Searching for Grouped Patterns of Heterogeneity in the Climate–Migration Link

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ABSTRACT

This paper investigates the extent to which international migration can be explained by climate change and whether this relationship varies systematically between groups of countries. The primary focus is to further investigate the heterogeneous effect found for countries with different income levels using a yearly migration dataset and allowing the country grouping to be data driven. For this purpose, a recently proposed statistical technique is used, the grouped fixed-effects (GFE) estimator, which groups the countries of origin according to the data generating process. The results indicate that, on average, increasing population-weighted temperatures are associated with an increase in emigration rates but that the pattern differs between groups. The relationship is driven by a group of countries mainly located in Africa and central Asia. No statistically robust association is found between population-weighted precipitation and emigration.

1. Introduction

The impact of climate change on migration has been a concern since the early 1990s, with environmentalists, economists, and political scientists expressing different points of view on this issue. The discussion intensified with the publication of the fourth and fifth IPCC reports (Bernstein et al. 2007; Pachauri et al. 2014) and during the multilateral climate negotiations that led to the Paris agreement and its implementation in November 2016. The Bernstein et al. (2007) report referred to the ‘‘potential for population migration’’ due to climate distress. The topic has received substantial media coverage and is the focus of abundant academic research from various disciplines (e.g., Piguet et al. 2011; Berlemann and Steinhardt 2017; Borderon et al. 2019; Cattaneo et al. 2019; Dell et al. 2014; Kaczan and Orgill-Meyer 2020). While the standard statistical studies in the migration literature traditionally placed heavy emphasis on the socioeconomic drivers of migration without considering climatic factors, a number of cross-country macroeconomic studies have focused on natural disasters and extreme events as drivers of migration (Warner et al. 2009; Belasen and Polachek 2013; Drabo and Mbaye 2015). Other large-scale studies have attempted to quantify the impacts on international migration of changes in local temperature and precipitation (Backhaus et al. 2015; Beine and Parsons 2015; Cai et al. 2016; Coniglio and Pesce 2015; Cattaneo and Peri 2016). This literature reports mixed results. Whereas Coniglio and Pesce (2015), using yearly observations and focusing on rainfall variability in the sending countries, find direct and indirect effects of climate shocks on migration that vary by income level, Beine and Parsons (2015), using 10-yr interval data, fail to find any direct effects of climate shocks when accounting for economic, political, demographic and social drivers of migration. Claiming that income and productivity are affected by temperature, Cattaneo and Peri (2016), also using 10-yr interval data, focus on the global effect of temperature changes on international emigration rates without controlling for the effect of other key drivers. The main result in Cattaneo and Peri (2016) indicates that the effect of local temperature changes on emigration varies depending on the average level of income of the sending countries: climate warming is associated with significantly higher emigration rates only in middle-income countries, whereas it is associated with lower rates in poor countries where families cannot afford the cost of emigrating.

The main focus of this paper is to further investigate the heterogeneous effect of climatic variations using annual international migration data. The data for migration cover the period from 1995 to 2006 and include migration flows from 142 origin countries to 19 Organisation for Economic Co-operation and Development (OECD) destinations. The main contribution of the study is that the country grouping is not exogenously decided, as in the previous

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literature, but instead obtained from the data. Grouped patterns of heterogeneity are consistent with the empirical evidence that international migration patterns tend to be clustered in time and space. For instance, there are waves of international migration induced by several factors that affect specific groups of countries (e.g., conflict, natural disaster). The main estimation technique to endogenously group the countries of origin is based on the grouped fixed-effects (GFE) estimator proposed by Bonhomme and Manresa (2015), which allows the origin countries to be grouped according to the data generation process. The main data are taken from Backhaus et al. (2015) since the yearly variation enables a more precise identification of the relationship and ensures that the exact timing of the climatic variations and the occurrence of the migration flows can be accounted for. Once a suitable country grouping has been found, a model for multiorigin countries augmented with climate variables is estimated.

The results show that local temperature increases lead to an increase in emigration, confirming major findings in the literature, but the average effect is quantitatively small and differs between groups. The positive link is driven by a group of countries located mainly in Africa and central Asia, whereas no significant association is found between the population-weighted local precipitation and emigration. Moreover, the effects of changes in precipitation levels on emigration differ between groups but are only weakly statistically significant or nonsignificant.

The rest of the paper is structured as follows. Section 2 summarizes the literature on international migration and climate change. Section 3 refers to the related theoretical models and derives the main empirical specification. Section 4 presents the empirical application, the main results, and the sensitivity analysis. Section 5 concludes the paper.

