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“Climate, Conflict and International Migration”

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Climate, Conflict and International Migration

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Abstract

Using a comprehensive dataset of bilateral migration flows and employing the Palmer index as a proxy for climate change, we demonstrate that conflict acts as an amplifying mechanism for climate-induced migration. Our results show that, as drought conditions worsen, middle- and high-income countries experiencing conflict are more inclined to have higher rates of international out-migration. In particular, we find that one standard deviation contraction in the Palmer index, indicating drier conditions, is associated with a 12% increase in out-migration flows from middle/high-income countries experiencing conflict. We also explore spatial autocorrelation and observe positive and significant origin- and destination-spatial dependence effects. Our findings contribute to understanding the intricate dynamics of climate change, conflict, and international migration while offering insights into migration patterns across countries.

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Keywords: Migration flows, climate change, conflict, droughts

1 Introduction

In recent decades, global warming has emerged as a significant concern, with rising temperatures and the increasing frequency of natural disasters exerting adverse effects on various economic dimensions (Dell et al., 2014; Burke et al., 2015b). Low- and middle-income countries are particularly vulnerable, given their heavy reliance on climate-dependent activities such as agriculture. In this context, migration has become a critical adaptation strategy for populations facing worsening economic conditions (Cai et al., 2016; Cattaneo and Peri, 2016). Climate-induced migration is influenced by many highly contextual factors, encompassing conditions in origin and destination countries. Notably, social conflict plays a crucial role in this dynamic. This paper investigates social conflict as an amplifying mechanism in the nexus between climate change and international migration.

To explore the role of conflict, we draw upon prior literature showing the correlation between vulnerability to weather shocks and the likelihood of conflict (Burke et al., 2015a; Miguel et al., 2004; Almer et al., 2017; Harari and La Ferrara, 2018; Unfried et al., 2022). We hypothesize that climate change may lead to higher conflict, which in turn induces larger migration flows. Additionally, we propose that the significance of conflict as an amplifying mechanism varies depending on a country's income level. The second innovative aspect of our approach involves accounting for spatial autocorrelation in migration flows, indicating spatial persistence. To address our research objectives, we construct a comprehensive global dataset encompassing migration flows between 155 origin countries and 122 destination countries from 1995 to 2020. We use the Palmer index (Palmer, 1965) as a proxy for climate change. To capture spatial spillovers, we employ state-of-the-art spatial econometrics techniques, necessitating the inclusion of spatial lags of the dependent variable.

Our study yields several key findings. First, we show that vulnerability to climate shocks does not inevitably lead to a higher probability of migration, consistent with Cattaneo et al.

(2019). Second, we document that drier conditions correlate with a higher probability of international migration in conflict-affected countries, with stronger effects in middle- and high-income countries. Specifically, a one standard deviation decrease in the Palmer index, indicating drier conditions, corresponds to a 12% increase in out-migration flows from middle/high-income countries experiencing conflict. In contrast, low-income countries under conflict exhibit a positive but statistically insignificant likelihood of migration under worsening conditions. One possible explanation for this are financial constraints. More prevalent liquidity constraints in poorer countries may hinder migration induced by adverse climate impacts, thus exacerbating their poverty trap. Conversely, conflict in middle- and high-income countries enhances the benefits of migration.

Third, we document the presence of spatial autocorrelation in migration flows. Specifically, we observe positive and significant origin- and destination-dependence effects. In our context, spatial dependence implies that larger observed migrations from an origin country A to a destination country Z are likely to be accompanied by: (1) increased migration flows from countries proximate to origin country A to destination country Z (origin-dependence effect); and (2) larger migration flows from origin country A to neighboring countries of destination country Z (destination-dependence effect). Our findings hence suggest that shocks are persistent in space, implying that even transitory shocks may have enduring effects on migration as they propagate across space.

The contribution of our paper is twofold. First, we investigate a novel amplifying mechanism in the relationship between climate change and international migration on a global scale over a long period of time. We do so by bridging two strands of literature. On the one hand, the literature on migration and climate change underlines the negative long-run effects of climate change –mainly measured by rising temperature– on agricultural productivity. Migration is one crucial adaptation strategy to declining agricultural productivity. However, this literature also demonstrates that the impact of long-term warming on migration differs depending on the initial income of populations, distinguishing between poor and middle-income countries. Indeed, Cattaneo and Peri (2016) show that higher temperatures in middle-income economies increase migration rates, while in poor countries, higher temperatures reduce the probability of migration.

On the other hand, we draw upon prior literature showing the correlation between vulnerability to weather shocks and the likelihood of conflict (Burke et al., 2015a; Miguel et al., 2004; Almer et al., 2017; Harari and La Ferrara, 2018; Unfried et al., 2022). In this study, we connect these two strands of literature to demonstrate that the presence of conflict acts as an amplifying mechanism encouraging people to migrate in response to weather shocks, provided their level of income is sufficiently high.

The second contribution is methodological. We model spatial dependence in migration flows through state-of-the-art spatial econometrics techniques that have seldom been applied in economics. In particular, our model includes spatially autoregressive terms to account for the fact that international migration flows may be correlated across space. This poses some challenges for estimation and constitutes a novel contribution to the empirical migration literature. In addition, we implement a novel methodology to compute the marginal effects on origin-destination migration flows assuming shocks to our proxy for climate.

Our approach yields two novel sets of methodological improvements. First, we quantify the role of neighboring countries and spatial dependence on migration flows. This is crucial because not accounting for spatial dependence when it exists leads to biased estimated coefficients. Second, we detect migration spillovers across countries.[1] Indeed, given a climate shock (drier conditions) at country i, we can decompose its impact into: the migration flows originating from the given country i (the origin effect); the migration flows arriving at coun-

[1] To the best of our knowledge, the only paper that assesses the role of neighboring regions at the macro level is Nowotny and Pennerstorfer (2019). The authors investigate migrants' location decisions within the European Union.

try i (the destination effect); and the migration flows that neither originate from nor arrive at the shocked country i (the network effect). Additionally, we present local decompositions of these origin, destination, and network effects by country. This opens an important avenue for future applications to further decompose shocks to origin-destination data.

The paper is structured as follows. Section 2 reviews the relevant literature, while Section 3 details the data and methods. Section 4 presents the main results. Section 5 investigates the heterogeneous effects of conflict in the climate-migration relationship, and Section 6 discusses the robustness of our findings. Section 7 concludes with the implications of our results. Additional robustness checks are provided in the Appendix.

2 Literature Review

Our paper relates to two main strands of literature: studies on global-scale international migration and climate change, and the literature examining the relationship between migration and conflict.

Recent studies have explored the relationship between climate change and international migration globally, identifying various mechanisms influencing this association (Cai et al. (2016); Cattaneo and Peri (2016); Falco et al. (2019). Cai et al. (2016) analyze data from 163 origin countries and 42 destination countries (mostly OECD countries) between 1980 and 2010, finding a positive and statistically significant relationship between temperature and international outmigration, particularly in agriculture-dependent countries. Similarly, Cattaneo and Peri (2016) use data from 115 countries between 1960 and 2000, observing that increasing temperatures lead to lower emigration rates in poor countries but higher rates in middle-income countries. Using a different identification strategy, Falco et al. (2019) also examine the relationship between agriculture, income, and migration, highlighting a stronger impact on migration in poor countries compared to middle-income countries.

Also at a global scale, Beine and Parsons (2015) investigates the influence of natural disasters and temperature on international migration globally. They find no evidence of long-term climatic factors affecting migration once economic, cultural, political, social, and demographic factors are controlled for. However, their results suggest that climatic factors may indirectly influence international migration through wage differentials. Flores et al. (2024) use high-frequency data to study the impact of soil moisture anomalies on migration within West Africa and toward Europe. They find a drop in international migration during the months following the crop-growing season, suggesting that weather anomalies affect agricultural production leading to liquidity constraints that prevent people from moving internationally.

The second strand of literature our paper relates to are studies that explore the link between climate and conflict. Previous studies suggest that drought and precipitation are significant determinants of social conflicts. In a meta-analysis, Hsiang et al. (2013) find that warmer temperatures or extreme rainfall can causally influence changes in interpersonal violence and civil war. Specifically, they observe that for each one standard deviation change in climate towards warmer temperatures or more extreme rainfall, the frequency of interpersonal violence increases by 4% and the frequency of intergroup conflict rises by 14%.

In earlier work, Miguel et al. (2004) demonstrate that rainfall shocks leading to decreased economic growth increase the likelihood of civil war in Sub-Saharan Africa. Also focusing in the Sub-Saharan African context, Almer et al. (2017) use disaggregated data at the month and cell level to investigate the link between water shocks and small-scale social conflict over the 1990-2011 period. They find that a one-standard-deviation decrease in the drought index (drier conditions) raises the likelihood of riots by 8.3%. In a related study, Harari and La Ferrara (2018) conduct a disaggregated empirical analysis using a gridded dataset of civil conflict at the subnational level in Africa from 1997 to 2011. They find that negative shocks during the growing season of local crops persistently affect conflict incidence, with local conflicts spilling over to neighboring cells. Couttenier and Soubeyran (2013) use the Palmer drought index as a measure of exposure to water stress and find a weak positive link between droughts and civil war in Sub-Saharan Africa. In a recent paper, Unfried et al. (2022) use grid-cell data for Africa and Central America over the years 2002 to 2017 and provide evidence that water scarcity is likely to provoke conflict.

While the connection between climate and various forms of social conflict has been identified, the specific mechanisms driving this relationship are still under investigation. Collier and Hoeffler (1998) investigate the economic causes of civil wars through a cost-benefit analysis framework. Building upon Chassang and Miquel (2009)'s theoretical approach, Ciccone (2013) proposes two instrumental variables approaches to test the opportunity-cost channel and examine civil conflict risk following transitory income shocks. Non-economic factors may also play a significant role. Missirian and Schlenker (2017) analyze data from 103 non-OECD countries reporting asylum applications to the EU between 2000 and 2014. They find a statistically significant relationship between fluctuations in asylum applications and weather anomalies. Given that asylum is granted because of personal persecution, not economic conditions, the paper sheds light on the intrinsic relation between climate, social conflict, and migration that drives people to seek refuge abroad.

At a global scale, few papers have explored the relationship between climate, social conflict, and migration. Martínez-Zarzoso et al. (2023) study bilateral migration from 76 developing countries from the Global South to OECD countries. They find that, for less developed countries, an increase in temperature in conflictive countries reduces out-migration relative to non-conflictive countries. We depart from this paper in several ways. First, we perform a global analysis. Second, we use the Palmer index instead of temperature as our proxy for climate change. Third, we employ a spatial model to account for neighboring effects.

We contribute to both strands of literature by studying conflict as a plausible mechanism in the association between climate patterns and migration. Climatic conditions per se do not precipitate conflict; rather, climate changes can alter the conditions under which certain social interactions occur, potentially increasing the likelihood of conflict (Burke et al., 2015a). For example, drier conditions or elevated temperatures can impact agricultural productivity, mortality rates, and a spectrum of related outcomes, all of which may collectively contribute to heightened social instability and conflict, and thus may induce more out-migration. Additionally, in this paper, we distinguish among low-, middle- and high-income countries since out-migration could be different depending on income level. For example, financial constraints could play a differential role in people's decision to migrate internationally depending on countries' level of income.

3 Data and methods

3.1 Data description

We now describe the migration data, as well as the climate and conflict data. Finally, we present the socioeconomic information we include as control variables, together with the summary statistics of all factors used in estimations.

3.1.1 Migration data

Bilateral migration stock matrices come from the UN Population Division (Desa, 2019),[2] covering the period 1995 to 2020 in 5-year periods. Originally, we have a dataset of 161 origin countries and 162 destination countries.[3] To convert migration stocks into flows, we rely on a stock difference method called the *reverse negative* method, as formulated by Abel

[2]UNPD data can be downloaded from https://www.un.org/development/desa/pd/content/international-migrant-stock

[3]The difference between these two sets of countries is Maldives which is a destination country but not an origin country.

and Cohen (2019) and modified by Laurent et al. (2023a). The method computes the number of migrants $Y_{od,t}$ from origin o to destination d during a time interval t by subtracting the migrant stock totals in each migration corridor (a one-directional flow from o to d between a pair o,d of countries). To formally present the reverse negative method, we start by defining the migrant stock table at time p, S_p, for a set of 4 countries: A, B, C, D:

$$S_p = \begin{pmatrix} & A & B & C & D & \vdots & \\ A & S_{AA}(p) & S_{AB}(p) & S_{AC}(p) & S_{AD}(p) & \vdots & TB_A(p) \\ B & S_{BA}(p) & S_{BB}(p) & S_{BC}(p) & S_{BD}(p) & \vdots & TB_B(p) \\ C & S_{CA}(p) & S_{CB}(p) & S_{CC}(p) & S_{CD}(p) & \vdots & TB_C(p) \\ D & S_{DA}(p) & S_{DB}(p) & S_{DC}(p) & S_{DD}(p) & \vdots & TB_D(p) \\ \cdots & TR_A(p) & TR_B(p) & TR_C(p) & TR_D(p) & \vdots & N(p) \end{pmatrix}$$

where countries A to D represent places of birth in the rows and places of residence in the columns. An element $S_{ij}(p)$ in matrix S_p represents the number of persons born in i and living in j at time p. $TB_i(p)$ corresponds to the total number of persons born in i at time p, $TR_j(p)$ denotes the total number of persons living in j at time p, and $N(p)$ is the total number of persons observed at time p. Let $Y_{od,t}$ be the number of people migrating from origin o to destination d during a time interval t. Beine and Parsons (2015) propose considering decreases in bilateral migrant stocks as a reverse migration flow from origin d to destination o as follows:

$$Y_{od,t} = \begin{cases} S_{od}(p+1) - S_{od}(p) & \text{if } S_{od}(p+1) > S_{od}(p) \text{ and } S_{do}(p+1) \geq S_{do}(p) \text{ and } o \neq d \\ S_{od}(p+1) - S_{od}(p) + S_{do}(p) - S_{do}(p+1) & \text{if } S_{od}(p+1) > S_{od}(p) \text{ and } S_{do}(p+1) < S_{do}(p) \text{ and } o \neq d \\ S_{do}(p) - S_{do}(p+1) & \text{if } S_{od}(p+1) \leq S_{od}(p) \text{ and } S_{do}(p+1) < S_{do}(p) \text{ and } o \neq d \\ 0 & S_{od}(p+1) \leq S_{od}(p) \text{ and } S_{do}(p+1) \geq S_{do}(p) \text{ or } o = d. \end{cases}$$

The way we modify the stock difference method in Abel and Cohen (2019) is as follows. First, the estimates of migration flows account for changes in births and deaths in the migrant stocks during the period of analysis. Second, we integrate an open demographic accounting system in the reverse negative method where persons can move to or from countries beyond the set of those in the input bilateral migrant stock tables (where data are available).[4]

[4]For further information, please refer to Laurent et al. (2023a); Abel and Cohen (2019); Abel (2013).

