and zero otherwise.

Other socio-economic factors sourced from the WDI database that we included in the models with respect to the country of origin are the unemployment rate (on total labor force) and natural resources rents, *i.e.* the percentage of the GDP of the country that comes from natural resources; in fact, one of the most significant aspects in some of the regions we are considering is the so-called *Natural Resource Curse*, that refers to the failure of resource-rich countries to fully benefit from their natural resource wealth because of the fact that they tend to be more authoritarian, more prone to conflict and less economically stable (Frankel, 2012).

The last socio-economic predictor included in our model is the bilateral migrant stock in the three decades preceding our analysis (*i.e.* 1960-1989), that is obtained from the Global Bilateral Migration dataset by World Bank;[14] this represents the potential effect on the choice of a destination of a pre-existing co-ethnic community.

Moving to the political factors, the first two predictors are sourced from *The Global State of Democracy Indices* from The Institute for Democracy and Electoral Assistance (IDEA).[15] In particular, we used two of the attributes of democracy developed by IDEA, namely Representative Government and Fundamental Rights, that are scaled to range from 0 (the lowest score) to 1 (the highest score), and for each of them we created a time-varying indicator that is equal to 1 if in year *t* the value of the attribute for the destination was higher than that for the origin, and 0 otherwise. These indicators allow verifying if a better political status in the destination represents a pull factor for forced migration.

[13] Available at: https://databank.worldbank.org/source/world-development-indicators

[14] Available at: https://databank.worldbank.org/source/global-bilateral-migration

[15] C. D. Tufis (2020). *The Global State of Democracy Indices Codebook.* International Institute for Democracy and Electoral Assistance, Stockholm

The two other political predictors that we have included in the analysis concern the lack of democracy and the occurrence of a coup d'état in the country of origin. In particular, for the former we built a time varying indicator that is equal 1 if in year *t* the country of origin had a non-democratic regime (and 0 otherwise), and was sourced again from the IDEA dataset. For the latter, we created a time-varying indicator that is equal to 1 if in year *t* the country of origin experienced an attempted coup d'état (and 0 otherwise). In this case the source was the *The Coup D'état Project* (CDP) dataset from the Cline Center of University of Illinois.[16] Interestingly, the occurrence of a coup d'état could represent both a push factor and a pull factor for forced migration. In fact, a successful or a failed *coup d'état* can indeed generate political refugees; on the other hand, if the coup d'état represents the end of a dictatorial regime, it could create favorable conditions for the arrival of forced migrants and it could be considered also as a pull factor. The CDP dataset, however, does not specify if a coup d'état has generated a democracy or a dictatorial regime; for this reason, in our empirical analysis we only included the coup d'état indicator with reference to the country of origin, both simultaneous and with one year lag.

Table 1 shows the mean values of the different variables included in our data set for each region. One point that immediately arise from it is the different size of forced migration flows in the different regions: the yearly mean number of migrants per route reaches its maximum in South and Southeast Asia, and its minimum in West and Central Africa. Moreover, internal displacement represents an important phenomenon in most of the regions taken into account, with a percentage of IDPs on total forced migrants ranging from 25,2% in South and Southeast Asia to 59,7% in West and Central Africa. On average, South and Southeast Asia is the region more affected by natural disasters, both from the point of view of the frequency and of the intensity, and by conflicts, again both from the point of view of the number of events and the number of deaths. Interestingly, on average the Middle East and North Africa is the least affected region in terms of the frequency of the conflicts, but shows a high number of deaths.

From the point of view of the country economies, Table 1 shows that in all the regions on average the GDP per capita of the country of origin is lower than that of the country of destination; the only exception is MENA. Table 1 also shows the percentage of the observations in our dataset that according to their GDP per capita are classified as under the poverty line or as a middle-lower income; with reference to the country of origin, we can see that such percentage reaches 89% in West and Central Africa, where we find the lower mean value of the GDP per capita. Interestingly, in West and Central Africa on average we also find a particularly high value of natural resources rents; this finding is in accordance with the aforementioned *Natural Resource Curse*.

[16] Available at: https://clinecenter.illinois.edu/project/research-themes/democracy-and-development/coup-detat-project-cdp

With respect to the political variables, notice that for both Representative Government and Fundamental Rights, the mean value for the country of origin is lower than that of the country of destination. In particular the lowest mean value for the former in found in the MENA region, while for the latter in South and Southeast Asia.

Table 1. Summary statistics (mean values and percentages)

Variables	South and Southeast Asia	Middle East and North Africa	West and Central Africa	East and Southern Africa
Migration Variables				
Total Migrants	12468,45	6886,76	3828,46	7123,80
Migrants btw 1960-1989	76509,27	29866,45	12415,46	13131,60
Cross-border Migrants	9411,12	2994,27	1549,10	4280,74
% IDPs on Total Migrants	25,2%	56,8%	59,7%	40,3%
Natural Disasters Variables				
Origin - Number of Disasters	4,31	0,85	0,66	1,11
Origin - Affected	4079790,06	108899,07	116616,01	441379,28
Conflict Variables				
Origin - Number of Conflicts	3,20	1,48	1,94	1,90
Destination - Number of Conflicts	1,30	1,43	1,46	1,50
Origin - Deaths in Conflicts	566,54	475,80	106,13	188,52
Economic Variables				
Origin - GDP per capita	4509,64	11506,45	1362,62	1817,63
Destination - GDP per capita	13925,62	13297,96	11774,39	11804,37
Origin - % Obs. Low GDP per capita	73%	35%	89%	75%
Destination - %Obs. Low GDP per capita	40%	43%	46%	47%
Origin - Unemployment	6,52	8,35	5,14	10,12
Origin - Natural Resources	4,39	16,67	13,60	7,7
Political Variables				
Origin - Repr_Gov	0,43	0,32	0,42	0,38
Destination - Repr_Gov	0,57	0,56	0,56	0,54
Origin - Fun_Rights	0,47	0,49	0,50	0,50
Destination - Fun_Rights	0,61	0,60	0,60	0,59