2. Empirical studies on migration and climatic factors

In this section, I focus on recent studies that consider domestic climatic factors as explanatory variables of international migration. I refer to Belasen and Polachek (2013), Backhaus et al. (2015), and Cattaneo et al. (2019) for a summary of recent studies focusing on the more general socioeconomic determinants of international migration and on environmental variables related to extreme events and natural disasters. To introduce the impact of climate change and other, economic, variables (income, trade, etc.) on migration in developing countries, I refer to the literature survey presented in Lilleor and Van den Broeck (2011), Dell et al. (2014), Choumert et al. (2015), and Cattaneo et al. (2019), which also refer to mitigation and adaptation strategies.

Two early studies that focus on climatic factors are Barrios et al. (2006) and Marchiori et al. (2012), which analyze internal and international migration, respectively. Both studies are focused on sub-Saharan African (SSA) countries. Whereas the former study finds that local rainfall shocks induce internal migration in SSA, but not in other developing countries, the latter study finds some indirect effects of local rainfall and temperature anomalies that work through the wage ratio and affect international migration.

Table A1 in the appendix presents a review of the cross-country macroeconomic studies that focus on the climate–migration link, including a summary of the main findings, the target climate and migration variables used, the datasets, and the method applied in each study. Among the existing studies, it is possible to distinguish between studies that use local average temperature and rainfall as the main climatic variables (Backhaus et al. 2015; Cai et al. 2016; Cattaneo and Peri 2016) and those that focus on the deviations of local rainfall and/or temperature from "normal" levels (Beine and Parsons 2015; Coniglio and Pesce 2015). A number of papers, also relevant in this context, review the existing literature or focus more specifically on natural disasters (Millock 2015; Cattaneo et al. 2019).

A second important characteristic of these studies is related to the migration data used. Whereas some of them use data from 1960 to 2000 at 10-yr intervals (e.g., Beine and Parsons 2015; Cattaneo and Peri 2016), other studies use yearly data starting in the 1980s or 1990s until the mid-2000s (e.g., Backhaus et al. 2015; Cai et al. 2016; Coniglio and Pesce 2015).

For the method used to estimate the statistical relationship between migration and climate change, the authors that focus on bilateral migration use the gravity model of trade, estimated with the most recent techniques proposed in the trade literature. Most of them include a number of fixed effects (dummy variables) to control for unobservable factors related to the destination country's migration policies, time-invariant origin country factors, and bilateral time-invariant factors (e.g., Backhaus et al. 2015; Beine and Parsons 2015; Cai et al. 2016; Coniglio and Pesce 2015). Beine and Parsons (2015) consider both natural disasters and climatic variation as potential drivers of bilateral migration flows. Since their data provide information on migration in 10-yr intervals, their analysis is oriented toward the long-run effects of climate volatility. Their results do not show any direct effect of the latter on international migration flows. It is worth mentioning that they do not consider weighted average local temperature and precipitation levels, unlike Cai et al. (2016) and Cattaneo and Peri (2016), who do find a direct effect of these climatic variables. Moreover, using a large number of controls in the analysis of the migration–climate relationship could make it difficult to investigate the indirect effects of the climatic variables on international migration. For this reason, as in Cattaneo and Peri (2016), I focus on the overall effect of local temperature on the emigration rate, without controlling for the effect of other determinants of migration.[1] I depart from their approach in that I use yearly observations and a data-driven empirical strategy to endogenously group the countries.

Although this paper primarily focuses on cross-country macro studies, it is worth mentioning that there is a huge microeconomic empirical literature, as well as research in other disciplines. Two excellent systematic reviews of recent works and their main results are presented in Borderon et al. (2019) for the African continent and in Kaczan and Orgill-Meyer (2020) for developing countries. The latter authors limit the review to national and subnational studies that use quantitative statistical analyses to establish causality.

3. Model specification

To study the relationship between climatic factors and migration flows over time and across countries, I use the GFE approach, which was proposed by Bonhomme and Manresa (2015).[2] Given that this statistical association has recently been investigated[3] and could become an important stylized fact, it becomes critical to establish whether it is heterogeneous across groups of countries. The GFE estimation introduces time-varying grouped patterns of heterogeneity in linear panel data models. The estimator minimizes a least squares criterion with respect to all possible groupings of the cross-sectional units. The most appealing feature of this approach is that group membership is left unrestricted. The estimator is suitable for big number of countries N and small number of periods T and it is consistent as both dimensions of the panel tend to infinity.