Finally, we calculate migration flow rates as the logarithm of the ratio between origin-destination migration flows and the population of the origin country at the beginning of the period. It is important to note that observations with zero values are excluded when taking the logarithm. Initially, our baseline estimations consider only observations with positive migration flows. However, we also conduct robustness analyses that involve zero flows. In these cases, we add one to the migration flow before calculating the migration rate, following the approach outlined in Cai et al. (2016).

3.1.2 Climate data

As a proxy for slow-onset meteorological events of climate change, we use the Self-Calibrated Palmer Drought Severity Index for global land, from now on the Palmer index. The index quantifies long-term drought, as it uses temperature data and a physical water balance model, capturing the basic effect of global warming on drought through changes in potential evapotranspiration (Dai, 2023; Wells et al., 2004). The self-calibrated Palmer index is a variant of the original Palmer Drought Severity Index (Palmer, 1965), with the aim to make results from different climate regimes more comparable. It ranges from -10 (dry) to +10 (wet).[5] Data are gridded at intervals of 1/2 degrees in longitude and latitude. We aggregate the data to the country level, weighting it by population. Thus, the climate conditions for populated regions within a country are given more weight. To compute population weights, we use data from Gridded Population of the World (CIESIN et al., 2005; CIESIN, 2018).[6] Finally, we compute the mean Palmer index over the 5-year periods.

As an alternative measure for the Palmer index, we use the Standardized Precipitation and Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010; Beguería et al., 2014,

[5]Data has been retrieved from https://crudata.uea.ac.uk/cru/data/drought/#global. References include van der Schrier et al. (2013); Barichivich et al. (2022).

[6]GPWv3 data can be downloaded from https://sedac.ciesin.columbia.edu/data/set/gpw-v3-population-count, and GPWv4 can be downloaded from https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-count-adjusted-to-2015-unwpp-country-totals-rev11.

2023).[7] Like the sc-PDSI, this index is designed to take into account both precipitation and potential evapotranspiration in determining drought (Vicente-Serrano, 2023). Unlike the Palmer index, the SPEI allows to monitoring climate conditions using different time scales. In particular, we consider the SPEI at a time scale of 48 months. Data are gridded at intervals of 1/2 degrees in longitude and latitude. As with the Palmer index, we aggregate it to the country level, weighting it by population. Lastly, we compute the mean SPEI index over the 5-year periods.

3.1.3 Conflict data

We incorporate social conflict data into our analysis from the Uppsala Conflict Data Program (UCDP), specifically the UCDP Georeferenced Event Dataset Global version 23.1 (Sundberg and Melander, 2013; Davies et al., 2023).[8] This dataset compiles information on armed conflicts and organized violence. UCDP defines conflict as a *contested incompatibility that concerns government and/or territory where the use of armed force between two parties, of which at least one is the government of a state, results in at least 25 battle-related deaths in one calendar year*. We construct the following variables to measure the presence of conflict: (i) a dummy variable that equals one if the total death rate of a country is above the top 25% of the distribution of death rates both calculated for each 5 years, and zero otherwise, (ii) a dummy variable that equals 1 if a specific country had 4 or 5 years of conflict in each 5-year period, and zero otherwise.

To further investigate what types of conflict are more likely to exert an influence on climate-related migration, we examine the actors participating in the conflict. The actors can be states (S), civilians (C), or armed groups (AG). According to UCDP definition, state conflict is defined as *either an internationally recognized sovereign government controlling*

[7]Data can be retrieved from https://spei.csic.es/spei_database/
[8]Data can be downloaded at https://ucdp.uu.se/

a specified territory, or an internationally unrecognized government controlling a specified territory whose sovereignty is not disputed by another internationally recognized sovereign government previously controlling the same territory. Conflict among civilians refers to *unarmed people who are not active members of the security forces of the state, or members of an organized armed militia or opposition group.* Finally, conflict among armed groups corresponds to any formally or informally organized group using armed force.[9] We then recompute the dummy variables outlined before to calculate the death rates depending on whether the conflict is between two states (which we denote as $S\ vs\ S$), between state and civilians ($S\ vs\ C$), between state and armed groups ($S\ vs\ AG$), between armed groups and civilians ($AG\ vs\ C$), and finally among armed groups ($AG\ vs\ AG$).

3.1.4 Socioeconomic and geographic information

We use country income level classification from World Development Indicators (World Bank, 2023) and real GDP per capita from Penn World Tables 10.01 (Feenstra et al., 2015).[10] As variables characterizing both the origin and destination countries, we include the distance,[11] whether the countries in a pair share a border or an official language (source: Dynamic Gravity Dataset, Gurevich and Herman, 2018).

We eliminate countries with missing information for at least one of the independent variables. We start from a dataset with 161 origins and 162 destinations from 1995 to 2020 in periods of five years. However, because the spatial regression does not allow for an unbalanced panel, we need to restrict our sample to country pairs that have positive migration in all the periods of the sample. As a result, we end up with a sample with 155 origin countries and 122

[9] For more details on definitions, please refer to: `https://www.uu.se/en/department/peace-and-conflict-research/research/ucdp/ucdp-definitions`.

[10] Data can be retrieved from `https://www.rug.nl/ggdc/productivity/pwt/?lang=en`

[11] The geographic distance between countries is based on the methodology of Mayer and Zignago (2005) and reflects the distance between pairs of cities, weighted by the proportion of the country´s population residing in each city, in kilometers.

destination countries.[12] In the forthcoming Section 6, we present robustness checks, where we estimate the linear model with the complete sample. Destination and origin countries in our sample account for 84% and 97% of the world population in 2020, respectively.

Table 1 presents summary statistics for our final sample. Statistics in this table are by origin country for each 5 years. Several aspects of the data are worth discussing. On average, GDP per capita is 16.74 thousands of USD and the average population is 42 million people. On average, the percentage of migration relative to total population is 0.97%, which corresponds to approximately an average of total migration of 149.96 thousand people for each country in each period. The mean Palmer index is -0.51. On average, countries experienced 1.57 years of conflict in a 5-year period leading to an average of 1.70 thousand deaths, which corresponds to 1% of the total country population. Overall, 26% of the origin countries experienced more than 3 years of conflict in a 5-year period.

Table 2 shows the same statistics but for the destination countries in our sample. On average, GDP per capita is 19.74 thousand of USD, slightly higher than for the set of origin countries. The average population is 47 million people, also slightly higher than the same number of origin countries. The Palmer index is on average -0.51. In terms of the conflict variables, destination countries experienced 1.36 years of conflict in a 5-year period leading to an average of 0.82 thousand deaths, lower than the average for destination countries. Finally, 22% of countries experienced more than 3 years of conflict in a 5-year period.

Since we consider bilateral migration flows, our total number of observations in the final dataset is 17390 (country pairs in a period). On average, for an origin country, about 6684 people migrate to another country during a specific period in our sample. During the period of analysis, about 116 million people migrated to another country. Finally, Table A4 in the appendix exhibits the correlation matrix of the variables used in the analysis and described above computed over the final dataset.

[12]Table A1 and A2 in the appendix list all destinations and origins, respectively

Table 1: Summary statistics for origin countries

Variable	Mean	Min	Max	Std. dev.	Obs.
Total outmigration (%)	0.97	0.00	14.28	1.38	775
Total outmigration (thousands of people)	149.96	0.07	4302.73	325.81	775
Palmer Index	-0.52	-3.93	2.76	1.06	775
SPEI-48	-0.33	-2.13	1.75	0.72	775
Conflict deaths (thousands of people)	1.70	0.00	213.18	11.21	775
Conflict deaths rate (%)	0.01	0.00	0.98	0.06	775
Years of conflict in a 5 year period	1.57	0.00	5.00	2.04	775
Conflict deaths rate dummy	0.25	0.00	1.00	0.43	775
Years of conflict >3 dummy	0.26	0.00	1.00	0.44	775
GDP per capita (thousands of USD)	16.74	0.44	151.23	19.70	775
Population (millions of people)	42.15	0.08	1408.96	146.26	775

Notes. The table exhibits summary statistics by origin country in 5-year periods. Sample: 1995-2020.

Table 2: Summary statistics for destination countries

Variable	Mean	Min	Max	Std. dev.	Obs.
Total inmigration (%)	1.48	0.00	62.29	3.95	610
Total inmigration (thousands of people)	190.52	0.00	3806.00	455.89	610
Palmer Index	-0.51	-3.93	2.76	1.07	610
SPEI-48	-0.31	-2.13	1.75	0.72	610
Conflict deaths (thousands of people)	0.82	0.00	37.08	3.28	610
Conflict deaths (%)	0.00	0.00	0.19	0.01	610
Years of conflict in a 5 year period	1.36	0.00	5.00	1.95	610
Conflict deaths rate dummy	0.20	0.00	1.00	0.40	610
Years of conflict >3 dummy	0.22	0.00	1.00	0.42	610
GDP per capita (thousands of USD)	19.10	0.46	110.18	19.51	610
Population (millions of people)	47.13	0.08	1408.96	163.37	610

Notes. The table exhibits summary statistics by destination country in 5-year periods. Sample: 1995-2020.

Table 3 and 4 present summary statistics for the origin and destination countries, disaggregated by country income level, respectively. Concerning origin countries, total outmigration is highest for middle-income countries, followed by low-income and then high-income nations. The Palmer index is the lowest for low-income countries, followed by middle-income and then high-income countries, indicating that drier conditions are typically associated with countries experiencing worse economic conditions. The average duration of conflict over a 5-year period was 2.43 years for low-income countries, 1.61 years for middle-income countries, and 0.48 years for high-income countries. Overall, 37% of low-income countries experienced more than three years of conflict within a 5-year period, while this figure is 29% for middle-income countries and 7% for high-income countries.

Regarding destination countries, the highest rate of in-migration corresponds to high-income countries. Both the Palmer index and the percentage of countries experiencing more than 3 years of conflict within a 5-year period exhibit the same pattern as for origin countries. GDP per capita is, on average, higher for low- and middle-income countries among destination countries, but slightly lower for high-income countries compared to origin countries. In terms of population, destination low- and middle-income countries are, on average, larger than their counterparts in origin countries, while for high-income countries, the mean population is similar.

Table 3: Summary statistics by income level for origin countries

	Low income			Middle income			High income		
Variable	Obs.	Mean	Std. dev.	Obs.	Mean	Std. dev.	Obs.	Mean	Std. dev.
Total outmigration (%)	218	0.90	1.02	373	1.21	1.74	184	0.55	0.64
Total outmigration (thousands of people)	218	161.30	329.47	373	182.20	378.46	184	71.16	143.43
Palmer Index	218	-0.62	0.83	373	-0.59	1.04	184	-0.25	1.30
SPEI-48	218	-0.34	0.58	373	-0.32	0.74	184	-0.32	0.82
Conflict deaths (thousands of people)	218	2.17	7.39	373	2.23	15.09	184	0.07	0.41
Conflict deaths (%)	218	0.01	0.05	373	0.01	0.07	184	0.00	0.00
Years of conflict in a 5 year period	218	2.43	2.02	373	1.61	2.12	184	0.48	1.25
Conflict deaths rate dummy	218	0.42	0.50	373	0.25	0.44	184	0.05	0.22
Years of conflict >3 dummy	218	0.37	0.48	373	0.29	0.45	184	0.07	0.25
GDP per capita (thousands of USD)	218	2.13	1.17	373	11.08	6.52	184	45.54	19.98
Population (millions of people)	218	43.99	153.66	373	48.71	170.70	184	26.66	53.96

Notes. The table exhibits summary statistics by origin country income level by 5-year period. Sample: 1995-2020. Middle income includes both lower-middle and upper-middle income countries.

Table 4: Summary statistics by income for destination countries

	Low income			Middle income			High income		
Variable	Obs.	Mean	Std. dev.	Obs.	Mean	Std. dev.	Obs.	Mean	Std. dev.
Total inmigration (%)	140	0.58	2.07	292	0.80	1.69	178	3.29	6.39
Total inmigration (thousands of people)	140	68.13	161.26	292	112.51	267.95	178	414.78	710.04
Palmer Index	140	-0.72	0.78	292	-0.61	1.03	178	-0.18	1.25
SPEI-48	140	-0.38	0.59	292	-0.29	0.72	178	-0.30	0.82
Conflict deaths (thousands of people)	140	1.10	2.78	292	1.14	4.28	178	0.07	0.42
Conflict deaths (%)	140	0.01	0.02	292	0.00	0.01	178	0.00	0.01
Years of conflict in a 5 year period	140	2.34	1.98	292	1.41	2.05	178	0.49	1.27
Conflict deaths rate dummy	140	0.39	0.49	292	0.20	0.40	178	0.05	0.22
Years of conflict >3 dummy	140	0.35	0.48	292	0.25	0.44	178	0.07	0.25
GDP per capita (thousands of USD)	140	2.26	1.25	292	11.87	6.63	178	44.22	17.04
Population (millions of people)	140	54.83	189.12	292	55.41	191.36	178	27.50	54.67

Notes. The table exhibits summary statistics by origin country income level by 5-year period. Sample: 1995-2020. Middle income includes both lower-middle and upper-middle income countries.

3.2 Methodology

Consider a model setting with n_o origins and n_d destinations, resulting in $N = n_o \times n_d$ pairs (o, d) of OD migration flows at time interval t. Let Y_t be the migration flow matrix at time interval t, where the n_d columns represent the destination countries 1 to n_d and the n_o rows correspond to origin countries 1 to n_o:

$$Y_t = \begin{pmatrix} Y_{11,t} & Y_{12,t} & \cdots & Y_{1n_d,t} \\ Y_{21,t} & Y_{22,t} & \cdots & \cdots \\ & & & Y_{n_o-1n_d,t} \\ & & & Y_{n_on_d,t} \end{pmatrix} \tag{1}$$

There are multiple ways to vectorize the flow matrix Y_t, depending on whether we stack its columns (destination centric) or its rows (origin centric). In this paper, we propose a destination-centric ordering and denote by y_t, the flow vector, of length $N \times 1$. Hence, the first n_d elements of y_t represent migration flows from origin country 1 to all n_d destination countries. All formulas below can be adapted to the origin-centric scheme. It is important to note from the definitions above that all countries in our dataset can potentially act as origins and destinations depending on their positions in the pair $Y_{od,t}$ and provided the corresponding migration flow exists.

Regarding the country characteristics, we define OX_t as the matrix of the k_o characteristics of the origin countries, which is of dimension $n_o \times k_o$. This matrix includes the relevant variables for the origin countries, like the Palmer index, the level of conflict or GDP for a given period t, as well as the interaction dummy variables. We denote as DX_t the matrix of k_d destination characteristics, with dimension $n_d \times k_d$ $(n_d \times l_d)$. We now construct the following matrices:

- $X_{o,t} = OX_t \bigotimes \iota_{n_d}$, of dimension $n_o n_d \times k_o$, contains the characteristics of the origin countries for period t,
- $X_{d,t} = \iota_{n_o} \bigotimes DX_t$, of dimension $n_o n_d \times k_d$, encompasses the characteristics of the destination countries.