4. A gravity-type approach for modelling forced migrations

4.1 Model specification and estimation methods

In what follows we model bilateral forced migrations with the following functional form:

$$log(Y_{ijt}) = X_{it}^{A}\beta_A + X_{jt}^{B}\beta_B + X_{ijt}^{C}\beta_C + X_{ij}^{D}\beta_D + \alpha_i + \alpha_j + \tau_t + \varepsilon_{ijt} \quad (1)$$

where Y_{ijt} represents the number of forced migrants from i to j in year t, X_{it}^{A} represents the time varying predictors related solely to the country of origin i, X_{jt}^{B} represents the time varying predictors related solely to the country of destination j, X_{ijt}^{C} represents the time varying predictors related to both the origin and the destination, X_{ij}^{D} represents the time constant predictors related to both the origin and the destination, $\alpha_i, \alpha_j, \tau_t$ represent country-specific (origin-specific and destination-specific) and year-specific fixed effects respectively, and ε_{ijt} is the error term.

Notice that the gravity model (1) can be estimated assuming either a fixed effects (FE) or a random effects (RE) specification. Under standard assumptions, FE models leads to unbiased and consistent estimators; however, although all time-constant characteristics are controlled for by the unit-specific fixed effects (country pair-specific fixed effects in our case), FE models do not allow estimating the effect of any time-constant bilateral determinant of the response such as the distance between the origin and the destination. It is worth noting that the inclusion of country pair-specific fixed effects into the FE model leads to the removal of origin-specific and destination-specific fixed effects, as well as of the dummy variable indicating migration flows representing IDPs, as the corresponding information is captured by the country pair-specific fixed effects. On the other hand, RE models require the additional assumption that the unit-specific unobserved heterogeneity is independent of the predictors of the model, and the failure of this assumption results in biased and inconsistent estimators. In the next section, both for the total number of forced migrants and for the number of cross-border forced migrants, for all regions we will show the results of FE gravity models; only for those regions for which the Hausman test does not reject the additional assumption required by RE models, we will also show the results of RE gravity models, that allow estimating also the effect of time-constant bilateral predictors X_{ij}^{D}.

It is also worth noting that the literature on trade recommends the use of time-varying importer fixed effects and time-varying exporter fixed effects to control for the unobservable multilateral resistances, and potentially for any other observable and unobservable characteristics that vary over time for each exporter and importer (Anderson and van Wincoop, 2003). Here we decided not to follow this approach as it would make all the time-varying predictors related to the origin or to the destination to disappear from the model. In fact, the aim of our study is to identify what are the characteristics of the origin, of the destination, of the origin-destination pair that mainly affect forced migrations. An alternative to this approach, that will be explored elsewhere, is the random intercept PPML (Prehn et al. 2015).

4.2 Results for total forced migrations under a fixed effects specification

Table 2 shows the estimates and the significance of the parameters of the gravity model (1) with fixed effects for total forced migrations in the different regions; the corresponding most significant fixed effects, that (after controlling for natural disasters, conflicts, economic and political factors) represent the migration routes whose intrinsic characteristics are most relevant for explaining forced migrations, are shown in Appendix A.1.

Several points arise from Table 2. First, the number of natural disasters is significant and acts as a push factor for forced migrations only in the MENA region, that as pointed out in Section 3 is the least affected region, and the effect is both simultaneous and lagged. It is interesting to notice that in the MENA region also the (simultaneous) number of people affected by the disasters is significant, showing that that forced migrations in this region are affected by both the frequency and the intensity of the disasters. The number of people affected by the disasters is significant also in East and Southern Africa. Another interesting point is that if we do not control for conflicts, the number of people affected by disasters is significant in all the regions, emphasizing the strong link between these two predictors and the role of conflicts caused by natural disasters.

A second point that emerges clearly from Table 2 is that conflicts represent a significant push factor for forced migrations in all the regions. In fact, with the exception of East and Southern Africa, where it is the number of deaths caused by conflicts that is significant, in all the other regions the number of conflicts is always significant and has the effect of increasing forced migrations. Interestingly, also the number of deaths caused by conflicts (either simultaneous or with one year lag) is significant in all the regions except in South and Southeast Asia, but in West and Central Africa the simultaneous effect has a negative coefficient; this, however, can be possibly explained by noting that, when controlling for the number of conflicts (that is significant and has a positive effect), a particularly high number of deaths can indeed lead to lower migration flows.

Another interesting result is that concerning the number of conflicts in the destination country, that is significant and negative in all regions. It follows that, under the same conditions, forced migrants prefer to move to countries with a lower number of conflicts. From a broader perspective, forced migrants run away from insecure and dangerous areas to find a safer place.