One of the most common approaches to model unobserved heterogeneity in panel data is the use of time-invariant fixed effects. This standard approach is sometimes subject to poorly estimated elasticities when there are errors in the data or when the explanatory variables vary slowly over time. Moreover, it is restrictive in that unobserved heterogeneity is assumed to be constant over time. The GFE introduces clustered time patterns of unobserved heterogeneity that are common within groups of countries. Although countries could change their group membership over time, the assumption of constant group membership is not unreasonable, given that the time span considered is relatively short (12 years). Both the group-specific time patterns and group membership are estimated from the data.

My benchmark specification is a linear model that explains emigration M_{it} with grouped patterns of heterogeneity and takes the form

$$\ln M_{it} = x_{it}^{\prime}\beta + \gamma_{g_j t} + u_{it} , \qquad (1)$$

where M_{it} is the emigration rate to OECD countries from country i in year t, which is defined as the flow of migrants from country i to OECD destinations in year t divided by country i's population[4] in year t. The $x_{it}^{\prime}$ are the covariates that are assumed to be contemporaneously uncorrelated with the error term u_{it} but are allowed to be arbitrarily correlated with group-specific heterogeneity $\gamma_{g_j t}$. The countries in the same group share the same time profile and the number of groups is decided or estimated by the researcher, with group membership remaining constant over time. Among the covariates, the climate variables that are considered are population-weighted annual temperature in degrees Celsius, denoted as wtemp_{it}, whereas wpre_{it} denotes population-weighted annual precipitation in millimeters. Following the approach proposed by Dell et al. (2014), the use of population weights makes the climate data more reflective of precisely how strongly the inhabitants within a given country are actually affected by variations in local temperature and precipitation.

In essence, countries that have similar time profiles of migration—net of the explanatory variables—are grouped together. The main underlying assumption is that group membership remains constant over time.

The model can be easily modified to allow for additive time-invariant fixed effects, which is the preferred specification.[5] I apply the within transformation

[1] For completeness, I also consider in the empirical analysis a number of potential transmission channels as control variables.

[2] This estimator has been used in Grunewald et al. (2017) to investigate the relationship between inequality and emissions.

[3] A previous version of the paper included a replication of the results in Cattaneo and Peri (2016), as well as the estimation of their model with yearly observations (see Martínez-Zarzoso 2017). The main results indicated that the estimates are more accurate with yearly data than with decadal data, but in both cases higher average temperatures seem to induce migration.

[4] To be in line with the microfoundations for the migration model specified in Beine et al. (2016), however, the denominator should be the native population of the country of origin, which could be obtained by subtracting the stock of migrants from the total population. Since the proposed estimation technique exploits the within-country variation and the stock of migrants does not vary much in the period under analysis, using total population instead should not affect the results.

[5] The idea is to control not only for time-variant group-specific heterogeneity, but also for time-invariant country-specific unobserved heterogeneity.

to the dependent and independent variables and estimate the model with variables in deviations with respect to the within mean. The new transformed variables are denoted as $\ddot{x}_{it} = (x_{it} - \overline{x}_i)$ and $\ddot{M}_{it} = (M_{it} - \overline{M}_i)$, and so on.

The GFE in the model in Eq. (1) is obtained by minimizing the following expression:

$$(\hat{\beta}, \hat{\gamma}, \hat{\alpha}) = \underset{(\beta,\gamma,\alpha)\in\Theta\times\mathscr{A}^{GT}\times\Gamma_G}{\operatorname{argmin}} \sum_{i=1}^{N}\sum_{t=1}^{T}(\ddot{M}_{it} - \ddot{x}_{it}'\beta - \ddot{\gamma}_{g_i t})^2, \quad (2)$$

where the minimum of all possible groupings $\alpha = \{g_1, \ldots, g_n\}$ is taken of the N units in groups G, parameters β, and group-specific time effects γ (Bonhomme and Manresa 2015). The optimal group assignment for each country is given by

$$\hat{g}_i(\beta, \gamma) = \underset{g\in\{1,\ldots,G\}}{\operatorname{argmin}} \sum_{t=1}^{T}\left(\ddot{M}_{it} - \ddot{x}_{it}'\beta - \ddot{\gamma}_{g_i t}\right)^2. \quad (3)$$

Last, the GFE estimates of beta and gamma are

$$(\hat{\beta}, \hat{\gamma}) = \underset{(\beta,\gamma)\in\Theta\times\mathscr{A}^{GT}}{\operatorname{argmin}} \sum_{i=1}^{N}\sum_{t=1}^{T}[\ddot{M}_{it} - \ddot{x}_{it}'\beta - \ddot{\gamma}_{\hat{g}_j(\beta,\gamma)t}]^2, \quad (4)$$

where the GFE estimate of g_j is $\hat{g}_j(\hat{\beta}, \hat{\gamma})$ and the group probabilities are unrestricted and individual specific.