To model bilateral migration flows accounting for the influence of climate change and the amplifying effects of conflict, we start by defining a spatial interaction or gravity model, where the dependent variable is the OD migration flow rate. The equation to estimate through an ordinary linear regression writes as follows:

$$\begin{aligned} y_t = {} & X_{o,t}\beta_o + X_{d,t}\beta_d + X_{od}\beta_{od} + X^P_{o,t} \times 1_{Deathrate}\beta_1 + X^P_{o,t} \times 1_{LI}\beta_2 \\ & + 1_{LI} \times 1_{Deathrate}\beta_3 + X^P_{o,t} \times 1_{Deathrate} \times 1_{LI}\beta_4 + \psi_o + \psi_d + \psi_t + \epsilon_t \end{aligned} \tag{2}$$

where β_o and β_d are the vectors of size $k_o \times 1$ and $k_d \times 1$, respectively, containing the coefficients to estimate for the origin and destination variables, respectively. X_{od} is a matrix of (time-invariant) gravity variables that characterize the country pairs and thus can affect the probability of migrating from one country to another. It includes a measure of distance between country pairs (*log distance)*, a dummy variable that takes the value of 1 if the countries in the pair share a border (*contiguity*), and a dummy variable that takes the value of 1 if the countries in the pair share a common language (*common language*). We also include origin- (ψ_o) and destination- (ψ_d) fixed effects to control for country time-invariant characteristics such as geography, culture, or institutions; we also include time-effects (ψ_t). Finally, ϵ_t is the error term that captures unobserved factors affecting the outcome variable.

As origin characteristics in $X_{o,t}$, we include the mean Palmer index and the conflict death rate dummy over time interval t. Let $X^P_{o,t}$ be the Palmer index vector. We include interaction terms between the Palmer index, the conflict death rate dummy ($1_{Deathrate}$), and a dummy variable indicating if the country of origin is classified as low-income in that period (LI). We aim to capture whether drier conditions (lower Palmer index) have a differential effect on migration when the country is conflict-ridden compared to countries that are not in conflict. Additionally, we add the triple interaction among the presence of conflict, the Palmer index, and the low-income dummy in equation (2) to identify whether drier conditions in conflictive and low-income countries have a differential effect on migration compared to middle- and high-income countries. As additional control variables, we include the average GDP per capita in time interval t for both the origin and destination countries.

3.2.1 The spatial autoregressive interaction model

To model bilateral migration flows accounting at the same time for the role of neighboring countries and for the influence of climate change, we rely on a spatial autoregressive interaction model. Interaction or gravity models, as the one in equation (2), attempt to explain the interaction between origin and destination locations using: (1) origin-specific attributes characterizing the ability of the origins to generate flows; (2) destination-specific characteristics representing the attractiveness of destinations; and (3) variables that characterize the way spatial separation of origins from destinations constrains or impedes the interaction. However, using spatial separation variables, such as distance, is generally not enough to eradicate the spatial dependence among the sample of origin-destination (OD) flows. For this reason, spatial autoregressive interaction models augment the gravity equation with spatially lagged dependent (and independent) variables (Margaretic et al., 2017).

Let OW be a $n_o \times n_o$ matrix characterizing the neighborhood in the set of origin countries, according to their geographic distance (as defined in Section 3.1.4). Precisely, OW represents a non-negative, sparse matrix, with element $ow_{lp} = 1$ if country p is one of the neighbors of country l and 0 otherwise. To identify neighboring countries, we rely on a $k-$nearest neighbor algorithm based on the distance between (pairs of cities in) each pair of countries in the dataset, with $k = 4$. Similarly, let DW of dimension $n_d \times n_d$ be a matrix characterizing the geographic proximity in the set of destination countries. We define proximity as for OW. We consider the following two types of neighborhood structures,

- $W_o = OW \bigotimes I_{n_d}$ is the origin-based spatial neighborhood matrix,
- $W_d = I_{n_o} \bigotimes DW$ is the destination-based spatial neighborhood matrix,

where $\bigotimes$ stands for the Kronecker product of two matrices. Note that the two weight matrices W_o and W_d are row-normalized and of dimension $N \times N$, with N being $N = n_o \times n_d$.[13]

The spatial autoregressive interaction model in its reduced form becomes,

$$\begin{aligned} y_t = {} & \rho_o W_o y_t + \rho_d W_d y_t + X_{o,t}\beta_o + X_{d,t}\beta_d + X_{od}\beta_{od} + X^P_{o,t} \times 1_{Deathrate}\beta_1 + X^P_{o,t} \times 1_{LI}\beta_2 \\ & + 1_{LI} \times 1_{Deathrate}\beta_3 + X^P_{o,t} \times 1_{Deathrate} \times 1_{LI}\beta_4 + \psi_o + \psi_d + \psi_t + \epsilon_t \end{aligned} \tag{3}$$

where the parameters ρ_o and ρ_d capture the strength of origin- and destination-spatial dependence, respectively. Thus, the terms $\rho_o W_o y_t$ and $\rho_d W_d y_t$ quantify the endogenous origin- and destination-spatial effects on international migration. In simple terms, a positive estimate for origin spatial dependence means that higher observed migration from an origin

[13] There is an additional technical point to make regarding the presence of zero flows. In order not to bias the parameter estimation, we eliminate them before fitting the model. This elimination results in some migration flows having no longer a neighbor in W_o or W_d. We hence take a two-step sequential procedure to address this issue. Specifically, for those migration flows without neighbors in a given weight matrix, we first look for new nearest neighbors by increasing the number of nearest neighbors until $k = 20$ such that all flows have at least one neighbor. However, in the second step, we eliminate those neighbors with a distance above 3000 km. This second step is to avoid having abnormal neighbors. Table A3 in the appendix exhibits the distribution of the number of neighbors per country pair.

country A to a destination country Z are likely to be accompanied by increased migration flows from countries near origin country A to destination country Z. In turn, the destination-dependence effect implies that larger observed migrations from an origin country A to a destination country Z may be accompanied by larger migration flows from origin country A to neighboring countries of destination country Z. For estimation, we rely on a maximum likelihood estimation procedure.

To illustrate the destination-dependence, consider migrants from Venezuela migrating to Chile. It is likely that Venezuelan people will also migrate to Peru and Ecuador (three neighboring countries according to DW), presumably due to the historical and cultural ties among the three destination countries, as well as their positively correlated economic cycles. In fact, the average correlation of real GDP in these three economies is almost 0.5. Over the period $2015-2020$, these three Latin American countries were among the top five destinations of Venezuelan emigrants.[14]

Interestingly, previous literature has shown, at the micro level, that migrants' location choices depend on differences in economic opportunities (such as unemployment and income per capita, Davies et al., 2001; Beine et al., 2021; welfare programs, amenities, and migration costs, Beine et al., 2011), but also that migrants tend to move where other migrants from the same ethnicity or country of birth have migrated previously (Nowotny and Pennerstorfer, 2019). Indeed, migrant networks play an important role in explaining the size and structure of international migration, as they affect the private costs and benefits of migration (the assimilation channel) and reduce legal entry barriers through family reunification programs (the policy channel, Beine et al., 2015). Sharing historical and/or cultural ties is a key factor explaining migrants' location choices (Fenoll and Kuehn, 2018). These mechanisms are hence

[14] When examining the economic cycles of these economies (by subtracting the Hodrick Prescott trend from real GDP), we find that the cycles in these three South American economies are less volatile, compared to the average economic cycle of the other Latin American countries in our sample. This could in turn explain why Chile, Peru, and Ecuador are in the top five of Venezuelan migrants' destinations.

consistent with the destination-dependence effects that we define in equation (3).

To illustrate the origin-dependence effect, consider migrants from Algeria, Morocco, and Tunisia (three neighboring countries according to OW) migrating to France, likely due to shared cultural and historical ties with France. Indeed, from 2015 to 2020, these three African countries were among the top five countries of origin for French immigration. We hypothesize that the origin-dependence effects in equation (3) may reflect economic, cultural, and historical factors that neighboring countries of origin share, such as correlated economic cycles or colonial ties. These shared factors may lead people from such countries to migrate to a common destination. However, to the best of our knowledge, there are no previous studies documenting these origin effects.

It is important to contrast these examples with the estimates of an ordinary linear model where $\rho_o = \rho_d = 0$. In such a model, for instance, the migration flows from Algeria to France, and from Tunisia to France would be considered independent. Note in addition that since the matrices W_o and W_d are row-normalized, the parameters ρ_o and ρ_d have to be smaller than 1. Finally, it is crucial to stress that the failure to account for spatial dependence, when it exists, leads to biased estimates for the determinants of migration, inefficient standard errors, and misprediction. Therefore, this paper contributes to the existing literature by investigating whether there is spatial dependence in migration flows among country pairs.

3.2.2 Model interpretation

In a spatial autoregressive interaction model, the impact of an independent variable X on the migration flow $Y_{od,t}$ is not entirely captured by the estimated coefficient of that variable. This is because a change in a given characteristic X in a country i does not only have a direct impact on country i. On the contrary, such a shock has an impact on the migration flows originating from country i; on the migration flows arriving at country i; and on the migration flows that do not originate nor arrive at the changed country i. The sum of these impacts is the total effect of a change in a characteristic X on the dependent variable Y (Laurent et al., 2023b).

Moreover, in this paper, we consider a general spatial interaction model, where the list of origins and the list of destinations do not coincide and where the origin characteristics are different from the destination characteristics. In such a framework, the definition of the total impact itself is unchanged but its decomposition has to be adapted. To adapt the decomposition of the total effects, we follow Laurent et al. (2022, 2023b), who decomposed, for the first time, the total effects in this general setting.

To quantify the total effects of a one-time shock, we conduct an exercise similar in spirit to the evaluation of an impulse response. In this paper, our interest is on the impact of climate shocks, as measured by the Palmer index, on international migration. With this aim, relying on a given spatial model estimate, we provide a hypothetical country with a one-time negative shock to the Palmer index equal to -1 standard deviation; we use the spatial estimates of the considered specification to track the local impacts of this shock on the dependent variable, leaving all other covariates at their initial levels.

More precisely, let $TE(i)$ denote the total impact of a change in a continuous characteristic X on country i. $TE(i)$ is the sum of the origin, destination and network effects, when these terms have a meaning (replaced by zero otherwise). In Laurent et al. (2023b), the origin effect or $OE(i)$ is the sum of all changes on the migration outflows starting from i resulting from a change in the characteristic X on country i. Therefore, this effect only has a meaning for origin countries. Symmetrically, the destination effect or $DE(i)$ only has a meaning for destination countries. In turn, for a changed variable X on countries that act as origins, destinations or both, the network effect or $NE(i)$ is the impact of a change in a given characteristic on all the flows that do not originate nor arrive at the changed location i. Hence, $TE(i) = OE(i) + DE(i) + NE(i)$.

As a scalar measure of the cumulative origin effect (respectively, destination effect, network effect), $TOE = \sum_i OE(i)$, we propose to normalize the total origin effect by the total number of flows N. This measure represents the impact of an origin characteristic change on a typical flow originating at its origin location (respectively, the impact of a destination characteristic change on a typical flow going to its destination location; the impact of a characteristic change on a typical flow not originating nor going to that changed location).

4 Empirical results

4.1 Linear models

Table 5 exhibits the OLS estimates of the parameters of equation (2). The first column only includes the Palmer index; column two adds the conflict death rate dummy and its interaction with the Palmer index. In turn, column three adds the interaction term between the Palmer index and the low-income country dummy. Finally, column four includes a triple interaction term between the Palmer index, the conflict death rate dummy and the low-income dummy. Table 6 reports the marginal effects of the Palmer index distinguishing countries among conflictive and non-conflictive ones, and low- and middle-income countries: baseline estimates. Results in Tables 5 and 6 consider non-zero international migration flows.

Table 5: OLS Baseline estimates

	Dependent variable: Log(origin-destination migration rate)			
	(1)	(2)	(3)	(4)
Palmer index	−0.001	0.016	0.015	0.014
	(0.010)	(0.011)	(0.012)	(0.012)
Log distance	−1.073***	−1.073***	−1.073***	−1.073***
	(0.041)	(0.041)	(0.041)	(0.041)
Contiguity	0.918***	0.918***	0.918***	0.918***
	(0.130)	(0.130)	(0.130)	(0.130)
Common language	1.128***	1.128***	1.128***	1.128***
	(0.073)	(0.073)	(0.073)	(0.073)
Death rate		0.101***	0.156***	0.160***
		(0.030)	(0.038)	(0.038)
Palmer x Death rate		−0.079***	−0.079***	−0.073**
		(0.024)	(0.025)	(0.028)
LI x Death rate			−0.130***	−0.142***
			(0.046)	(0.049)
Palmer x LI			0.004	0.011
			(0.024)	(0.028)
Palmer x Death rate x LI				−0.028
				(0.051)
Observations	17,390	17,390	17,390	17,390
GDP/capita - Orig	Yes	Yes	Yes	Yes
GDP/capita - Dest	Yes	Yes	Yes	Yes
Orig + Dest FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
R^2	0.697	0.697	0.697	0.697
Adjusted R^2	0.692	0.692	0.692	0.692

Notes. This table exhibits the OLS estimates of equation (2) including fixed effects for origin, destination, and time. The dependent variable is the bilateral migration flow rate in logarithm. For details on the independent variables, please refer to Section 3.1. LI stands for low income and corresponds to the low-income dummy variable. Death rate refers to the Death rate dummy variable proxying for conflict presence. Regressions also include GDP per capita at both origin and destination as control variables. GDP/capita stands for GDP per capita. Orig abbreviates origin and Dest refers to destination. Clustered standard errors by country pairs are presented in parentheses. *p<0.1; **p<0.05; ***p<0.01.

To begin with, Table 5 shows that, on average, the Palmer index is not significantly related to the probability of migration, while the presence of conflict unconditionally increases the probability of migration. However, the interaction between the Palmer index and the conflict death rate dummy indicates that when climatic conditions are drier, being a conflict-affected country is associated with a higher probability of migration compared to a non-conflict-affected country. Finally, Table 5 demonstrates, as expected, that the distance between countries in a given pair is negatively related to a higher probability of migration. Additionally, if the countries in a pair share a common language or a common border, it is positively related to migration.

To provide a clearer interpretation of the marginal impacts of drier conditions among different groups of countries, Table 6 presents the marginal impacts of a 1 standard deviation contraction in the Palmer index (drier conditions) by country groups (low- and middle/high-income countries). Results in Table 6 confirm that drier conditions are associated with a higher probability of migration in conflict-affected countries (column (2)). Conversely, the overall impact of drier conditions on the probability of migration is non-significant when the origin country does not experience conflict. Furthermore, when distinguishing between low- and middle/high-income countries with and without conflict (column (4)), the marginal effect of drier conditions on the probability of migration remains positive and significant for conflict-affected countries but is similar across the two income groups. In contrast, there is no significant association between climate shocks (as measured by drier conditions) and international migration when countries are not experiencing conflict, regardless of their income level.