From the point of view of the size and health of the countries' economy, the results of Table 2 show that a low GDP per capita in the country of origin (lower that 3.255$) has the effect of increasing forced migrations in all regions except South and Southeast Asia. Instead, with the exception of the

MENA region, where we find that a low GDP per capita in the country of destination discourages forced migrations, in all the other regions forced migrations do not appear to have a specific economic expectation determined by the destination.

Table 2. Fixed Effects and Random Effects gravity models estimates for total forced migrations

	South and Southeast Asia	Middle East and North Africa		West and Central Africa	East and Southern Africa	
	FE	FE	RE	FE	FE	RE
O_No disasters $_{it}$	-0,001	**0,036*** **	**0,036*** **	-0,019	-0,007	-0,009
O_No disasters $_{it-1}$	0,001	**0,035*** **	**0,035*** **	-0,009	0,004	0,004
O_No Affected $_{it}$	0,003	**0,007** **	**0,007* **	0,002	**0,006** **	**0,007** **
O_No Affected $_{it-1}$	0,004	0,001	0,001	0,002	-0,001	-0,001
O_No Conflicts $_{it}$	**0,030*** **	**0,036*** **	**0,037*** **	**0,020* **	-0,001	0,000
O_No Conflicts $_{it-1}$	**0,042*** **	**0,036*** **	**0,036*** **	**0,059*** **	0,005	0,004
O_No Conflict Deaths $_{it}$	0,000	**0,014* **	**0,014* **	**-0,012* **	**0,016** **	**0,015* **
O_No Conflict Deaths $_{it-1}$	0,001	**0,022*** **	**0,022*** **	**0,015* **	**0,024*** **	**0,024*** **
D_No Conflicts $_{jt}$	**-0,039*** **	**-0,021*** **	**-0,021*** **	**-0,074*** **	**-0,054*** **	**-0,053*** **
O_Coup Attempted $_{it}$	-0,009	**0,181*** **	**0,178*** **	0,011	-0,059	-0,060
O_Coup Attempted $_{it-1}$	0,098	**0,156*** **	**0,149** **	**0,063* **	-0,055	-0,055
O_Low GDPpc $_{it}$	0,067	**0,077* **	0,074	**0,487*** **	**0,371*** **	**0,385*** **
D_Low GDPpc $_{jt}$	0,006	**-0,138** **	**-0,133** **	0,021	-0,026	-0,017
O_Regime Status $_{it}$	**0,265*** **	-0,002	0,003	**0,199*** **	-0,018	-0,025
O_Unemployment $_{it-1}$	0,002	**0,006* **	**0,006* **	**-0,020*** **	-0,055	-0,005
O_Population $_{it-1}$	**0,000*** **	**0,001* **	**0,001* **	0,000	**-0,001*** **	**-0,001*** **
D_Population $_{jt-1}$	**-0,000*** **	0,000	0,000	**0,001*** **	0,000	0,000
O_Natural Resources Rents $_{it}$	-0,009	**-0,003* **	**-0,003* **	**0,006*** **	**0,009*** **	**0,009*** **
D_O_Representative Gov $_{ijt}$	0,063	-0,080	-0,085	**0,150*** **	**0,191*** **	**0,162*** **
D_O_Fundamental Rights $_{ijt}$	**-0,717*** **	**0,176** **	**0,122* **	0,065	0,002	-0,029
Migrants 1960-1989 $_{ij}$			**0,256*** **			**0,126*** **
Distance btwn Capitals $_{ij}$			**-0,414*** **			**-0,536*** **
Colony $_{ij}$			-0,014			-0,006
Common Language $_{ij}$			0,240			**0,319* **
Contiguity $_{ij}$			**0,703** **			**1,940*** **
Dummy IDP $_{it}$			**5,005*** **			**5,444*** **
Intercept			-0,012			**4,045* **
Hausman Test P-Value	$6{,}172e^{-07}$	0,9943		$1{,}458e^{-05}$	1	

Note: *** p < 0.001; ** p < 0.01; * p < 0.05; the number of people affected, the number of deaths because of conflicts, the number of migrants between 1960 and 1989, the distance between capitals are log-transformed.

Another interesting result from Table 2 concerns the role of unemployment in the country of origin. Controlling for everything else, unemployment does not affect forced migrations in South and Southeast Asia and in East and Southern Africa, while it represents a push factor in the MENA region. Instead, for forced migrations originating in West and Central Africa, unemployment has a negative coefficient; this result seems to confirm migration transition theory, according to which higher levels of economic and human development are associated to higher overall levels of migration, while poor populations of the least developed countries have less capabilities to move (Flahaux and De Haas, 2016).

The last economic aspect taken into account by our gravity model is natural resources rents, and from this point of view there is a clear division between the MENA region and the rest of Africa. In fact, in MENA it has a negative coefficient, which is expected, while both in West and Central Africa and in East and Southern Africa it has a positive coefficient. One possible explanation for this is the aforementioned *Natural Resource Curse*, *i.e.* the failure of many African resource-rich countries to benefit fully from their natural resource wealth because of the high level of exploitation.

Looking now at the countries' political situation, we can see from Table 2 that there is a lot of variability across regions; most of the times, when the predictors are significant, they have the effect of increasing forced migrations: the lack of a democratic regime in the country of origin is significant both in South and Southeast Asia and in West and Central Africa, the occurrence of a coup d'état is significant both in the MENA region (both simultaneous and with one year lag) and in West and Central Africa, the Representative Government indicator (that measure how inclusive popular elections are in the destination with respect to the origin) is significant both in West and Central Africa and in East and Southern Africa. One predictor that is particularly interesting to look at is the one representing the respect of fundamental rights. In fact, in the MENA region is significant and has a positive coefficient: controlling for everything else, forced migrants fleeing this region tend to move to countries with a higher respect of human rights. On the other hand, in South and South-East Asia it has a negative coefficient; one possible explanation for this is the fact that one of the major destinations of forced migration originating in this region is China.