There are two algorithms available to minimize Eq. (4). The first one uses a simple iterative strategy and is suitable for small-scale datasets, whereas the second, which exploits recent advances in data clustering, is preferred for larger-scale problems. Given that this paper uses a small dataset, the former is employed.

Following the related literature, the model includes the two aforementioned climatic variables, the weighted average local temperature and precipitation. The nonclimate explanatory variables derived from neoclassical theory—namely, the economic, demographic, geographic, and cultural controls as well as the trade-to–gross domestic product (GDP) ratio—are only included when investigating the transmission channels of the migration–climate link. With this aim, the specification considered is

$$\begin{aligned}\ln\ddot{M}_{it} = {} & \alpha_0 + \beta_{1j}\,\mathrm{ln}\ddot{\mathrm{wtemp}}_{it} + \beta_{2j}\,\mathrm{ln}\ddot{\mathrm{wpre}}_{it} + \beta_3\,\mathrm{ln}\ddot{\mathrm{GDP}}_{it} + \beta_4\ln\mathrm{Trade}\ddot{\mathrm{GDP}}_{it} + \mathrm{Dem}\ddot{\mathrm{Pres}}_{it} \\ & + \beta_6\,\mathrm{lnPolSt}\ddot{\mathrm{a}}\mathrm{bility}_{it} + \beta_7\ddot{U}_{it} + \beta_8\mathrm{Nat}\ddot{\mathrm{u}}\mathrm{rDis}_{it} + \beta_9\mathrm{ShareA}\ddot{\mathrm{g}}\mathrm{riLand}_{it} + \gamma_{g_i t} + u_{it},\end{aligned} \quad (5)$$

where the double dots indicate that the variables are expressed in deviations with respect to the within mean. Variables M_{it}, wtemp$_{it}$, and wpre$_{it}$ have already been described below Eq. (1), and ln denotes natural logs. I also estimate a second specification of the model with the climatic variables in levels. The coefficients of the climatic variables are group specific, and the groups are indexed with j. GDP$_{it}$ denotes purchasing power parity (PPP)-adjusted GDP in thousands of U.S. dollars in the origin country in year t. A squared term of GDP$_{it}$ was also included to account for the nonlinear effects of income in the origin country but was never found to be significant. TradeGDP$_{it}$ denotes the openness ratio (exports + imports)/GDP in the country of origin at time t. DemPres$_{it}$ denotes the share of young people in the country of origin's working-age population. PolStability$_{it}$ denotes absence of violence and terrorism and is measured on a scale from −2.5 to +2.5 (as an alternative, I also considered a state fragility index from the Center of Systemic Peace that is measured on a scale from 0 to 25). U_{it} denotes the unemployment rate in the country of origin at time t, which controls for the absorptive capacity of the sending country's labor market.

Nat$\ddot{\mathrm{u}}$rDis$_{it}$ is proxied with four variables: the number of tsunami deaths as a share of the total population and three dummy variables that take the value of 1 when floods, droughts, or landslides occur in a given country and year, and 0 otherwise. Share$\ddot{\mathrm{A}}$griland$_{it}$ denotes the share of sending country i's land area that is arable, under permanent crops, or under permanent pastures. The term $\gamma_{g_i t}$ captures time-variant group heterogeneity, and u_{it} is the error term.

4. Empirical strategy

a. Data and variables

The dataset is taken from Backhaus et al. (2015).[6] The climatic variables used are yearly weighted average temperature and precipitation in the countries of origin

[6] I also estimated some models using the dataset from Cattaneo and Peri (2016). The results are available upon request.

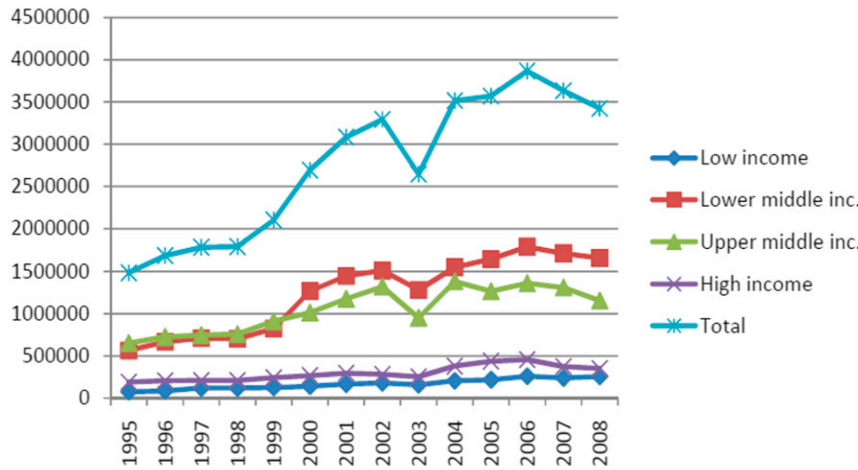

FIG. 1. Evolution over time of emigration by income level.