Finally, it is worth stressing that the positive relationship between drier conditions and migration for conflict-affected middle/high-income countries is mainly driven by middle-income economies. This is because conflict is not very frequent among high-income economies. As some illustrations, Table 3 shows that the average duration of conflicts among high-income economies is 0.48 years, well below the 2.43 mean duration for low-income countries. In the same line, 7% of high-income economies experienced more than three years of conflict within a 5-year period, compared to 37% of low-income countries.

Table 6: Marginal effects of a one standard deviation contraction in the Palmer index (implying drier conditions), distinguishing countries among conflict and non-conflict categories, as well as low- and middle-income countries

<table>
<tr><th>Variable</th><th>Conflictive</th><th>Income</th><th>Column (2)</th><th>Column (4)</th></tr>
<tr><td rowspan="4">Palmer</td><td>No</td><td>Middle/High</td><td rowspan="2">-0.016</td><td>-0.014</td></tr>
<tr><td>No</td><td>Low</td><td>-0.025</td></tr>
<tr><td>Yes</td><td>Middle/High</td><td rowspan="2">0.063^{***}</td><td>0.059^{**}</td></tr>
<tr><td>Yes</td><td>Low</td><td>0.075^{**}</td></tr>
</table>

Notes. This table exhibits the marginal effects of a one standard deviation contraction in the Palmer index (implying drier conditions). The marginal effects in columns (2) and (4) are obtained based on the model specifications in columns (2) and (4), respectively, of Table 5. Clustered standard errors by country pairs are presented in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Before concluding this section, Figures A1 and A2 in the appendix exhibit the results of the Moran tests computed on the residuals of the OLS estimates, fourth column in Table 5. Regardless of the spatial weight matrix we consider, that is, W_o or W_d, Figures A1 and A2 show that we reject the null hypothesis that there is no spatial association. We hence conclude that there is spatial dependence in the residuals of the linear model, thus justifying the spatial model. As explained above, not accounting for spatial dependence, when it exists, leads to biased estimates.

4.2 Spatial models

Table 7 exhibits the estimates of the spatial autoregressive interaction models. The set of results in columns 1 to 3 consider as spatial weight matrix W_o, whereas the set of results in columns 4 to 6 rely on W_d as the spatial weight matrix. Each set of results shares the same structure: the first column includes the Palmer index, together with the spatial autoregressive parameter (ρ_o or ρ_d when corresponding); the second column adds to the first one the interaction term between the Palmer index and the dummy variable for conflict. Finally, the third column adds to the second one the triple interaction term between the Palmer index, the dummy variable for conflict, and the indicator variable for low-income countries.

Table 7: Spatial regression estimates with origin and destination spatial effects

	Dependent variable: Log(origin-destination migration rate)					
	(1)	(2)	(3)	(4)	(5)	(6)
ρ_o	0.345***	0.345***	0.345***			
	(0.007)	(0.007)	(0.007)			
ρ_d				0.270***	0.269***	0.269***
				(0.008)	(0.008)	(0.008)
Palmer index	−0.006	0.013	0.010	−0.014	0.002	0.001
	(0.015)	(0.017)	(0.018)	(0.015)	(0.017)	(0.018)
Log distance	−0.811***	−0.810***	−0.810***	−0.910***	−0.910***	−0.911***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Contiguity	1.111***	1.112***	1.112***	1.079***	1.079***	1.079***
	(0.060)	(0.060)	(0.060)	(0.062)	(0.062)	(0.062)
Common language	0.974***	0.974***	0.973***	1.027***	1.027***	1.027***
	(0.033)	(0.033)	(0.033)	(0.034)	(0.034)	(0.034)
Death rate		0.049	0.087*		0.007	0.019
		(0.042)	(0.052)		(0.044)	(0.053)
Palmer index x Death rate		−0.083**	−0.094**		−0.071**	−0.083**
		(0.032)	(0.038)		(0.033)	(0.039)
LI x Death rate			−0.098			−0.032
			(0.072)			(0.074)
Palmer index x LI			0.018			0.008
			(0.042)			(0.044)
Palmer index x Death rate x LI			0.025			0.036
			(0.074)			(0.076)
Observations	17390	17390	17390	17390	17390	17390
GDP/capita - Orig	Yes	Yes	Yes	Yes	Yes	Yes
GDP/capita - Dest	Yes	Yes	Yes	Yes	Yes	Yes
Orig + Dest FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
AIC	63074.0	63064.3	63067.0	63873.6	63870.5	63875.9

Notes. This table exhibits the spatial estimates of equation (3) including fixed effects for origin, destination, and time. The dependent variable is the logarithm of the bilateral migration flow rate. For details on the independent variables, please refer to Section 3.1. LI stands for low income and corresponds to the low-income dummy variable. Death rate refers to the death rate dummy variable proxying for conflict presence. Regressions also include GDP per capita at both origin and destination as control variables. GDP/capita stands for GDP per capita. Orig abbreviates origin and Dest refers to destination. *p<0.1; **p<0.05; ***p<0.01.

There are several elements to highlight from Table 7. First, there is considerable spatial dependence on migration flows. This is because the estimates for the spatial parameters ρ_o and ρ_d are positive and significant, ranging between 0.27 and 0.35. These estimates are hence indicating that the degree of spatial dependence is substantial (as explained in Section 3.2.1, the maximum possible value of ρ_o and ρ_d is 1). Second, we find that the strength of the origin-dependence effect is similar to the destination-dependence effect. This implies that migration flows from an origin country A to a destination country Z are likely to be accompanied by increased migration flows from countries nearby the origin country A to destination country Z (origin-dependence effect) and by heightened migration flows from origin country A to neighboring countries of destination country Z (destination-dependence effect).

As discussed in Section 3.2.1, previous literature has shown, at the micro level, that migrant networks play an important role in explaining the size and structure of international migration. Sharing historical and/or cultural ties is a key factor in explaining migrants' location choices (Beine et al., 2015; Fenoll and Kuehn, 2018). These mechanisms are consistent with the positive destination-dependence effects that we document in Table 7. However, our results also highlight the importance of origin-spatial effects, thereby adding to the existing literature. Intuitively, this origin-dependence may reflect economic, cultural, and historical factors shared by neighboring origin countries, such as correlated economic cycles, which in turn may lead people in these countries to migrate to common destinations.

We now analyze results in Table 7 regarding the role of climate and the amplification effects of conflict. As explained in Section 3.2.2, and to interpret our spatial results, Table 8 reports the origin, destination, and network effects of a 1 standard deviation contraction in the Palmer index (implying drier conditions) distinguishing between conflictive and non-conflictive countries and low- and middle/high-income economies. In turn, Table 9 reports the aggregated total effects of the same shock following the same classification of countries. Regarding the statistical significance of the effect computations, Margaretic et al. (2017) suggest simulating the distribution of the origin, destination, and network effects using the variance covariance matrix implied by the maximum likelihood estimates. To do so, we draw 1,000 simulations from the multivariate normal distribution implied by the maximum likelihood estimates of the corresponding spatial model.

Table 8: Effects of a one standard deviation contraction in the Palmer index based on the spatial regression estimates in Table 7

	Column (2)		Column (3)			
			Middle/high-income		Low income	
	Non-conflictive	Conflictive	Non-conflictive	Conflictive	Non-conflictive	Conflictive
OE	-0.013	0.074**	-0.009	0.088**	-0.027	0.042
t-stat	-0.746	2.472	-0.465	2.544	-0.678	0.800
DE	0.000	0.000**	0.000	0.001**	0.000	0.000
t-stat	-0.745	2.469	-0.464	2.533	-0.677	0.798
NE	-0.005	0.028**	-0.003	0.033**	-0.010	0.016
t-stat	-0.745	2.469	-0.464	2.533	-0.677	0.798
TE	-0.018	0.102**	-0.012	0.122**	-0.038	0.058
t-stat	-0.746	2.473	-0.465	2.543	-0.678	0.800

Notes. This table exhibits the impacts of a one standard deviation contraction of the Palmer index (implying drier conditions) based on the estimates of columns (2) and (3) of Table 7. TE, TOE, TDE, and TNE correspond to the total effects, total origin effects, total destination effects, and total network effects, respectively. For the exercise, we classify as conflictive countries those that are within the top 25% of the distribution of death rates in a given 5-year period. t-stat corresponds to the t-statistic. *p<0.1; **p<0.05; ***p<0.01.

Table 9: Total effects of a one standard deviation contraction in the Palmer index based on the spatial regression estimates in Table 7

Variable	Conflictive	Income	Column (2)	Column (3)
Palmer	No	Middle/High	−0.018	−0.012
	No	Low		−0.038
	Yes	Middle/High	0.102**	0.122**
	Yes	Low		0.058

Notes. This table exhibits the total effects of a one standard deviation contraction in the Palmer index based on the spatial model estimates. Total impacts in columns (2) and (3) are obtained based on the model specifications in columns (2) and (3), respectively, of Table 7. For the exercise, we classify as conflictive countries those that are within the top 25% of the distribution of death rates in a given 5-year period. t-stat corresponds to the t-statistic. *p<0.1; **p<0.05; ***p<0.01.

There are three main conclusions to draw from Table 8. First, when distinguishing between conflictive and non-conflictive countries, we find that the origin, destination, network, and total effects following a negative shock on the Palmer index (implying drier conditions) only have significant effects for conflictive countries (column (2)). This finding is consistent with the linear model results, although of course the spatial model allows us to decompose the effects into the OE, DE, NE, and TE. We conclude from these results that conflict acts as a mechanism of amplification increasing the probability of migration when drier conditions in a given conflict-affected country worsen. In contrast, for non-conflictive countries, the impact of drier conditions on the migration rate is statistically insignificant (also column (2)). Second, when distinguishing among conflictive, non-conflictive, low-income, and middle/high-income countries (column (3)), we find that the positive probability of migration given drier conditions mainly occurs among middle/high-income countries experiencing conflict, especially middle-income countries. This result contrasts with the linear model estimates.

Third, when analyzing the OE, DE, NE for conflict-affected and middle/high-income countries, we find that their origin effects are larger than their network effects. In simple terms, drier conditions are associated with a higher probability of people migrating *from* the countries experiencing these drier conditions; the impact of these drier conditions on other countries *not directly impacted by the shock* (the network effects) is less important. Indeed, the origin effects account for 72% of the total effects (0.088/0.122 in the case of column (3), for conflictive and middle/high-income countries), while the network effects are 27% of the average origin effects (0.033/0.122, same column). Finally, the destination effects are small, because the Palmer index is only an origin characteristic.

To summarize the results, Table 9 aggregates the information on Table 8 and focuses on the total effects distinguishing among low- and middle/high-income countries with and without conflict. Results confirm that the positive impact of drier conditions on the probability of international migration is primarily driven by middle- and high-income countries. The marginal effect is positive but statistically insignificant in the case of poor countries experiencing conflict. One possible explanation for the lack of significance for low-income countries experiencing conflict is the presence of liquidity constraints that may prevent individuals in poor countries experiencing conflicts from migrating when climate conditions in their home countries deteriorate.

In the same line, Cattaneo and Peri (2016) show that in poor countries, liquidity constraints are binding. Hence, lower agricultural productivity due to climate shocks makes people poorer, decreasing their ability to pay migration costs, hence reducing the emigration rate. However, Cattaneo and Peri (2016) do not account for the amplifying role of conflict, which we show is active for middle/high-income countries. We interpret our result as indicating that in these countries, the liquidity constraints do not bind. Finally, when we examine the total effects for countries not experiencing conflict, Table 9 confirms that drier conditions have a statistically insignificant impact on the probability of migration (columns (2) and (3)).

5 Heterogeneous effects

Our baseline estimates show that drier conditions are associated with a higher probability of migration if the country is under conflict and it is middle/high-income. We interpret the presence of conflict as an amplification mechanism that further increases the gains from international migration for middle-income countries, countries that are less likely to experience binding liquidity constraints. We now examine heterogeneous effects in the amplifying role of conflict in the climate–migration relationship. To do so, first, we decompose the local impacts of a contraction in the Palmer index (by country), distinguishing among conflictive, low- and middle-income countries. Second, we investigate what types of conflict are more likely to exert an influence on climate-related migration, based on the actors participating in the conflict.

5.1 Analysing the local origin, destination and network effects

To further dig into the local impacts of a contraction in the Palmer index, Figures 1 and 2 exhibit the decomposition of origin, destination, and network effects by country experiencing the shock. Figure 1 focuses on the conflictive, middle/high-income countries as of 1995, whereas Figure 2 depicts the decomposition of the same effects for the conflictive, low-income countries (also, as of 1995). For this exercise, we classify as conflictive those countries for which the death rate dummy equals 1 for at least two periods of five years.

Figure 1: Local origin, destination, and network effects for most conflictive middle/high-income countries after a contraction of one standard deviation in the Palmer index

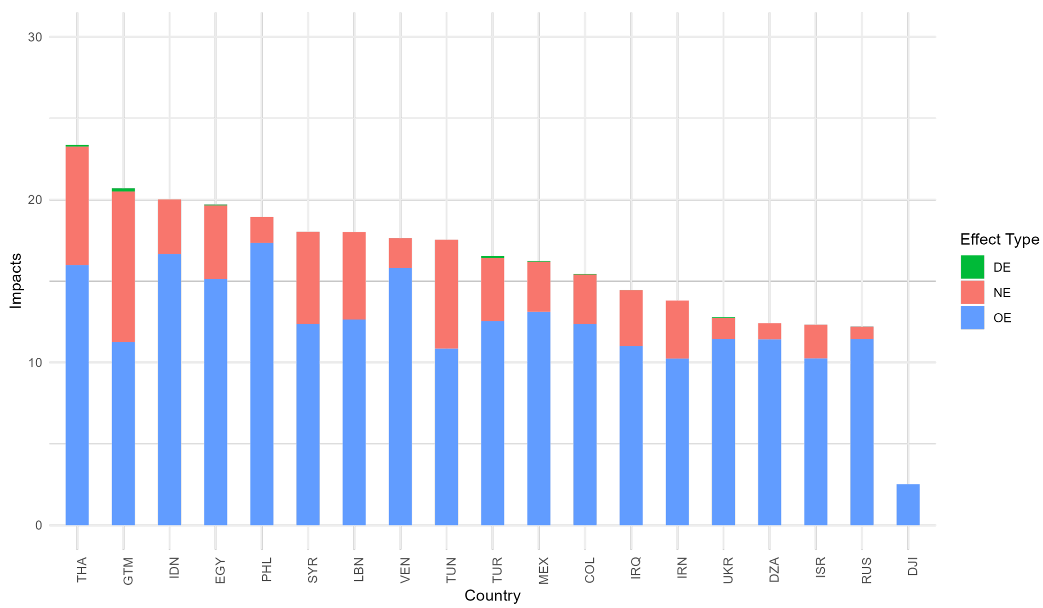
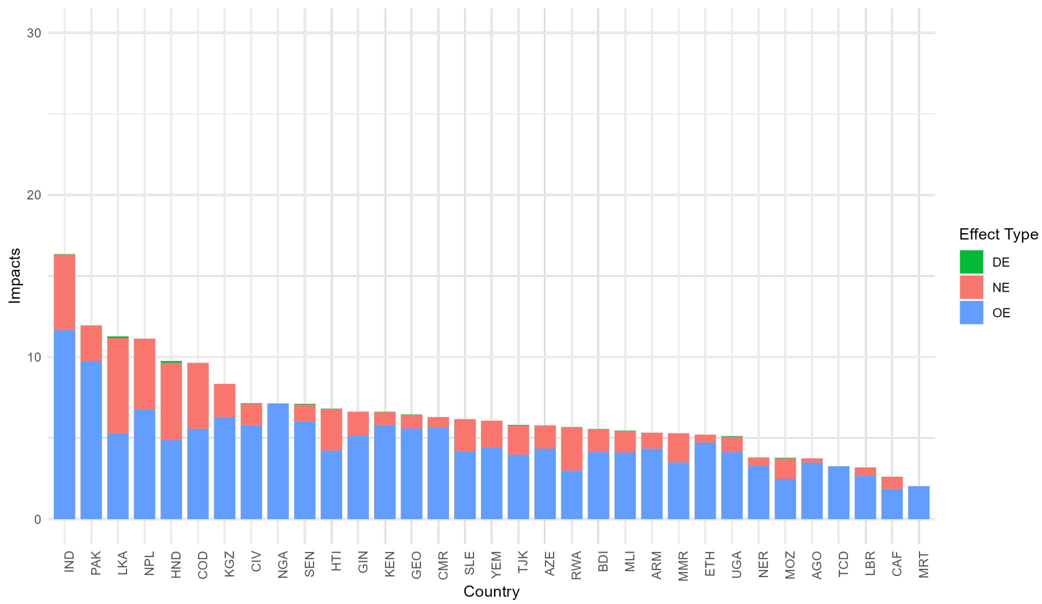