4.3 Results for total forced migrations under a random effects specification

Notice that, as mentioned in Section 4.1, the effect of time-constant predictors such as the distance between the origin and the destination or the presence of a pre-existing community of migrants can be estimated only under a RE specification. The Hausman test, however, whose results are also reported in Table 2, allows estimating a RE gravity models only for two regions, namely the Middle East and North Africa and East and Southern Africa. The results are presented in Table 2, and do not differ much from the fixed effects ones with respect to time-varying predictors, but offer interesting indications as far as time-constant predictors are concerned.

A first point that arise from the results of the random effects models for total forced migrations is that the distance between the origin and the destination and the dummy representing contiguity of the two countries are significant in both regions and have opposite signs; this shows that, under the same conditions, forced migrants prefer to move to neighboring (or even bordering) countries.

It is interesting to notice that the role of distance is confirmed also by the most significant country pair fixed effects corresponding to the FE gravity models of Table 2 shown in Appendix A.1. For East and Southern Africa, for instance, among the most significant routes in the first column of Table 7 we find five that represent IDPs and involve Sudan, Somalia, Uganda, Tanzania and Angola; all the others catch routes between bordering countries. Similarly, for the MENA region we find that the first five fixed effects in the first column of Table 5 represent IDPs and involve Iraq, Cyprus, Lebanon, Yemen, Libya; interestingly, unlike other major conflicts in the region, both the Turkish invasion of Cyprus in 1974, that caused around 40% of the population being displaced (Kourvetaris, 1978), and the internal conflicts in Lebanon, Yemen and Libya have not triggered large-scale cross-border movements but mainly IDPs. All the other fixed effects catch migration routes between neighboring countries with a few exceptions, namely Turkey-Germany, Iraq-Sweden, Iraq-Netherlands and Syria-Germany, that are worth a few considerations.

Iraq, in particular, in the last four decades has experienced a long period of war: the Iran-Iraq War (1980-1988), the Gulf War (1990-1991), the Iraq War (2003-2011), the Iraqi conflict against the Islamic State (2013-2017), that was a spillover of the Syrian civil war. According to Fawcett and Tanner (2002), in this scenario often the thought of being able to return home and be compensated for lost property made Iraqis lean for internal displacement rather than resettlement. Still, it is estimated that one third of the migrants who left Iraq between 1990 and 2002 had settled in a western country, mainly as asylum seekers. And in the early 2000s, besides Australia, the United Kingdom and the USA, new migratory poles appeared in Northern Europe, primarily Sweden, which is in accordance with the aforementioned Iraq-Sweden and Iraq-Netherlands routes in Table 5 (Chatelard, 2009).

Instead, the Turkey-Germany route can be explained in light of the estimate of a different predictor in the RE model for the MENA region, namely the presence of a pre-existing community of migrants in the country of destination. In fact, besides distance, both in the MENA region and in East and Southern Africa also the number of migrants in the time span 1960-1989 is a significant predictor of forced migrations, with a positive coefficient. Notice that Turkish migration to western Europe began with the signing of the recruitment agreement for labor between Turkey and Germany in 1961: the first waves of Turkish migrants consisted of male laborers who were recruited due to the shortage of manpower in Germany. It was originally a temporary measure, but over the time these laborers settled permanently, making up the largest Turkish community in western Europe. In fact, although labor recruitment from Turkey stopped in the early 1970s, migration to Germany continued in the form of family reunification or politically motivated migrations, mainly involving asylum seekers of Kurdish origin. An important pull factor in this sense has been the size of the Turkish population already settled in the host country: the large organizations built up by the Turks in Germany have led to the creation of an infrastructure to provide for their special demands and needs, including shops, food varieties, religious communities, cultural services, newspapers and so on (Şen, 2003).

Another time-constant predictor that is significant in the RE model for forced migration originating in East and Southern Africa is the dummy representing common language between origin and destination. Interestingly, this fact is confirmed also by some of the most significant fixed effects in the first column of Table 7, namely Eritrea-Sudan, Somalia-Kenya and Somalia-Ethiopia. In fact, along the common frontier, Western Eritrea and Eastern Sudan present ethnic, religious and linguistic similarities: they are predominantly Sunni Muslims, and they both speak Tigre and Arabic (Venkataraman, 2005). Similarly, despite the large number of ethnolinguistic groups that can be found in what is known as the Horn of Africa, among the most spoken languages in Somalia, Ethiopia and Kenya are Cushitic languages such as Somali and Oromo, that belong to the Afro-Asiatic language family.