obtained from Dell et al. (2012). The data cover the period from 1995 to 2006, yielding 12 time periods for the analysis.[7] Both climate variables are population-weighted averages at the country-year level (using 1990 population figures for the weighting). According to Dell et al. (2014) the temperature and precipitation data have to be aggregated to a suitable level to match the availability of socioeconomic data. Two approaches have been proposed in the literature: one is to aggregate spatially, and the second consists of using a fixed set of population weights. However, the first approach would give more weight to large areas with low population density and very little economic activity. For this reason, the latter is preferred in this setting, in which the crucial concept is the average temperature/precipitation experienced by a person in a given administrative area, and not the average weather that affects a certain place. Although in general the yearly changes in the climatic variables appear to be small, with only 5.4% of the temperature changes in the sample falling outside the 1°C interval $[-1, 1]$ and only 1.65% of the changes in precipitation outside an interval of 5 mm $[-5, 5]$, the within variation is not that small and could have an effect on emigration, which is in any case expected to be moderate.

The data on yearly migration flows from the countries of origin to the OECD comes from the OECD's International Migration Database (IMD; OECD 2014). It comprises 19 OECD members as destination countries, on the basis of data availability, while examining inflows from a maximum of 142 countries of origin (see Fig. 1). Some of the latter are also members of the OECD, for example, Mexico, Chile, and New Zealand. Although these countries might be important destinations from the perspective of less developed countries, their role as a sending country is also important.

A complete list of the source and destination countries can be found in Table A3 in the appendix. The IMD is constructed on the basis of statistical reports from the OECD member countries, which implies that the data across countries might not be strictly comparable, as the criteria for registering an immigrant population and the conditions for granting residence permits varies by country.[8] Given that inflows into Italy are missing for many source countries and completely unavailable for the years 1995–97 and 2003, observations from the Eurostat online database (Eurostat 2014) were used to fill some of the gaps. For Austria, Switzerland, and the United Kingdom, the Eurostat database enabled the addition of numerous source countries and the replacement of some rounded and inaccurate figures for the United Kingdom. These additions and replacements were only done if the figures from the OECD and Eurostat databases coincided for countries in which data were available in both databases. In this way, the same definitions of immigration are used in both data sources. The data are mostly complete for France, Spain, and Germany, which together account for about 60% of the migratory flows to Europe in the sample; as well as for Australia, Canada, and the United States, which reflects the long history of immigration in these countries.

[7] A list of variables and their sources are presented in Table A2 in the appendix.

[8] Illegal migration flows are not covered by definition since flow data are usually collected through residence or work permits. This could induce a downward bias in the results if most illegal migrants were migrating because of climate change and its impact on agricultural productivity.

TABLE 1. Summary statistics for the dataset 1996–2006. See Table A2 in the appendix for the definitions of the variables. ''Weighted'' indicates that the corresponding variable is population weighted. The dataset is from Backhaus et al. (2015).

Variables (short name)	Obs	Mean	Std dev	Min	Max
Emigration rate (M)	1704	0.0137	0.0247	0	0.3296
Ln of emigration rate (ln$M$)	1693	−4.441	1.301	−8.238	−0.233
Weighted temperature (wtemp)	1704	20.643	6.888	−1.562	29.583
Weighted precipitation (wpre)	1704	10.910	7.415	0.066	40.567
GDP per capita USD 1000	1605	5.580	7.922	0.123	65.182
Ln of population	1704	15.814	1.689	11.759	20.994
Demographic pressure	1704	59.478	6.487	47.724	81.718
Political stability	1134	−0.369	0.925	−3.079	1.426
State fragility index	1613	11.777	5.942	0	25
Unemployment rate	778	10.023	6.454	0.6	39.3
Share_tsunami_deaths	1704	0.000 19	0.0049	0	0.1815
Floods	1604	0.0162	0.1263	0	1
Droughts	1604	0.0973	0.2964	0	1
Landslides	1604	0.0561	0.2302	0	1
Share_agriculture land	1704	41.107	22.445	0.467	91.160