Figure 2: Local origin, destination and network effects for most conflictive low-income countries after a contraction of one standard deviation in the Palmer index



To begin with, Figures 1 and 2 confirm, locally, that the origin effects are larger than the network effects, thus indicating that a climate shock on country i has a larger impact on the migration flows departing from that country i relative to the impact on the migration flows not departing nor arriving to the shocked country i (as explained before, the destination effects are almost zero for the Palmer index). Second, on average, local network effects tend to be larger for middle/high-income countries, compared to low-income countries experiencing conflict.

The third result to highlight from Figures 1 and 2 is that there is considerable heterogeneity across countries in their local network effects, especially within middle- and high-income countries experiencing conflict, with some economies recording larger network effects while some others exhibiting smaller impacts. There are two forces that may be driving this heterogeneity across countries: on the one hand, how central a country is, in the sense of having several neighboring countries (in the spatial weight matrix), which in turn, may or may not be connected to several other countries. On the other hand, there is the number of counterparties that a given origin (destination) country has in the bilateral migration matrix, that is, the number of destinations (respectively, origins) where people from a given origin country migrate (respectively, from where a destination country receives migrants from).

To assess the importance of these forces, we start by exhibiting the local network effects, as a function of countries' eigenvector centrality. Eigenvector centrality, according to one spatial weight matrix, is a measure of the influence that a country has on a given spatial neighborhood structure (Bonacich, 2007). To compute the eigenvector centralities, we need to associate our spatial neighborhood matrices W_o and W_d to their corresponding adjacency matrices. Note however that the spatial neighborhood matrices W_o and W_d are of dimension $N \times N$, where each element corresponds to a pair of countries. Therefore, we compute the eigenvector centralities for each country pair and then average these values by country.

The adjacency matrices contain indicators for the corresponding weights being non-zero in the spatial neighborhood matrices. The adjacency matrix indicates whether two country pairs are neighbors or not, and, therefore, whether two vertices of the network are connected or not. Relative scores are assigned to all country pairs in the neighborhood matrix based on the concept that connections to high-scoring country pairs contribute more to the score of the country pair in question than equal connections to low-scoring country pairs. Finally, we average the country pairs' eigenvector centralities by countries of origin or destination, depending on the neighborhood structure of interest, at origin or destination. This way, countries with high eigenvector centralities (close to 1) for a given weight matrix W_o and W_d are those which are connected to many other countries which are, in turn, connected to many others (and so on). Figure 3 (Figure 4) relates the local network effects with the countries' eigenvector centralities based on the origin-based (destination-based) spatial proximity matrix W_o (W_d). The left panel focuses on conflictive, low-income economies, whereas the right panel exhibits the scatter plots for conflictive, middle/high-income economies.

The second force that may explain the heterogeneity in the local network effects is the number of counterparties that a given origin (destination) country has in the bilateral migration matrix. To assess the relevance of this second force, Figures 5 and 6 depict the local network effects as a function of the total number of origins and destinations, respectively, that a given country has.[15] As before, in each figure, the left panel focuses on conflictive, low-income economies, whereas the right panel exhibits the scatter plots for conflictive, middle/high-income economies.

Figure 3: Local network effects and eigenvector centrality for most conflictive countries, assuming W_o. Left: low-income economies. Right: middle/high-income economies

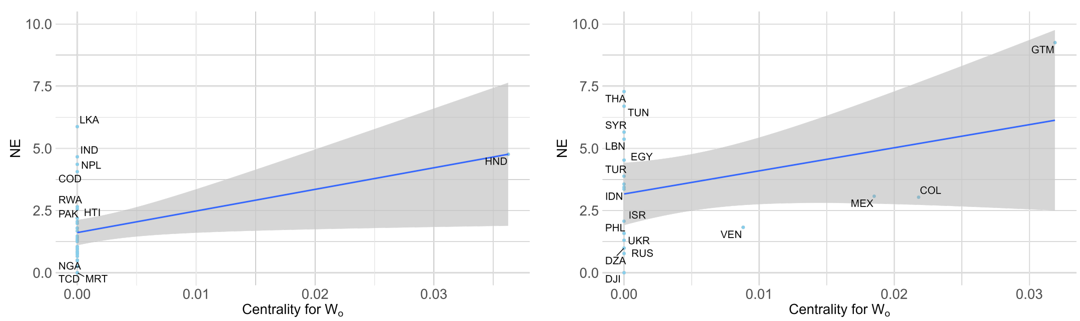
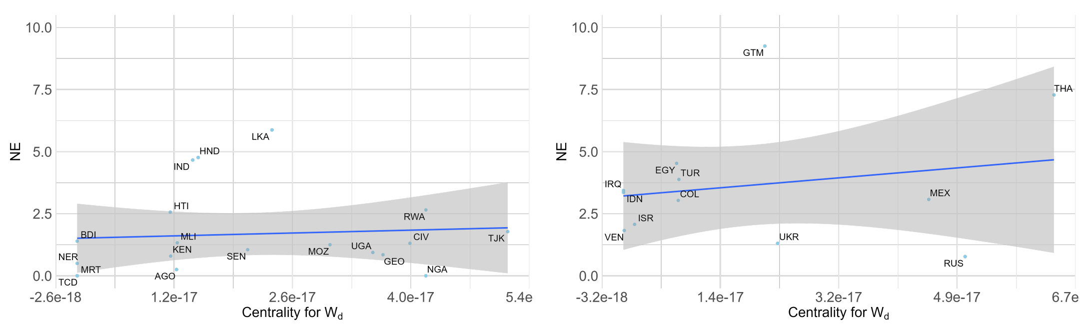


Figure 4: Local network effects and eigenvector centrality for most conflictive countries, assuming W_d. Left: low-income economies. Right: middle/high-income economies



[15]For completeness, in the appendix, Figure A3 and A4 exhibit the relationships between the local network effects and the degree of the neighborhood matrices W_o and W_d, with the latter measuring the number of direct connections per country.

Figure 5: Local network effects and number of destinations per origin for most conflictive countries. Left: low-income economies. Right: middle/high-income economies

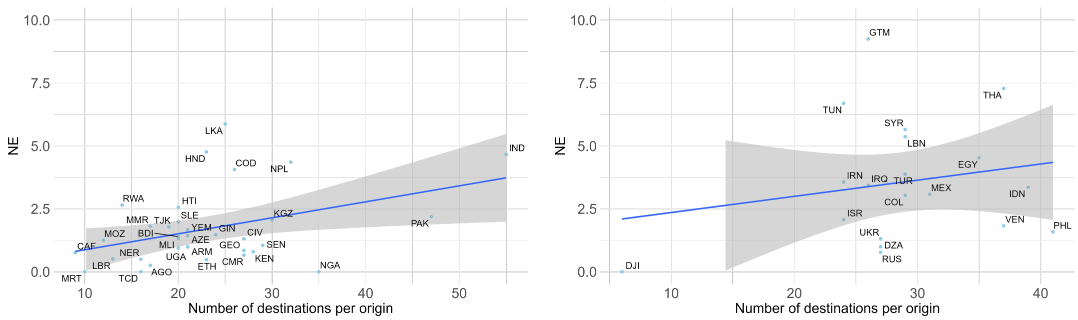
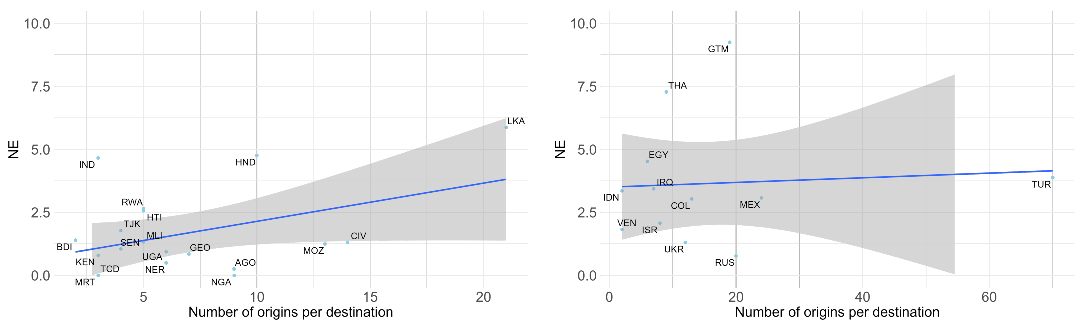


Figure 6: Local network effects and number of origins per destination for most conflictive countries. Left: low-income economies. Right: middle/high-income economies



Figures 3 and 4 show that, overall, the local network effects increase with the eigenvector centrality of both origins and destinations, as computed from the proximity matrices W_o and W_d, respectively. This finding suggests that countries with largest network effects are those that are more central, and as such may be subject to higher-order effects. Higher-order effects occur when a shock to a given country is transmitted to other countries not directly linked to the affected country. Therefore, more central countries can transmit shocks to and/or be exposed to shocks from many more countries, thus impacting and being affected by a larger number of migration flows. Figures 5 and 6 present a similar picture, indicating that local network effects also increase with the number of destinations and origins a country has in the migration matrix. In other words, countries that have more out-migration or receive more migrants are more likely to exhibit larger network effects following events such as a climate shock in a foreign country that indirectly affects them.

To sum up, we conclude from the evidence above that the heterogeneity in the local network effects documented in the figures above may result from a combination of factors, including how central the countries are in the spatial neighborhood matrix and how connected they are in the migration matrix. This result has important policy implications, as it suggests that not all countries will be equally affected by climate-induced migration following climate shocks.

5.2 Type of conflict

We now explore what types of conflict are more likely to exert an influence on climate-induced migration, based on the actors participating in the conflict. The actors we consider are states (S), civilians (C), or armed groups (AG). To do so, Tables 10 and 11 present the specifications of columns 3 and 6, respectively, of Table 7 with different death rate dummies depending on the actors involved in the conflict (state versus state, state versus civilians, state versus armed group, armed group versus civilians). For instance, column 1 in Table 10 (Table 11) shows the spatial model estimates considering W_o (W_d) as the spatial weight matrix for conflicts where the actors involved are both states.

Table 10: Spatial regression estimates distinguishing by conflict-involved actors. Estimates rely on W_o as the spatial weight matrix

	Dependent variable: Log(origin-destination migration rate)				
	S vs S	S vs C	S vs AG	AG vs C	AG vs AG
ρ_o	0.345***	0.346***	0.345***	0.345***	0.345***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Palmer index	−0.009	0.007	−0.004	−0.007	−0.003
	(0.016)	(0.017)	(0.017)	(0.016)	(0.016)
Log distance	−0.810***	−0.809***	−0.810***	−0.809***	−0.810***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Contiguity	1.111***	1.113***	1.112***	1.112***	1.112***
	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)
Common language	0.974***	0.974***	0.973***	0.973***	0.973***
	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
Death rate	0.032	0.237**	0.188***	0.115	0.205*
	(0.133)	(0.095)	(0.069)	(0.078)	(0.123)
Palmer index x Death rate	−0.275**	−0.266***	−0.090	−0.117	−0.192*
	(0.130)	(0.068)	(0.062)	(0.072)	(0.107)
LI x Death rate dummy	−0.076	−0.303**	−0.086	−0.088	−0.316**
	(0.210)	(0.121)	(0.105)	(0.118)	(0.146)
Palmer index x LI	0.014	0.014	0.026	0.029	0.016
	(0.036)	(0.037)	(0.037)	(0.037)	(0.037)
Palmer index x Death rate x LI	0.713**	0.153	−0.041	−0.012	0.166
	(0.350)	(0.106)	(0.110)	(0.120)	(0.142)
Observations	17390	17390	17390	17390	17390
GDP/capita - Orig	Yes	Yes	Yes	Yes	Yes
GDP/capita - Dest	Yes	Yes	Yes	Yes	Yes
Orig + Dest FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
AIC	63074.5	63036.0	63064.2	63067.3	63055.4

Notes. This table presents the spatial estimates of equation (3) for different death rate dummies based on involved conflict actors using W_o as spatial weight matrix. S, C, and AG stand for State, Civilian, and Armed group, respectively. Please refer to Table 7 for details.

Table 11: Spatial regressions estimates by conflict-involved actors using W_d as spatial weight matrix

	Dependent variable: Log(origin-destination migration rate)				
	S vs S	S vs C	S vs AG	AG vs C	AG vs AG
ρ_d	0.269***	0.269***	0.269***	0.269***	0.269***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Palmer index	−0.015	−0.004	−0.011	−0.013	−0.011
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Log distance	−0.910***	−0.911***	−0.911***	−0.911***	−0.911***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Contiguity	1.079***	1.079***	1.079***	1.079***	1.079***
	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)
Common language	1.027***	1.027***	1.027***	1.027***	1.026***
	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)
Death rate	−0.051	0.158	0.104	0.055	0.148
	(0.137)	(0.098)	(0.071)	(0.081)	(0.126)
Palmer index x Death rate	−0.265**	−0.176**	−0.069	−0.094	−0.125
	(0.134)	(0.070)	(0.064)	(0.074)	(0.110)
LI x Death rate	0.015	−0.209*	−0.053	−0.047	−0.239
	(0.216)	(0.125)	(0.108)	(0.122)	(0.150)
Palmer index x LI	0.003	0.006	0.016	0.019	0.008
	(0.037)	(0.038)	(0.038)	(0.038)	(0.038)
Palmer index x Death rate x LI	0.663*	0.089	−0.047	−0.021	0.087
	(0.360)	(0.109)	(0.114)	(0.124)	(0.146)
Observations	17390	17390	17390	17390	17390
GDP/capita - Orig	Yes	Yes	Yes	Yes	Yes
GDP/capita - Dest	Yes	Yes	Yes	Yes	Yes
Orig + Dest FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
AIC	63877.6	63860.9	63875.0	63877.1	63869.6

Notes. This table exhibits the spatial estimates of equation (3) for different death rate dummies based on involved conflict actors using W_d as spatial weight matrix. S, C, and AG stand for State, Civilian, and Armed group respectively. Please refer to Table 7 for details. *p<0.1; **p<0.05; ***p<0.01.