It is interesting to note, however, that despite such ethnic, religious and linguistic similarities, Sudan, Kenya and Ethiopia impose significant restrictions on the refugees that they host, so that prospects for local integration are rather limited. Somali refugees, in particular, fled from four decades of conflicts that originated from the long-standing cultural and socioeconomic differences among the major clans in the country that led to a civil war among nationalist and Islamic groups, warlords, clan militias, with no one controlling the nation as a whole (Clarke and Gosende, 2004). A large scale humanitarian crisis then developed, characterized by mass starvation and mass displacement especially to Kenya and Ethiopia. Notice that the arrivals of Somali refugees in these countries increased again in 2011 due to drought, famine and ongoing insecurity in the home country; in fact another source of displacement in Somalia is natural disasters.[17] In any case, although both Kenya and Ethiopia are signatories to the 1951 Refugee Convention and 1969 OAU Convention, in both countries Somali refugees live in camps and they have very limited access to employment.[18] Notice that similar comments hold for Eritrea-Sudan. In fact, the first refugees crossed the border into

[17] https://www.unhcr.org/news/stories/2021/8/611a2bca4/displaced-somalis-refugees-struggle-recover-climate-change-brings-new-threats.html

[18] *Somali refugees in Kenya and Ethiopia.* Available at: https://www.resettlement.eu/page/somali-refugees-kenya-ethiopia

Eastern Sudan during the Eritrean War of Independence with Ethiopia (1961-1991); successive waves of people fleeing repression, insecurity, famine and drought arrived during the following three decades. Notice that most Eritrean refugees returned home after the end of the Eritrean-Ethiopian War (1998-2000), but the ongoing deterioration in human rights in Eritrea has again caused many to flee. This is the case even if Sudan, as Kenya and Ethiopia for the Somali refugees, imposes rules that collide with 1951 Refugee Convention and 1969 OAU Convention. The Sudanese government, for instance, does not recognize the refugees right to freedom of movement.[19]

One last point is worth a few considerations. As mentioned earlier, the Hausman test for forced migrations allows estimating a random effect model only for the MENA region and East and Southern Africa. As a consequence, in the remaining regions we cannot verify the significance of time-constant predictors such as the distance, contiguity, common language. However, as the analysis of this section shows, interesting information on these factors can be gathered also by looking at the most significant country pair fixed effects. For total forced migrations originating in South and Southeast Asia, for instance, nearly half of the fixed effects in the first column of Table 4 represent IDPs and involve Pakistan, Afghanistan, Sri Lanka, Philippines, Myanmar; all the others catch migration routes between bordering countries, the only exception being Afghanistan-India. Similarly, for total forced migrations originating in West and Central Africa, the ten most significant fixed effects in the first column of Table 6 represent IDPs, pointing out that internal displacement is a massive problem in this region; the other three catch migration routes between bordering countries. Thus, controlling for everything else, also in these regions distance is found to discourage migrations. It is also important to point out that this finding does not depend on the fact that we have been modelling forced migrations, and forced migrations include IDPs; in fact, as the results of the next sections will show, distance and contiguity remain significant factors even when we model cross-border forced migrations.

4.4 Results for cross-border forced migrations under a fixed effects specification

As pointed out in the Introduction, given the bilateral nature of gravity models, that makes them particularly natural for modelling flows between two different locations, and given the significant share of IDPs among the forced migrations originating in the different regions shown in Table 1, it is interesting to repeat the analysis of the previous section without taking into account internal displacements. Table 3 shows the estimates of the gravity model (1) under a FE and a RE specification for modelling cross-border forced migrations.

[19] *Eritrean refugees in eastern Sudan.* Available at: https://www.resettlement.eu/page/eritrean-refugees-eastern-sudan

Table 3. Fixed Effects and Random Effects gravity models estimates for cross-border forced migrations (no IDPs)

	South and Southeast Asia		Middle East and North Africa	West and Central Africa	East and Southern Africa
	FE	RE	FE	FE	FE
O_No disasters it	0,000	0,000	**0,035*** **	-0,019	-0,005
O_No disasters it-1	0,001	0,000	**0,035*** **	-0,010	0,001
O_No Affected it	0,002	0,002	**0,007** **	0,001	**0,006***
O_No Affected it-1	0,004	0,005	0,001	0,002	0,000
O_No Conflicts it	**0,028*** **	**0,028*** **	**0,036*** **	**0,018***	-0,002
O_No Conflicts it-1	**0,042*** **	**0,042*** **	**0,036*** **	**0,059*** **	0,005
O_No Conflict Deaths it	0,000	0,001	**0,014***	-0,012	**0,016** **
O_No Conflict Deaths it-1	-0,002	-0,002	**0,022*** **	**0,017** **	**0,025*** **
D_No Conflicts jt	**-0,047*** **	**-0,043*** **	**-0,023*** **	**-0,075*** **	**-0,057*** **
O_Coup Attempted it	-0,007	-0,003	**0,179*** **	0,020	-0,061
O_Coup Attempted it-1	0,077	0,083	**0,154*** **	**0,061***	-0,064
O_Low GDPpc it	0,051	0,031	**0,077***	**0,488*** **	**0,376*** **
D_Low GDPpc jt	0,025	-0,015	**-0,134** **	0,025	-0,019
O_Regime Status it	**0,250*** **	**0,245*** **	0,000	**0,185*** **	-0,056
O_Unemployment it-1	0,003	0,004	**0,006***	**-0,020*** **	-0,005
O_Population it-1	**0,000*** **	**0,000*** **	**0,001***	0,000	**-0,002*** **
D_Population jt-1	**-0,000*** **	**0,000*** **	0,000	**0,001*** **	0,000
O_Natural Resources Rents it	-0,008	-0,009	**-0,003** **	**0,006*** **	**0,009*** **
D_O_Representative Gov ijt	0,065	0,057	-0,081	**0,152*** **	**0,199*** **
D_O_Fundamental Rights ijt	**-0,710*** **	**-0,631*** **	**0,175** **	0,067	0,004
Migrants 1960-1989 ij		**0,078***			
Distance btwn Capitals ij		**-1,178*** **			
Colony ij		**1,842*** **			
Common Language ij		0,122			
Contiguity ij		**2,376*** **			
Intercept		**0,126*** **			
Hausman Test P-Value	0,35		< 2,2e-16	9,785e-05	1,079e-11

Note: *** p < 0.001; ** p < 0.01; * p < 0.05; the number of people affected, the number of deaths because of conflicts, the number of migrants between 1960 and 1989, the distance between capitals are log-transformed.