Data for the economic and demographic variables are obtained from the World Bank's World Development Indicators (World Bank 2019) database, and data for natural disasters are obtained from the International Disasters Database (https://www.emdat.be). Table 1 presents summary statistics of the main variables used in the empirical application.

b. Main results

The migration empirical model presented in section 3 is estimated for bilateral flows using yearly data from 1995 to 2006. I estimate the model in Eq. (1) using the GFE estimator, and hence I allow the time-variant group effects $\gamma_{g_j t}$ to be correlated with the explanatory variables.[9] The reasoning behind this assumption is based on the possibility that each group has its own unobservable, time-varying mentality toward emigration that affects actual emigration rates or that there are specific commonalities shared by some source countries. The results are presented in Table 2.

The baseline GFE specification is presented in columns 1 and 2 of Table 2. The results in column 1 are obtained with the local climatic variables in levels,[10] and those in column 2 are obtained with the local climatic variables in natural logarithms. I prefer the second specification with climatic variables in logs because the estimates are more accurate after the transformation.[11] In both columns, the coefficient for weighted average temperature is positive and statistically significant indicating that higher weighted average temperatures are associated with higher emigration rates from developing countries to OECD countries. The results for population-weighted precipitation indicate that lower precipitation levels in the origin countries are associated with higher emigration rates, but the corresponding estimate is only statistically significant at the 10% level. The magnitude of the coefficient indicates that a decrease in precipitation of about 10% will increase the emigration rate by about 0.7% (column 2). For the results for population-weighted temperature, according to column 2 an increase of 10% in the temperature increases the emigration rate by 4.9%. Given that the annual average emigration rate in the sample is 0.014%, the average impact is quantitatively small.

Two additional specifications with nonlinearities are estimated in columns 3 and 4. Column 3 presents the results for a model in which the climatic variables are interacted with a *poor-country*[12] dummy variable. The results

[9] I estimated this model with a yearly dataset, given that the GFE is not suitable for a panel with a time dimension that consists of only a few periods, as is the case for decadal data.

[10] Similar to Backhaus et al. (2015), who considered weighted temperature/precipitation (in levels) but estimated a model for bilateral migration flows with variables in first differences. In their results, a number of control variables are also positive and statistically significant.

[11] Another reason is that when estimating the model in column 1 of Table 2 using the same number of observations as in column 2, the R^2 is higher and the RMSE smaller for the model with log-transformed climate variables. The dropped observations are those for negative weighted average temperatures, which correspond to only one country: Mongolia.

[12] Poor countries are defined as those in the bottom quartile of the simple income distribution: Afghanistan, Benin, Burkina Faso, Burundi, Cambodia, Central African Republic, Democratic Republic of Congo, Equatorial Guinea, Ethiopia, Gambia, Ghana, Guinea-Bissau, Laos, Lesotho, Liberia, Madagascar, Malawi, Mali, Mozambique, Nepal, Niger, Nigeria, Rwanda, Somalia, Sudan, Tanzania, Togo, Uganda, Yemen, and Zambia.

TABLE 2. Grouped fixed effects (FE) estimation results using annual data. Three asterisks, two asterisks, and one asterisk denote significance levels at the 1%, 5%, and 10% level, respectively. Robust standard errors are reported in parentheses. Group-year dummy variables are included in all columns; coefficients are not reported.

	Column 1: GFE_no ln	Column 2: GFE_ln	Column 3: GFE_ln	Column 4: GFE_ln
Dependent variable				
Ln of emigration rate				
Explanatory variables				
(ln) wtem_dm	0.0643*** (0.0231)	0.490** (0.237)	0.390 (0.290)	−1.341 (1.145)
(ln) wpre_dm	0.001 75 (0.005 01)	−0.0729* (0.0467)	−0.183*** (0.0558)	−0.114* (0.0582)
Ln wtempoor_dm			1.527** (0.763)	
Ln wprepoor_dm			0.318** (0.133)	
Ln wtem_squared_dm				0.444* (0.265)
Ln wpre_squared_dm				0.0283* (0.0162)
FE group 2	−0.142 (0.156)	0.671*** (0.145)	−0.203* (0.107)	1.912*** (0.216)
FE group 3	−0.299*** (0.0846)	0.382** (0.161)	1.196*** (0.122)	−0.771*** (0.155)
FE group 4	−0.976*** (0.142)	1.955*** (0.232)	0.0631 (0.282)	0.225** (0.0884)
FE group 5	−0.588*** (0.111)	2.105*** (0.179)	0.125 (0.110)	−0.312*** (0.108)
FE group 6	0.969*** (0.196)	0.481*** (0.153)	1.921*** (0.205)	0.922*** (0.135)
FE group 7	1.001*** (0.127)	1.060*** (0.146)	0.206 (0.130)	1.197*** (0.119)
FE group 8				0.143 (0.157)
Obs	1693	1681	1681	1681
R^2	0.676	0.655	0.660	0.679
R^2 adjusted	0.657	0.637	0.639	0.659
RMSE	0.312	0.321	0.327	0.311