Tables 10 and 11 show that conflicts between states and conflicts between states and civilians exert the largest influence on climate-related migration. This conclusion holds regardless of the spatial weight matrix used to capture spatial dependence. We interpret this finding to mean that when drier conditions worsen, people are more likely to react to these particular types of conflicts because they perceive them as more serious and permanent, thus significantly affecting their expected gains from migrating. To examine this interpretation, Table A7 in the appendix exhibits the mean and median duration of conflicts by type. Interestingly, these two types of conflicts are indeed the longest-lasting, thus providing support to the interpretation that these types of conflicts may be perceived as the most significant or serious.

Moreover, Tables 10 and 11 also indicate that our estimates are robust to changing the dummy variables for conflict, as the estimates for the spatial parameters and coefficients barely change (compared to Table 7), except for the coefficient for the triple interaction term which is only statistically significant in the first column of Table 10.

To sum up, in this paper, we demonstrate that conflict acts as an amplification mechanism in the relationship between climate shocks (as measured by dryness conditions) and international migration. Furthermore, we document that this mechanism is mainly active for people in middle-income countries, who are less likely to experience binding liquidity constraints. The analysis in this section adds to our previous results by showing that people are more sensitive to the types of conflict that are perceived as more permanent.

6 Robustness

In this section, we run alternative specifications to explore the robustness of our results.

6.1 Sensitivity to sample size: the unrestricted sample

As explained before, for the spatial model, we need a balanced panel, therefore if a country-pair has a zero flow in a given period, we do not consider that country-pair for the main regressions. This restricts the country pairs' observations in our sample from 38362 country pairs per period to 17390. Tables A5 and A6 in the appendix show summary statistics for the whole sample without considering zeros for the 160 origin countries and 161 destinations.

Note that except for Maldivia those origins are also destinations.

As a robustness check, we consider an alternative transformation of the migration variable. Following Cai et al. (2016), we add 1 to the migration flow before calculating the migration rate. This transformation allows us to consider the complete sample including the zero flows. Table A8 and Table A9 show the spatial model estimates with the transformed dependent variable and the complete sample including the zero flows.

Consistent with the spatial baseline estimates (in Tables 7 and 9), Column (2) of Table A9 documents that drier conditions in conflictive countries are associated with a higher probability of migration. Column (3) of the same table shows that when drier conditions worsen, the probability of migration increases in conflictive and middle/high-income countries; the total effects are barely significant (at the 10% level of significance) if the country is conflictive and low-income. In contrast, the probability of migration decreases with drier conditions if the country is not-conflicted affected. The additional findings in Table A9 with respect to the spatial baseline estimates may be due to the larger number of observations when allowing for zero flows or for country pairs that are not constantly present in the sample.

6.2 An alternative distribution for migration data: fixed effects Poisson pseudo-maximum likelihood

As a robustness check, we apply the Poisson Pseudo Maximum Likelihood (PPML) to estimate the spatial interaction model (without spatial effects). The reason for conducting this analysis is that the Poisson distribution is a discrete probability distribution, which gives the probability of a discrete (i.e., countable) outcome—in our case, the number of people migrating from a given country o to a destination country d. Another advantage of this estimator is that it includes zeros for the dependent variable, ruling out any selection bias of this kind.

Table A10 presents the estimates. Results are similar to the baseline specification in Table 5. The second and third columns show that for countries experiencing conflict, the probability of migration is higher. As with the linear baseline model (in Table 5), the interaction between the Palmer index and the conflict death rate dummy indicates that when climatic conditions are drier, being a conflictive country is associated with a higher probability of migration compared to being a non-conflictive country. Finally, the last column shows that the coefficient of the triple interaction is statistically insignificant, as in the baseline spatial estimates.

6.3 Alternative dryness index and conflict measure

We explore the robustness of our results using: i) an alternative dryness index to the Palmer index, that is, the SPEI-48 index; ii) an alternative measure for the presence of conflict. Regarding the first robustness check, as explained in Section 3.1, the SPEI index uses data on precipitation and evapotranspiration to determine dry conditions. We consider a time scale of 48 months as it is more representative of medium-term climate conditions, consistent with the Palmer index. Table A11 in the appendix shows the estimates of the spatial model specifications in equation (3): the first three columns of results use W_o as the spatial weight matrix, whereas the last three columns rely on W_d. Additionally, Table A12 exhibits the total effects of a 1 standard deviation contraction in the Palmer index on international migration, distinguishing among low- and middle/high-income countries with and without conflict.

Regarding the second robustness check, in our baseline regressions, we use the death rate dummy variable as our measure of conflict. As explained in Section 3.1, this variable measures conflict in relative terms as it takes the value 1 if the death rate of a country is within the top 25% of the distribution over a given 5-year period. As an alternative proxy for the presence of conflict, we use an absolute measure represented by a dummy variable that indicates if a country experienced more than 3 years of conflict over 5 years. Tables A13 and A14 in the appendix exhibit the results following the same structure as Tables A11 and A12.

To begin with, relying on SPEI-48 as an alternative proxy for dryness conditions, Table A11 and Table A12 show that the effect of drier conditions is not significant when we distinguish between conflictive and non-conflictive countries (column (2)). However, in line with our spatial baseline results (Tables 7 and 9), column (3) in Table A12 documents a positive probability of migration when dry conditions worsen if the country is experiencing conflict and it is a middle/high-income country. Second, concerning the alternative measure for the presence of conflict, results in Tables A13 and A14 are in line with our spatial baseline regressions in Tables 7 and 9. Drier conditions in conflicting, middle/high-income countries are associated with a higher probability of migration.

6.4 Alternative weight matrix

As an alternative weight matrix, we consider contiguity as the criterion to define proximity in the set of origin and destination countries. Table A15 and A16 in the appendix reports the spatial estimates we obtain when relying on contiguity to define the neighborhood structure. Importantly, Table A15 shows that our results are robust to considering an alternative definition of geographic proximity. Indeed, the estimates for the spatial parameters are similar to the ones reported in Table 7.

7 Conclusions

This paper explores the role of social conflict as an amplifying mechanism in the relationship between climate change and international migration. Drawing from literature on the correlation between vulnerability to weather shocks and conflict likelihood, we hypothesize that climate change may increase conflict, thereby inducing larger migration flows. We also account for spatial autocorrelation in migration flows, indicating spatial persistence.

Using a comprehensive dataset of bilateral migration flows from 1995-2020 and employing the Palmer index as a proxy for climate change, we demonstrate that conflict amplifies climate-induced migration, especially in middle-income countries. Drier conditions lead to higher migration probabilities in conflict-affected and middle-income countries. Additionally, we find evidence of significant origin- and destination-effects, suggesting that migration flows across countries are spatially correlated. This study bridges the gap between migration, climate change, and conflict literature, providing a methodological contribution by modeling spatial dependence in migration flows among country pairs using advanced spatial econometrics techniques.

Our findings have significant policy implications. We propose an empirical approach to accurately estimate migration flows while accounting for spatial dependence, which can be utilized to project migration flows under various climate change scenarios. This methodology offers valuable insights into the ongoing policy debate surrounding climate risk management strategies and their influence on migration patterns. Having an accurate methodology to project migration flows is particularly valuable for policymakers: i) seeking to assess the effectiveness of programs aimed at mitigating migration flows induced by natural disasters, and ii) responsible for designing targeted interventions and support for vulnerable populations.

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A1 Appendix

A1.1 Additional tables

Table A1: List of destination countries and population shares in 2020

Country	Population share	Cumulative pop.	Country	Population share	Cumulative pop.
China	18.17%	18.17%	Jordan	0.14%	80.84%
India	17.81%	35.98%	Czechia	0.13%	80.97%
United States of America	4.28%	40.27%	Greece	0.13%	81.11%
Indonesia	3.47%	43.73%	Sweden	0.13%	81.24%
Brazil	2.72%	46.45%	Portugal	0.13%	81.37%
Nigeria	2.66%	49.11%	Honduras	0.13%	81.5%
Bangladesh	2.14%	51.24%	Hungary	0.12%	81.63%
Russian Federation	1.86%	53.1%	Belarus	0.12%	81.75%
Mexico	1.61%	54.71%	Tajikistan	0.12%	81.87%
Japan	1.6%	56.31%	United Arab Emirates	0.12%	81.99%
Egypt	1.37%	57.68%	Austria	0.11%	82.1%
Viet Nam	1.23%	58.91%	Israel	0.11%	82.21%
Türkiye	1.07%	59.98%	Switzerland	0.11%	82.32%
Germany	1.06%	61.04%	Togo	0.11%	82.43%
Thailand	0.91%	61.96%	Bulgaria	0.09%	82.52%
United Kingdom	0.86%	62.81%	Nicaragua	0.09%	82.61%
France	0.82%	63.63%	El Salvador	0.08%	82.69%
United Republic of Tanzania	0.79%	64.42%	Singapore	0.08%	82.76%
Italy	0.76%	65.18%	Denmark	0.07%	82.84%
South Africa	0.75%	65.93%	Finland	0.07%	82.91%
Kenya	0.66%	66.59%	Slovakia	0.07%	82.98%
Republic of Korea	0.66%	67.25%	Norway	0.07%	83.05%
Colombia	0.65%	67.9%	Costa Rica	0.07%	83.11%
Spain	0.6%	68.51%	State of Palestine	0.06%	83.18%
Argentina	0.57%	69.08%	Ireland	0.06%	83.24%
Uganda	0.57%	69.65%	Oman	0.06%	83.3%
Ukraine	0.56%	70.21%	Mauritania	0.06%	83.35%
Iraq	0.54%	70.75%	Kuwait	0.06%	83.41%
Poland	0.49%	71.24%	Panama	0.05%	83.46%
Canada	0.48%	71.72%	Croatia	0.05%	83.52%
Morocco	0.47%	72.19%	Georgia	0.05%	83.56%
Saudi Arabia	0.46%	72.65%	Uruguay	0.04%	83.61%
Uzbekistan	0.43%	73.08%	Mongolia	0.04%	83.65%
Angola	0.43%	73.51%	Jamaica	0.04%	83.69%
Peru	0.42%	73.93%	Gambia	0.03%	83.72%
Malaysia	0.42%	74.35%	Botswana	0.03%	83.75%
Ghana	0.41%	74.76%	Gabon	0.03%	83.78%
Mozambique	0.4%	75.16%	Lesotho	0.03%	83.81%
Venezuela (Bolivarian Republic of)	0.36%	75.52%	Slovenia	0.03%	83.84%
Madagascar	0.36%	75.88%	North Macedonia	0.03%	83.86%
Côte d'Ivoire	0.34%	76.23%	Latvia	0.02%	83.89%
Niger	0.31%	76.54%	Equatorial Guinea	0.02%	83.91%
Sri Lanka	0.28%	76.81%	Trinidad and Tobago	0.02%	83.93%
Burkina Faso	0.27%	77.09%	Bahrain	0.02%	83.95%
Mali	0.27%	77.36%	Estonia	0.02%	83.96%
Romania	0.25%	77.61%	Mauritius	0.02%	83.98%
Malawi	0.25%	77.85%	Cyprus	0.02%	84%
Chile	0.25%	78.1%	Eswatini	0.02%	84.01%
Kazakhstan	0.24%	78.34%	Comoros	0.01%	84.02%
Ecuador	0.22%	78.57%	Bhutan	0.01%	84.03%
Netherlands	0.22%	78.79%	Luxembourg	0.01%	84.04%
Guatemala	0.22%	79.01%	Suriname	0.01%	84.05%
Chad	0.21%	79.22%	Cabo Verde	0.01%	84.05%
Senegal	0.21%	79.43%	Malta	0.01%	84.06%
Zimbabwe	0.2%	79.63%	Maldives	0.01%	84.07%
Rwanda	0.17%	79.8%	Brunei Darussalam	0.01%	84.07%
Benin	0.16%	79.96%	Bahamas	0.01%	84.08%
Burundi	0.16%	80.12%	Belize	0.01%	84.08%
Bolivia (Plurinational State of)	0.15%	80.27%	Iceland	0%	84.09%
Belgium	0.15%	80.42%	Seychelles	0%	84.09%
Haiti	0.14%	80.56%			
Dominican Republic	0.14%	80.7%			