The comparison between Table 2 and Table 3 does not point out great differences between the model for total forced migrations and that for cross-border forced migrations. In particular, natural disasters remain a significant push factor for forced migration mainly in the MENA region, and at least some of the predictors related to conflicts are significant in all regions. A low GDP per capita in the country of origin acts as a push factor in all regions except South and Southeast Asia, while a low GDP per capita in the country of destination discourages only forced migrations originating in the MENA region. Different political factors such as the lack of a democratic regime or the occurrence of a coup d'état in the country of origin, or a more representative government in the destination with respect to the origin, have the effect of increasing forced migrations in different regions. As in the case of total forced migrations, the predictor representing respect of fundamental rights has a positive coefficient in MENA, but a negative coefficient in South and Southeast Asia, as a consequence of the fact that one of the major destinations of forced migration originating in this region is China. The predictor representing natural resources rents in sub-Saharan Africa has a positive coefficient and is in accordance with the *Natural Resource Curse*.

4.5 Results for cross-border forced migrations under a random effects specification

Notice that when we focus on cross-border forced migrations, the Hausman test allows estimating RE models only in one region, namely South and Southeast Asia; the corresponding results are also shown in Table 3, and several points arise from it. Again, as in the results for total forced migrations, the distance between the origin and destination and the dummy representing contiguity between the two countries indicate that under the same conditions, forced migrants prefer to move to neighboring countries. This fact is confirmed also by the most significant country pair fixed effects in the second column of Table 4 where we find Vietnam-China, Sri-Lanka-India, Afghanistan-Pakistan, Afghanistan-Iran, among many others.

The estimate of the RE model for cross-border forced migrations originating in South and Southeast Asia shows that also the presence of a pre-existing community of migrants in the country of destination is a significant pull factor for forced migration. This finding is confirmed also by some of the most significant country pair-specific fixed effects shown in Table 4, where we find for instance Vietnam-China and Sri Lanka-India; in both cases, prior to the time span of our analysis, the country of destination already hosted a significant community of migrants.

In fact, Vietnam-China originated from the so-called *Indochina Refugee Crisis*. The upheavals which followed the communist victories in 1975 in the former French colonies of Indochina, namely Vietnam, Cambodia and Laos, caused more than 3 million people to flee these countries over the next two decades. Notice that these so called "boat people" were not recognized as refugees by most countries in the region as they hadn't signed on to the 1951 Refugee Convention. In fact, China was the only country in East Asia granting asylum and local settlement for Vietnamese refugees; indeed, integrating them into China has been easier than in other countries because many of them were ethnic Chinese (Lam, 2000). Instead, Sri Lanka has suffered from one of the longest civil wars in the world (1983-2009). The armed attempt of the *Liberation Tigers of Tamil Eelam* for creating an independent

Tamil state ended in their defeat by the government forces and caused more than 800.000 IDPs, who were transferred to camps and detained there against their will (Dickwella et al., 2013; Siriwardhana & Wickramage, 2014). During the civil war a large number of Sri Lankan refugees migrated to India; in fact, the migratory flows to India began in the early 1900s, and has remained an important escape route for refugees. Tsunamis, flooding, landslides contributed significantly to the number of IDPs in this country.

Finally, the results of Table 3 show that in South and Southeast Asia cross-border forced migration is affected also by the dummy representing a past colonial history. In fact, Portugal, Spain, the Netherlands, England, France and the United States all had colonies in South-East Asia at some stage. Only after World War II there has been a withdrawal of European power from this region, and between 1948 and 1984 the different countries achieved independence. Notice that this finding is confirmed for instance by the most significant country pair-specific fixed effects shown in Table 4, where we find Cambodia-France. In fact, immigration to France started in the 1860s when Cambodia became a French protectorate, but the majority of Cambodians arrived as refugees in the 1970s and in the 1980s after the country suffered from a civil war (1970-1975), the Khmer Rouge takeover (1975-1979), and the Vietnamese intervention (1979-1989). Notice that because of the strong link between the two countries, Cambodians in France have integrated into the society relatively well and have created a strong community, although their organizations, commerce and activities mostly stay out of the public eye (Wijers, 2011); it follows that the route Cambodia-France can be interpreted also in light of the presence of a pre-existing community of migrants in the country of destination.

Notice that also in the case of cross-border forced migrations, some indication about the effects of time-constant predictors for the regions that do not allow estimating RE models can be gathered by looking at the most significant fixed effects of the FE models, that are presented in Table 5, Table 6 and Table 7 respectively.