for the average temperature indicate that only people from poor countries tend to emigrate at a higher rate as a result of an increase in the weighted average local temperature and the estimated elasticity is three times the average elasticity for the whole sample in column 2. Hence, these results do not confirm the ‘‘poverty trap’’ argument for the weighted average temperature shown in Cattaneo and Peri (2016). The difference in the results are mainly due to the methodology used in this paper, which allows the time-variant group effects to be correlated with the explanatory variables, rather than to the use of yearly versus decadal data. In a preliminary version, I also applied the Cattaneo and Peri (2016) method to the yearly sample, and the results obtained when varying the frequency of the data were similar.

For the population-weighted precipitation variable, while decreasing precipitation induces migration in less poor countries, in poor countries decreasing precipitation is associated with decreasing emigration. This second outcome differs from the findings reported in Cattaneo and Peri (2016), since those authors did not find any significant effect of precipitation on emigration.

The results in column 4, obtained from a model that includes the squared terms of the climatic variables, show that the squared term is weakly relevant—statistically significant at the 10% level—for the weighted average local temperature and precipitation. This lack of statistical significance could be due to having specified unobserved patterns of time-variant heterogeneity.

The GFE model presents the lowest RSME and the highest adjusted R^2 when the selected number of groups is seven. Figure 2 shows a map with the country grouping and also a graph with the time-variant patterns of heterogeneity that correspond to the results in column 2 of Table 2. The list of countries in each group is shown in Table A4 in the appendix.

In Table 3, I present results showing the group-specific coefficients for the climatic variables, assuming that the groups remain constant over time, and I also investigate a number of transmission channels through which temperature operates on migration. The results indicate that the positive relationship found for the weighted average temperature and migration from developing to developed countries is driven by group 6, which contains 23 countries, 14 of which are located in Africa, with a few in Asia and other world regions (see appendix Table A4 for a list of countries by group). Most of the countries in this group share two commonalities: the agricultural sector represents more than 10% of value added, and in more than one-half of the countries it is even above 20%; the average temperature is the highest in comparison with other groups, with the exception of three countries (Bosnia and Herzegovina, Bhutan, and Lesotho).

Conversely, for group 2, the coefficient for the average local temperature is negative and statistically significant at the 10% level. In this group, higher local