Table A2: List of origin countries and population shares in 2020

Country	Population share	Cumulative pop.	Country	Population share	Cumulative pop.
China	18.17%	18.17%	Czechia	0.13%	92.49%
India	17.81%	35.98%	Greece	0.13%	92.63%
United States of America	4.28%	40.27%	Sweden	0.13%	92.76%
Indonesia	3.47%	43.73%	Portugal	0.13%	92.89%
Pakistan	2.9%	46.63%	Azerbaijan	0.13%	93.02%
Brazil	2.72%	49.35%	Honduras	0.13%	93.15%
Nigeria	2.66%	52.01%	Hungary	0.12%	93.28%
Bangladesh	2.14%	54.14%	Belarus	0.12%	93.4%
Russian Federation	1.86%	56%	Tajikistan	0.12%	93.52%
Mexico	1.61%	57.61%	United Arab Emirates	0.12%	93.64%
Japan	1.6%	59.2%	Austria	0.11%	93.75%
Ethiopia	1.49%	60.7%	Israel	0.11%	93.86%
Philippines	1.43%	62.13%	Switzerland	0.11%	93.97%
Egypt	1.37%	63.5%	Togo	0.11%	94.08%
Viet Nam	1.23%	64.73%	Sierra Leone	0.11%	94.19%
Democratic Republic of the Congo	1.18%	65.92%	Lao People's Democratic Republic	0.09%	94.28%
Iran (Islamic Republic of)	1.11%	67.03%	Bulgaria	0.09%	94.37%
Türkiye	1.07%	68.1%	Nicaragua	0.09%	94.46%
Germany	1.06%	69.17%	Paraguay	0.08%	94.54%
Thailand	0.91%	70.08%	Kyrgyzstan	0.08%	94.62%
United Kingdom	0.86%	70.93%	El Salvador	0.08%	94.7%
France	0.82%	71.75%	Turkmenistan	0.08%	94.78%
United Republic of Tanzania	0.79%	72.54%	Singapore	0.08%	94.86%
Italy	0.76%	73.3%	Denmark	0.07%	94.93%
South Africa	0.75%	74.05%	Congo	0.07%	95%
Myanmar	0.68%	74.73%	Lebanon	0.07%	95.08%
Kenya	0.66%	75.39%	Finland	0.07%	95.15%
Republic of Korea	0.66%	76.06%	Slovakia	0.07%	95.22%
Colombia	0.65%	76.71%	Norway	0.07%	95.29%
Spain	0.6%	77.31%	Central African Republic	0.07%	95.35%
Argentina	0.57%	77.88%	Costa Rica	0.07%	95.42%
Uganda	0.57%	78.45%	Liberia	0.06%	95.48%
Ukraine	0.56%	79.01%	State of Palestine	0.06%	95.55%
Algeria	0.55%	79.56%	Ireland	0.06%	95.61%
Iraq	0.54%	80.11%	Oman	0.06%	95.67%
Poland	0.49%	80.6%	Mauritania	0.06%	95.73%
Canada	0.48%	81.08%	Kuwait	0.06%	95.78%
Morocco	0.47%	81.55%	Panama	0.05%	95.84%
Saudi Arabia	0.46%	82.01%	Croatia	0.05%	95.89%
Uzbekistan	0.43%	82.43%	Georgia	0.05%	95.94%
Angola	0.43%	82.86%	Uruguay	0.04%	95.98%
Peru	0.42%	83.29%	Bosnia and Herzegovina	0.04%	96.02%
Malaysia	0.42%	83.71%	Mongolia	0.04%	96.06%
Yemen	0.41%	84.12%	Republic of Moldova	0.04%	96.1%
Ghana	0.41%	84.53%	Albania	0.04%	96.14%
Mozambique	0.4%	84.93%	Jamaica	0.04%	96.18%
Nepal	0.37%	85.3%	Lithuania	0.04%	96.21%
Venezuela (Bolivarian Republic of)	0.36%	85.67%	Armenia	0.04%	96.25%
Madagascar	0.36%	86.03%	Qatar	0.04%	96.28%
Côte d'Ivoire	0.34%	86.37%	Gambia	0.03%	96.32%
Cameroon	0.34%	86.71%	Botswana	0.03%	96.35%
Niger	0.31%	87.02%	Namibia	0.03%	96.38%
Sri Lanka	0.28%	87.29%	Gabon	0.03%	96.41%
Burkina Faso	0.27%	87.57%	Lesotho	0.03%	96.44%
Mali	0.27%	87.84%	Slovenia	0.03%	96.47%
Syrian Arab Republic	0.26%	88.1%	North Macedonia	0.03%	96.49%
Romania	0.25%	88.35%	Guinea-Bissau	0.03%	96.52%
Malawi	0.25%	88.6%	Latvia	0.02%	96.54%
Chile	0.25%	88.85%	Equatorial Guinea	0.02%	96.56%
Kazakhstan	0.24%	89.09%	Trinidad and Tobago	0.02%	96.58%
Zambia	0.24%	89.33%	Bahrain	0.02%	96.6%
Ecuador	0.22%	89.55%	Estonia	0.02%	96.62%
Netherlands	0.22%	89.78%	Mauritius	0.02%	96.63%
Guatemala	0.22%	90%	Cyprus	0.02%	96.65%
Chad	0.21%	90.21%	Eswatini	0.02%	96.67%
Senegal	0.21%	90.42%	Djibouti	0.01%	96.68%
Cambodia	0.21%	90.63%	Comoros	0.01%	96.69%
Zimbabwe	0.2%	90.83%	Bhutan	0.01%	96.7%
Guinea	0.17%	91%	Luxembourg	0.01%	96.71%
Rwanda	0.17%	91.16%	Suriname	0.01%	96.72%
Benin	0.16%	91.32%	Cabo Verde	0.01%	96.72%
Burundi	0.16%	91.48%	Malta	0.01%	96.73%
Tunisia	0.16%	91.64%	Brunei Darussalam	0.01%	96.73%
Bolivia (Plurinational State of)	0.15%	91.79%	Bahamas	0.01%	96.74%
Belgium	0.15%	91.94%	Iceland	0%	96.74%
Haiti	0.14%	92.08%	Sao Tome and Principe	0%	96.75%
Dominican Republic	0.14%	92.22%	Seychelles	0%	96.75%
Jordan	0.14%	92.36%			

Table A3: Distribution of the number of neighbors per country pair

Number of neighbors:	1	2	3	4
W_o	149	169	296	2864
W_d	201	213	378	2686

Table A4: Correlation matrix from our variables

	Migration flows	Palmer index	GDP/capita - Orig	GDP/capita - Dest	SPEI-48	Conflict death rate	Years of conflict	Distance
Migration flows	1.00	-0.02	-0.04	-0.01	-0.02	0.07	-0.05	-0.11
Palmer index	-0.02	1.00	0.11	-0.07	0.73	-0.05	-0.05	0.02
GDP/capita - Orig	-0.04	0.11	1.00	0.02	-0.00	-0.08	-0.35	-0.11
GDP/capita - Dest	-0.01	-0.07	0.02	1.00	-0.07	0.01	-0.02	0.12
SPEI-48	-0.02	0.73	-0.00	-0.07	1.00	-0.09	0.01	0.16
Conflict death rate	0.07	-0.05	-0.08	0.01	-0.09	1.00	0.16	-0.03
Years of conflict	-0.05	-0.05	-0.35	-0.02	0.01	0.16	1.00	0.13
Distance	-0.11	0.02	-0.11	0.12	0.16	-0.03	0.13	1.00

Table A5: Summary statistics for origin countries

Variable	Mean	Min	Max	Std. dev.	Obs.
Total outmigration (%)	1.56	0.05	27.20	1.97	796
Total outmigration (thousands of people)	223.74	1.21	5942.79	434.40	796
Palmer Index	-0.52	-3.93	2.76	1.06	796
SPEI-48	-0.33	-2.13	1.75	0.71	796
Conflict deaths (thousands of people)	1.67	0.00	213.18	11.07	796
Conflict deaths (%)	0.01	0.00	0.98	0.06	796
Years of conflict in a 5 year period	1.54	0.00	5.00	2.04	796
Conflict deaths rate dummy	0.25	0.00	1.00	0.43	796
Years of conflict >3 dummy	0.25	0.00	1.00	0.44	796
GDP per capita (thousands of USD)	16.92	0.44	151.23	19.63	796
Population (millions of people)	41.31	0.08	1408.96	144.41	796

Notes. The table exhibits summary statistics by origin country in 5-year periods. Sample: 1995-2020.

Table A6: Summary statistics by income level for origin countries

	Low income			Middle income			High income		
Variable	Obs.	Mean	Std. dev.	Obs.	Mean	Std. dev.	Obs.	Mean	Std. dev.
Total outmigration (%)	218	1.40	1.57	384	1.85	2.34	194	1.18	1.45
Total outmigration (thousands of people)	218	216.32	393.96	384	276.25	525.86	194	128.13	198.17
Palmer Index	218	-0.62	0.83	384	-0.58	1.03	194	-0.28	1.29
SPEI-48	218	-0.34	0.58	384	-0.32	0.73	194	-0.33	0.81
Conflict deaths (thousands of people)	218	2.17	7.39	384	2.21	14.88	194	0.07	0.40
Conflict deaths (%)	218	0.01	0.05	384	0.01	0.07	194	0.00	0.00
Years of conflict in a 5 year period	218	2.43	2.02	384	1.59	2.12	194	0.46	1.23
Conflict deaths rate dummy	218	0.42	0.50	384	0.25	0.44	194	0.05	0.21
Years of conflict >3 dummy	218	0.37	0.48	384	0.28	0.45	194	0.06	0.24
GDP per capita (thousands of USD)	218	2.13	1.17	384	11.04	6.48	194	45.18	19.59
Population (millions of people)	218	43.99	153.66	384	47.55	168.38	194	25.94	52.67

Notes. The table exhibits summary statistics by origin country income level by 5-year period. Sample: 1995-2020. Middle income includes both lower-middle and upper-middle income countries.

Table A7: Summary statistics of conflict duration by actors involved

Type	Mean duration	Median duration	Min duration	Max duration	S.D
State vs civ	21.06	25.00	0	25.99	6.10
State vs state	20.62	25.00	0	25.94	9.29
State vs armed group	16.70	13.16	0	26.00	8.28
Armed group vs civ	14.35	14.21	0	25.73	7.79
Armed group vs armed group	7.15	5.59	0	25.01	6.50

Table A8: Spatial regression estimates with complete dataset and transformed flows as a robustness check

	Dependent variable: Log(origin-destination migration rate)					
	(1)	(2)	(3)	(4)	(5)	(6)
ρ_o	0.391***	0.391***	0.391***			
	(0.003)	(0.003)	(0.003)			
ρ_d				0.336***	0.336***	0.336***
				(0.003)	(0.003)	(0.003)
Palmer index	0.006	0.019***	0.015*	0.004	0.014**	0.011
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
Log distance	−0.602***	−0.602***	−0.602***	−0.689***	−0.690***	−0.690***
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)
Contiguity	1.852***	1.852***	1.852***	1.920***	1.920***	1.920***
	(0.037)	(0.037)	(0.037)	(0.038)	(0.038)	(0.038)
Common language	0.570***	0.570***	0.570***	0.587***	0.587***	0.587***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Death rate		0.038**	0.082***		0.024	0.046*
		(0.019)	(0.025)		(0.019)	(0.025)
Palmer index x Death rate		−0.071***	−0.074***		−0.051***	−0.052***
		(0.014)	(0.018)		(0.015)	(0.018)
LI x Death rate			−0.100***			−0.051
			(0.033)			(0.034)
Palmer index x LI			0.023			0.016
			(0.017)			(0.017)
Palmer index x Death rate x LI			−0.002			−0.003
			(0.031)			(0.032)
Observations	124820	124820	124820	124820	124820	124820
GDP/capita - Orig	Yes	Yes	Yes	Yes	Yes	Yes
GDP/capita - Dest	Yes	Yes	Yes	Yes	Yes	Yes
Orig + Dest FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
AIC	483269.4	483226.3	483216.2	487663.7	487644.4	487649.8

Notes. This table exhibits the spatial estimates of equation (3) including fixed effects by origin, destination and time. The dependent variable is the bilateral migration rate in logarithms. All migration flows are added to one before calculating migration flow rates, and then take the natural logarithm. For details on the independent variables, please refer to Section 3.1. LI stands for low-income and corresponds to the low-income dummy variable. Death rate refers to the Death rate dummy variable proxying for conflict presence. Regressions also include GDP per capita at both origin and destination as control variables. GDP/capita stands for GDP per capita. Orig abbreviates origin and Dest refers to destination. *p<0.1; **p<0.05; ***p<0.01.

Table A9: Total effects of a one standard deviation contraction in the Palmer index based on the spatial regressions estimates for column 2 and 3 of Table A8

Variable	Conflictive	Income	Column (2)	Column (3)
Palmer index	No	Middle/High	-0.031^{***}	-0.024^{*}
	No	Low		-0.062^{**}
	Yes	Middle/High	0.085^{***}	0.097^{***}
	Yes	Low		0.064^{*}

Notes. This table exhibits the total effects of a one standard deviation contraction in the Palmer index based on the spatial model estimates. Total impacts in columns (2) and (3) are obtained based on the model specifications in columns (2) and (3), respectively, of Table A8. For the exercise, we classify as conflictive countries those that are within the top 25% of the distribution of death rates in a given 5-year period. t-stat corresponds to the t-statistic. *p<0.1; **p<0.05; ***p<0.01.

Table A10: Fixed effects Poisson pseudo-maximum likelihood estimates of equation (2) as a robustness check

	Dependent variable: origin-destination migration rate			
	(1)	(2)	(3)	(4)
Palmer index	−0.026	0.023	0.000	0.007
	(0.037)	(0.040)	(0.043)	(0.044)
Log distance	-1.285^{***}	-1.286^{***}	-1.287^{***}	-1.286^{***}
	(0.095)	(0.095)	(0.095)	(0.095)
Contiguity	0.359^{**}	0.359^{**}	0.359^{**}	0.359^{**}
	(0.146)	(0.146)	(0.146)	(0.146)
Common language	0.992^{***}	0.992^{***}	0.992^{***}	0.992^{***}
	(0.124)	(0.124)	(0.124)	(0.124)
Death rate		0.153	0.290	0.221
		(0.129)	(0.191)	(0.166)
Palmer index x Death rate		-0.260^{**}	-0.254^{**}	-0.331^{**}
		(0.109)	(0.099)	(0.133)
LI x Death rate			−0.323	−0.197
			(0.203)	(0.179)
Palmer index x LI			0.120^{*}	0.068
			(0.072)	(0.081)
Palmer index x Death rate x LI				0.243
				(0.177)
Observations	17390	17390	17390	17390
GDP/capita - Orig	Yes	Yes	Yes	Yes
GDP/capita - Dest	Yes	Yes	Yes	Yes
Orig+Dest FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
R2	0.447	0.449	0.449	0.450

Notes. This table exhibits the FEPPML estimates including fixed effects by origin, destination, and time. The dependent variable is the bilateral migration flow rate. For details on the independent variables, please refer to Section 3.1. LI stands for low income and corresponds to the low-income dummy variable. Death rate refers to the Death rate dummy variable proxying for conflict presence. Regressions also include GDP per capita at both origin and destination as control variables. GDP/capita stands for GDP per capita. Orig abbreviates origin and Dest refers to destination. Clustered standard errors by country pairs are presented in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A11: Spatial regression estimates using SPEI-48 instead of Palmer index, as a robustness check

	Dependent variable: Log(origin-destination migration rate)					
	(1)	(2)	(3)	(4)	(5)	(6)
ρ_o	0.345***	0.345***	0.345***			
	(0.007)	(0.007)	(0.007)			
ρ_d				0.270***	0.269***	0.269***
				(0.008)	(0.008)	(0.008)
SPEI-48	−0.006	0.021	0.013	−0.015	0.010	0.004
	(0.020)	(0.023)	(0.025)	(0.021)	(0.024)	(0.026)
Log distance	−0.810***	−0.810***	−0.810***	−0.910***	−0.910***	−0.910***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Contiguity	1.112***	1.112***	1.113***	1.079***	1.080***	1.080***
	(0.060)	(0.060)	(0.060)	(0.062)	(0.062)	(0.062)
Common language	0.974***	0.974***	0.973***	1.027***	1.027***	1.027***
	(0.033)	(0.033)	(0.033)	(0.034)	(0.034)	(0.034)
Death rate		0.064	0.096*		0.015	0.022
		(0.041)	(0.050)		(0.042)	(0.051)
SPEI-48 x Death rate		−0.093**	−0.126***		−0.087*	−0.119**
		(0.043)	(0.049)		(0.044)	(0.050)
LI x Death rate			−0.067			−0.008
			(0.068)			(0.070)
SPEI-48 x LI			0.040			0.030
			(0.056)			(0.058)
SPEI-48 x Death rate x LI			0.141			0.135
			(0.103)			(0.106)
Observations	17390	17390	17390	17390	17390	17390
GDP/capita - Orig	Yes	Yes	Yes	Yes	Yes	Yes
GDP/capita - Dest	Yes	Yes	Yes	Yes	Yes	Yes
Country pairs FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
AIC	63072.9	63065.9	63065.4	63873.9	63871.7	63874.7

Notes. This table exhibits spatial regression estimates for equation (3) using SPEI-48 instead of the Palmer index as a robustness check. See notes of table 7 for details.