For the MENA region, for instance, as regards the role of distance, we notice that less than half of the migration routes shown in the second column of Table 5 involve neighboring countries, while all the others have a European destination. Instead, for the other two African regions all the most significant fixed effects shown in the second column of Table 6 and Table 7 involve bordering or neighboring countries. However, notice that MENA is closer to Europe than any other region in our panel, so that also the results of Table 5 are in fact in accordance with the discouraging effect of travelling long distances. Related to this is another point that arises from Table 5, namely the decisive role of Germany in the so-called *European migrant crisis*, as it appears as the host country in nearly half of the migration routes. In fact, with more than 1,5 million refugees and asylum seekers reported in the middle of 2021, Germany is the main host country for refugees in Europe.[20]

5. Conclusions

The literature identifies five categories of factors that affect migration flows: economic, political, demographic, social and environmental drivers (Abel et al. 2019). In particular, voluntary migrations can be considered as the outcome of a utility maximization process, so that distance is not really an issue when choosing a destination. Instead, forced migrations are usually short to medium-distance moves without a specific economic expectation determined by the destination (Conigliani et al. 2021); the main recognized drivers in this case are conflict, food insecurity, and natural and man-made disasters, although the literature finds no empirical consensus on the association between climate change and migrations. According to Abel et al. (2019), this lack of consensus is partly due to the complexity of migration processes and to the complex interactions among migration drivers.

Aim of this study is to identify the different push and pull factors of forced migration in different regions of the world by means of gravity-type models. Particular attention is devoted to determining the effects of climatic factors (as measured by natural disasters) and conflicts, while controlling for the economic, political and social relationship between the origin and the destination countries. Indeed, the relative impact of natural disasters depends on both the strength of the event and on the vulnerability of the affected societies; similarly, the impact of conflicts can be substantially different across regions depending on the characteristics of local communities. Accordingly, both natural disasters and conflicts have the potential to create a vicious cycle of poverty and vulnerability, that could lead to the decision to move. We also distinguish between total forced migrations and cross-border forced migrations in order to isolate the role of internal displacements, which in some regions represent more than 50% of total forced migrations. In fact, given that the 1951 Refugee Convention does not recognize environmental factors as criteria to define a refugee, we find essential to include IDPs in our analysis in order avoid underestimating in particular the effect of natural disasters on forced migration flow. Finally, we consider a full panel data analysis and estimate both fixed effects and random effects model specifications (when appropriate). The former offers interesting insights when looking at the most significant country pair fixed effects, that after controlling for all the different drivers, represents the migration routes whose intrinsic characteristics are most relevant for explaining forced migrations. The latter, on the other hand, allows estimating also the effect of time-constant bilateral predictors.

A first finding of our analysis is that the link between natural disasters, conflicts and forced migrations depends on the region where the migration flow originates. Natural disasters, for instance,

[20] UNHCR: Germany. Available at: https://www.unhcr.org/germany.html

after controlling for everything else and in particular for conflicts, affect forced migration mainly in the MENA region. It is interesting to notice that this result is in accordance with Banerjee et al. (2014), that consider water scarcity, increasing climate variability and a fast-growing population concentrated in urban areas as the main causes of the vulnerability of this region to natural hazards. Another region where we find that natural disasters (and in particular the number of people affected by natural disasters) influence forced migrations is East and Southern Africa. Interestingly, if we do not control for conflicts, the number of people affected by disasters becomes significant in all the regions, emphasizing the strong link between these two predictors and the role of conflicts caused by natural disasters. Conflict, on the other hand, affects forced migration in all the regions; in particular, conflict in the country of origin acts as a push factor, while the lack of conflicts in the country of destination acts as a pull factor.

Notice that also the effects of the predictors related to the socio-economic characteristics of the origin and destination countries are region-specific. In fact, none of them is significant in South and Southeast Asia, both for total and cross-border forced migration. At the opposite end, in the MENA region all the socio-economic predictors are found to affect forced migration: controlling for everything else, a low GDP per capita and unemployment in the origin country act as push factors, while a low GDP per capita in the destination and natural resources rents discourage forced migrations. In between we find the two regions that make up sub-Saharan Africa, where we find that, controlling for everything else, a low GDP per capita in the origin is a significant push factor but forced migrations do not appear to have a specific economic expectation determined by the destination. Moreover, in both regions natural resources rents are found to increase (and not discourage, as in MENA) forced migrations, which is in accordance with the *Natural Resource Curse*. One difference between the two sub-Saharan regions concerns unemployment, that does not affect forced migrations in East and Southern Africa, while discourages them in West and Central Africa, which is in agreement with migration transition theory (Flahaux and De Haas, 2016). Region-specific (and with a lot of variability across regions) are also the effects of the predictors related to the political characteristics of the countries, namely the instability of the origin country (as measured by the occurrence of coups d'état), the presence of a non-democratic regime, the respect of fundamental rights, the representativeness of the government.

Another finding of the present work, that arise both from the analysis of the most significant country pair fixed effects in the FE model specification and from the analysis of the RE model specification (when appropriate), is that when modelling forced migrations distance matters. In fact, controlling for everything else, forced migrants tend to move to neighboring or even bordering countries. Interestingly, distance is found to discourage migrations both when we model total forced migrations, that include IDPs, and when we model cross-border forced migrations. This fact emphasizes once again for instance the role of Europe in the Mediterranean region, where the geographical distance between countries exposed and not exposed to risks of extreme events and conflicts is relatively short, while their economic gap is significant. Other time-constant bilateral factors that are significant in at least some of the regions and that increase force migration include the presence of a pre-existing community of migrants in the country of destination and the fact that the origin and the destination share a common language or a past colonial history.

More in general, our analysis shows that the link between natural disasters, conflicts and forced migrations depends on the affected region, suggesting that a one fits all policy to improve the adaptive capacity to deal with the effects of climate change in developing countries is not appropriate. Instead, site-specific adaptation actions might be more effective in reducing the vulnerability of the societies and therefore forced migration flows. Moreover, given the tremendous share of IDPs on total forced migrations observed in some of the regions, the results of our analysis show that until climate-related migrants obtain the recognition of the status of refugees, all empirical analyses aiming at informing future adaptation and migrations policies cannot disregard IDPs; in fact, they represent a fundamental component of the complex linkage between natural disasters, conflicts and forced migrations.

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Appendix A.1. Country pair-specific fixed effects

Table 4. South and Southeast Asia: most significant pair-specific fixed effects for forced migrations

Total migration		Cross-border migration	
Country pair: Origin - Destination	**Estimates**	**Country pair: Origin - Destination**	**Estimates**
Vietnam - China	16,88	Vietnam - China	16,95
Sri Lanka - India	16,24	Sri Lanka - India	16,46
Afghanistan - Pakistan	15,52	Afghanistan - Pakistan	15,61
Afghanistan - Iran	14,33	Afghanistan - Iran	14,31
Afghanistan - India	14,11	Afghanistan - India	14,28
Pakistan - Pakistan	13,73	Myanmar - India	13,34
Myanmar - India	13,09	Laos - China	11,97
Afghanistan - Afghanistan	13,00	Myanmar - Bangladesh	11,90
Sri Lanka - Sri Lanka	12,62	Myanmar - Thailand	11,51
Philippines - Philippines	12,45	Afghanistan - Germany	11,09
Myanmar - Myanmar	11,98	Myanmar - Malaysia	10,81
Laos - China	11,90	Sri Lanka - France	10,80
Myanmar - Bangladesh	11,80	Cambodia - France	10,57

Table 5. Middle East and North Africa: most significant pair-specific fixed effects for forced migrations

Total migration		Cross-border migration	
Country pair: Origin - Destination	**Estimates**	**Country pair: Origin - Destination**	**Estimates**
Iraq - Iraq	12,58	Iraq - Iran	10,24
Cyprus - Cyprus	12,18	Mauritania - Senegal	9,41
Lebanon - Lebanon	11,85	Iraq - Syrian Arab Republic	8,67
Yemen - Yemen	11,44	Turkey - Germany	8,63
Libya - Libya	10,74	Iraq - Sweden	8,54
Iraq - Iran	10,23	Mauritania - Mali	8,33
Mauritania - Senegal	9,41	Iraq - Netherlands	8,15
Iraq - Syrian Arab Republic	8,67	Syrian Arab Republic - Germany	8,01
Turkey - Germany	8,61	Iran - Iraq	7,92
Iraq - Sweden	8,53	Iraq - Jordan	7,77
Mauritania - Mali	8,33	Iran - Germany	7,70
Iraq - Netherlands	8,14	Iraq - Germany	7,64
Syrian Arab Republic - Germany	8,01	Lebanon - Germany	7,59

Table 6. West and Central Africa: most significant pair-specific fixed effects for forced migrations

Total migration		Cross-border migration	
Country pair: Origin - Destination	**Estimates**	**Country pair: Origin - Destination**	**Estimates**
Sierra Leone - Sierra Leone	12,18	Mali - Niger	8,42
Nigeria - Nigeria	11,18	Chad - Sudan	8,27
Guinea Bissau - Guinea Bissau	11,09	Liberia - Coté d'Ivoire	8,06
Liberia - Liberia	10,78	Ghana - Togo	7,91
Central African Rep - Central African Rep	10,57	Central African Rep - Chad	7,86
Cameroon - Cameroon	9,90	Liberia - Guinea	7,80
Mali - Mali	9,86	Sierra Leone - Guinea	7,79
Chad - Chad	9,29	Senegal - Guinea Bissau	7,72
Niger - Niger	9,17	Chad - Cameroon	7,65
Coté d'Ivoire - Coté d'Ivoire	8,51	Nigeria - Niger	7,60
Mali - Niger	8,42	Central African Rep - Cameroon	7,39
Chad - Sudan	8,25	Mali - Mauritania	7,36
Liberia - Coté d'Ivoire	8,05	Liberia - Sierra Leone	7,34

Table 7. East and Southern Africa: most significant pair-specific fixed effects for forced migrations

Total migration		Cross-border migration	
Country pair: Origin - Destination	**Estimates**	**Country pair: Origin - Destination**	**Estimates**
Sudan - Sudan	14,42	Mozambique - Malawi	13,10
Somalia - Somalia	13,38	Eritrea - Sudan	12,27
Mozambique - Malawi	13,10	Somalia- Kenya	12,26
Uganda - Uganda	12,52	Somalia - Yemen	11,53
Eritrea - Sudan	12,24	Somalia - Ethiopia	11,47
Somalia- Kenya	12,23	Sudan - Uganda	10,94
Tanzania - Tanzania	11,84	Mozambique - Zimbabwe	10,87
Angola - Angola	11,83	Burundi - Tanzania	10,83
Somalia - Yemen	11,51	Sudan - Ethiopia	10,79
Somalia - Ethiopia	11,45	Sudan - Chad	10,71
Sudan - Uganda	10,88	Mozambique - Tanzania	10,60
Mozambique - Zimbabwe	10,85	Ethiopia - Kenya	10,48
Burundi - Tanzania	10,82	Sudan - Kenya	10,26