Table A12: Total effects of a one standard deviation contraction in the SPEI-48 based on the spatial regressions estimates for columns 2 and 3 of Table A11

Variable	Conflictive	Income	Column (2)	Column (3)
SPEI-48	No	Middle/High	-0.030	-0.017
	No	Low		-0.071
	Yes	Middle/High	0.1^{*}	0.161^{***}
	Yes	Low		-0.094

Notes. This table exhibits the total effects of a one standard deviation contraction in the SPEI-48 based on the spatial model estimates. Total impacts in columns (2) and (3) are obtained based on the model specifications in columns (2) and (3), respectively, of Table A11. For the exercise, we classify as conflictive countries those that are within the top 25% of the distribution of death rates in a given 5-year period. t-stat corresponds to the t-statistic. *p<0.1; **p<0.05; ***p<0.01.

Table A13: Spatial regression estimates using a conflict dummy based on more than 3 years of conflict in a period as a robustness check

	Dependent variable: Log(origin-destination migration rate)					
	(1)	(2)	(3)	(4)	(5)	(6)
ρ_o	0.345***	0.345***	0.345***			
	(0.007)	(0.007)	(0.007)			
ρ_d				0.270***	0.270***	0.270***
				(0.008)	(0.008)	(0.008)
Palmer index	−0.006	0.007	0.007	−0.014	0.001	0.001
	(0.015)	(0.017)	(0.018)	(0.015)	(0.018)	(0.019)
Log distance	−0.810***	−0.811***	−0.810***	−0.910***	−0.907***	−0.907***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Contiguity	1.111***	1.111***	1.111***	1.079***	1.080***	1.080***
	(0.060)	(0.060)	(0.060)	(0.062)	(0.062)	(0.062)
Common language	0.974***	0.974***	0.973***	1.027***	1.030***	1.029***
	(0.033)	(0.033)	(0.033)	(0.034)	(0.034)	(0.034)
Conflict years > 3		0.003	0.045		−0.118**	−0.087
		(0.049)	(0.054)		(0.050)	(0.056)
Palmer index x Conflict years > 3		−0.048	−0.069**		−0.052*	−0.070**
		(0.030)	(0.034)		(0.031)	(0.035)
LI x Conflict years > 3			−0.113			−0.082
			(0.071)			(0.074)
Palmer index x LI			−0.010			−0.013
			(0.046)			(0.047)
Palmer index x Conflict years > 3 x LI			0.074			0.068
			(0.071)			(0.074)
Observations	17390	17390	17390	17390	17390	17390
GDP/capita - Orig	Yes	Yes	Yes	Yes	Yes	Yes
GDP/capita - Dest	Yes	Yes	Yes	Yes	Yes	Yes
Country pairs FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
AIC	63072.7	63075.1	63072.0	63872.6	63871.7	63871.3

Notes. This table exhibits the OLS estimates for equation (7) using a dummy variable that equals 1 if a country experienced 4 or 5 years of conflict within a 5-year period, as a robustness check, instead of using the death rate dummy. See notes of Table 7 for details.

Table A14: Total effects of a one standard deviation contraction in the Palmer index based on the spatial regressions estimates for columns 2 and 3 of Table A13

Variable	Conflictive	Income	Column (2)	Column (3)
Palmer index	No	Middle/High	-0.012	-0.010
	No	Low		-0.008
	Yes	Middle/High	0.057	0.087**
	Yes	Low		-0.002

Notes. This table exhibits the total effects of a one standard deviation contraction in the Palmer index based on the spatial model estimates. Total impacts in columns (2) and (3) are obtained based on the model specifications in columns (2) and (3), respectively, of Table A13. For the exercise, we classify as conflictive countries those that are within the top 25% of the distribution of death rates in a given 5-year period. t-stat corresponds to the t-statistic. *p<0.1; **p<0.05; ***p<0.01.

Table A15: Spatial regression estimates with contiguity matrix for the neighborhood structure as a robustness check

	Dependent variable: Log(origin-destination migration rate)					
	(1)	(2)	(3)	(4)	(5)	(6)
ρ_o	0.355***	0.356***	0.356***			
	(0.007)	(0.007)	(0.007)			
ρ_d				0.273***	0.272***	0.272***
				(0.008)	(0.008)	(0.008)
Palmer index	−0.007	0.012	0.009	−0.014	0.002	0.001
	(0.015)	(0.017)	(0.018)	(0.015)	(0.017)	(0.018)
Log distance	−0.804***	−0.803***	−0.804***	−0.912***	−0.912***	−0.912***
	(0.021)	(0.021)	(0.021)	(0.022)	(0.022)	(0.022)
Contiguity	1.120***	1.121***	1.121***	1.054***	1.054***	1.054***
	(0.060)	(0.060)	(0.060)	(0.061)	(0.061)	(0.061)
Common language	0.958***	0.958***	0.957***	1.026***	1.027***	1.026***
	(0.033)	(0.033)	(0.033)	(0.034)	(0.034)	(0.034)
Death rate		0.047	0.086*		0.007	0.019
		(0.042)	(0.052)		(0.044)	(0.053)
Palmer index x Death rate		−0.084***	−0.095**		−0.071**	−0.083**
		(0.032)	(0.037)		(0.033)	(0.039)
LI x Death rate			−0.099			−0.031
			(0.072)			(0.074)
Palmer index x LI			0.017			0.007
			(0.042)			(0.044)
Palmer index x Death rate x LI			0.026			0.036
			(0.074)			(0.076)
Observations	17395	17395	17395	17395	17395	17395
GDP/capita - Orig	Yes	Yes	Yes	Yes	Yes	Yes
GDP/capita - Dest	Yes	Yes	Yes	Yes	Yes	Yes
Orig + Dest FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
AIC	63002.5	62992.0	62994.7	63883.8	63883.9	63887.0

Notes. This table exhibits the spatial estimates of equation (3) including fixed effects for origin, destination, and time using a contiguity matrix for the neighborhood structure. See notes of table 7 for details.

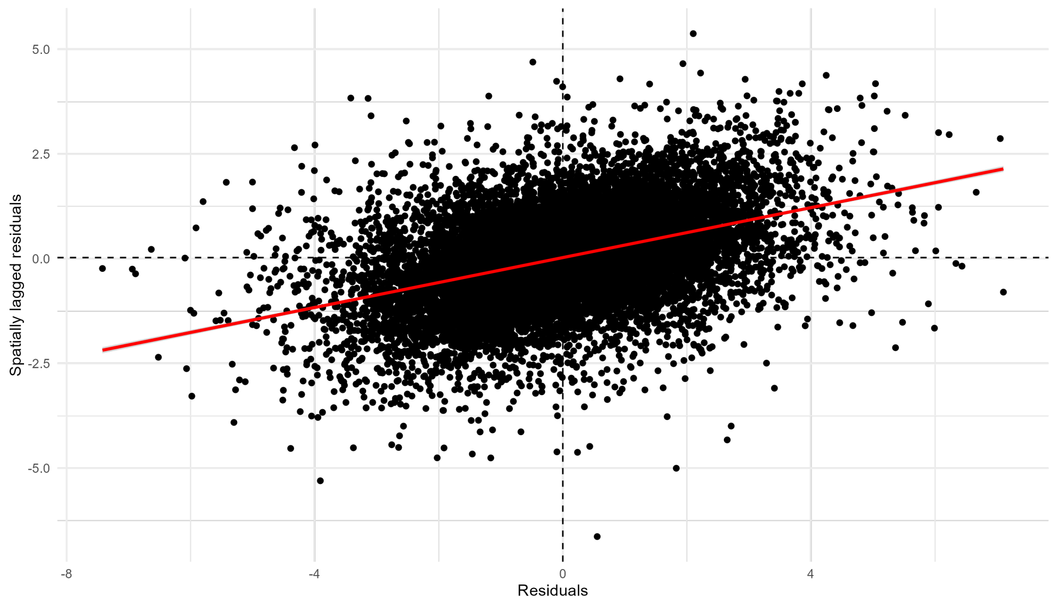
Table A16: Total effects of a one standard deviation contraction in the Palmer index based on the spatial regressions estimates for columns 2 and 3 of Table A15

<table>
<tr><th>Variable</th><th>Conflictive</th><th>Income</th><th>Column (2)</th><th>Column (3)</th></tr>
<tr><td rowspan="4">Palmer</td><td>No</td><td>Middle/High</td><td rowspan="2">-0.038</td><td>-0.014</td></tr>
<tr><td>No</td><td>Low</td><td>-0.044</td></tr>
<tr><td>Yes</td><td>Middle/High</td><td rowspan="2">0.101**</td><td>0.124**</td></tr>
<tr><td>Yes</td><td>Low</td><td>0.061</td></tr>
</table>

Notes. This table exhibits the total effects of a one standard deviation contraction in the Palmer index based on the spatial model estimates. Total impacts in columns (2) and (3) are obtained based on the model specifications in columns (2) and (3), respectively, of Table A15. For the exercise, we classify as conflictive countries those that are within the top 25% of the distribution of death rates in a given 5-year period. t-stat corresponds to the t-statistic. *p<0.1; **p<0.05; ***p<0.01.

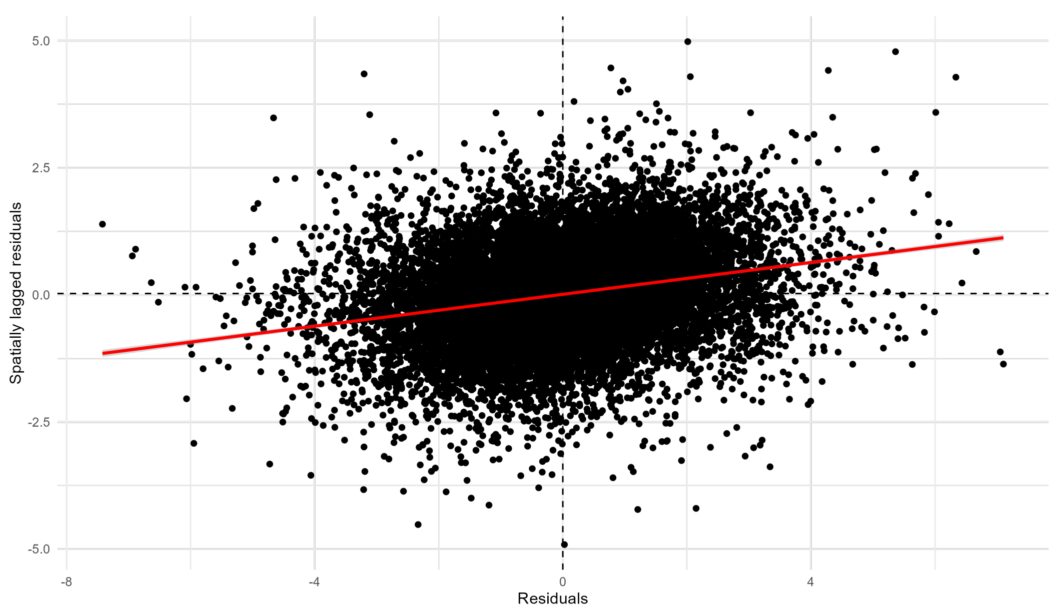
A1.2 Additional figures

Figure A1: Moran plot of the residuals of the OLS estimates - W_o



Notes. This figure exhibits the Moran scatter plot of the residuals of the model estimates in column (4) of Table 5 relying on W_o as the spatial weight matrix.

Figure A2: Moran plot of the residuals of the OLS estimates - W_d



Notes. This figure exhibits the Moran scatter plot of the residuals of the model estimates in column (4) of Table 5 relying on W_d as the spatial weight matrix.

Figure A3: Local network effects and degree centrality for most conflictive countries, assuming W_o. Left: low-income economies. Right: middle/high-income economies

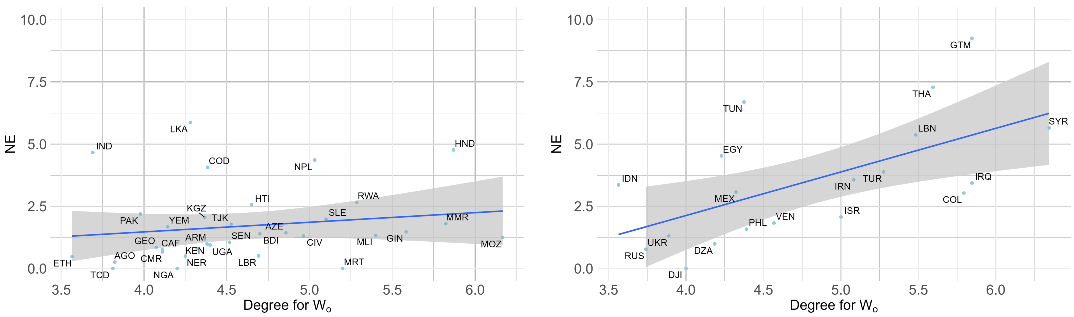
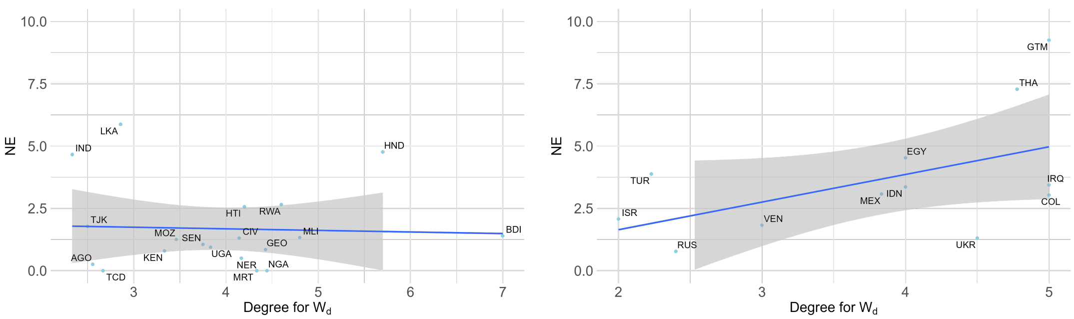


Figure A4: Local network effects and degree centrality for most conflictive countries, assuming W_d. Left: low-income economies. Right: middle/high-income economies



A1.3 Internet appendix

All codes and data associated with this article can be found in the following link: `https://drive.google.com/drive/u/0/folders/1tWlRXBpz3bxug4YtgHyhUG1lDDJsvvsz`