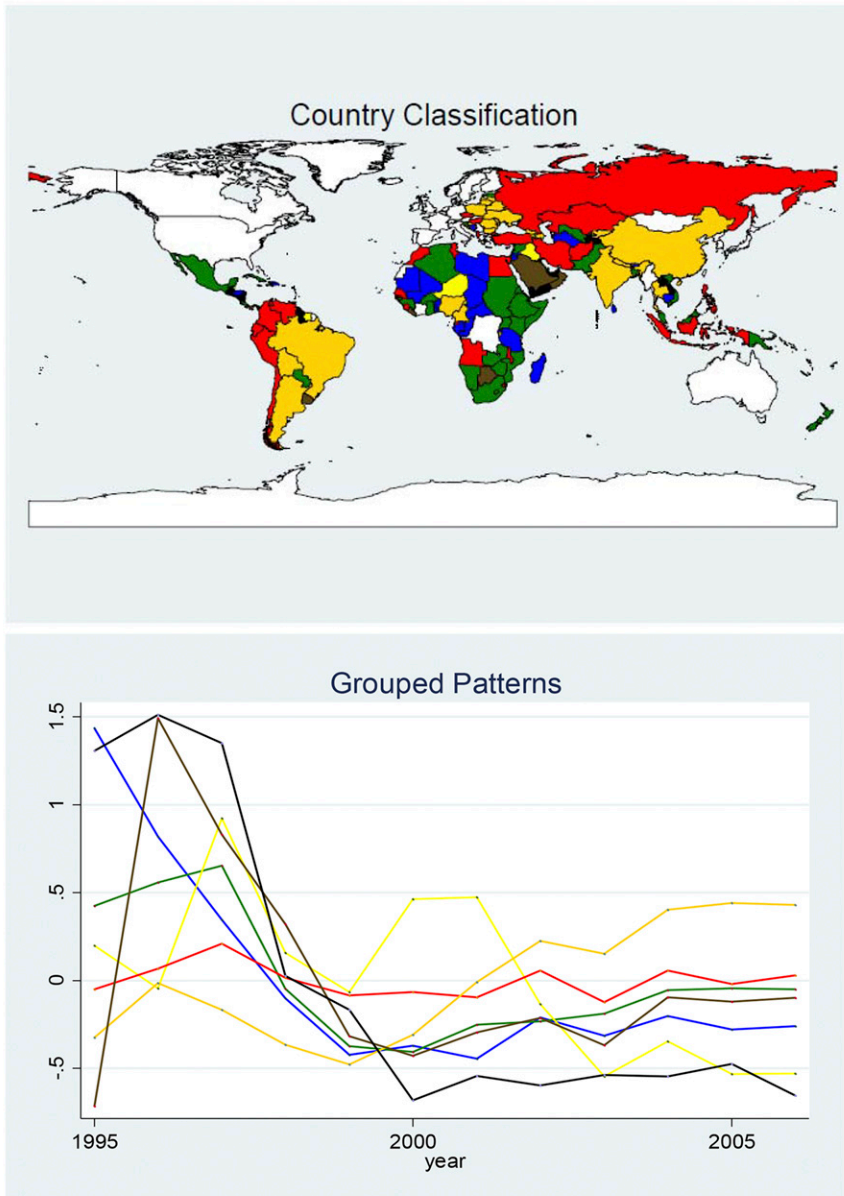

FIG. 2. (top) Map and (bottom) graph for seven groups (column 2 of Table 2). The colors in the graph correspond to the colors on the map, as described in Table A4 of the appendix.

temperatures are weakly associated with decreases in the emigration rate. This group is composed of 10 countries in Africa, 5 in South America, 4 in eastern European, 4 in central Asia, Indonesia, the Philippines, and a few small islands. In general, the countries in this group register lower average temperatures, but this could be due to the fact that two big countries in the Northern Hemisphere—Kazakhstan and Russia—are in this group. Nevertheless, these results are not robust, and further research is needed for these specific countries.

For the transmission channels, I add a number of controls to the model to see if the statistical significance of the climate variables remains similar, starting with the GDP of origin countries in column 1, for which the coefficient is not statistically significant.[13] A similar outcome is obtained when adding the trade-to-GDP ratio

[13] I also tried a specification with the squared term of the GDP, but again the coefficient was not statistically significant. Results are available upon request.

TABLE 3. Group-specific coefficients and transmission channels. Three asterisks, two asterisks, and one asterisk denote significance levels at the 1%, 5%, and 10% levels, respectively. Robust standard errors are reported in parentheses. Group-year dummy variables are included in all columns; coefficients are not reported. Dataset from Backhaus et al. (2015).

Estimations with GFE	Column 1: GDP origin	Column 2: trade share	Column 3: demographic pressure	Column 4: political stability	Column 5: unemployment origin	Column 6: natural disasters	Column 7: share agriculture
				Dependent variable: ln emigration rate			
lnwtemg1	0.217 (0.299)	0.242 (0.300)	0.0117 (0.325)	−0.0963 (0.370)	0.123 (0.397)	−0.005 55 (0.326)	−0.0155 (0.317)
lnwtemg2	-0.703^{*} (0.417)	-0.621^{*} (0.344)	-0.742^{*} (0.407)	-1.113^{**} (0.437)	−0.0618 (0.276)	-0.757^{*} (0.406)	-0.767^{*} (0.420)
lnwtemg3	1.435 (9.465)	−0.554 (9.464)	0.509 (9.634)	9.256 (6.361)	-47.53^{***} (0.0808)	0.517 (9.647)	0.490 (9.608)
lnwtemg4	2.369 (2.838)	2.477 (2.580)	2.675 (2.617)	6.224^{**} (2.721)	1.851 (2.034)	2.647 (2.654)	2.685 (2.610)
lnwtemg5	0.189 (0.623)	0.334 (0.688)	0.754 (0.780)	0.553 (0.949)	0.0591 (0.557)	0.779 (0.783)	0.756 (0.777)
lnwtemg6	2.485^{**} (1.003)	2.405^{**} (0.964)	2.429^{**} (0.972)	1.750 (1.140)	5.600^{***} (1.610)	2.358^{**} (0.961)	2.401^{**} (0.962)
lnwtemg7	−1.819 (1.450)	−2.219 (1.432)	−1.900 (1.437)	-4.081^{**} (1.666)	0.242 (8.538)	−1.942 (1.447)	−1.923 (1.430)
lnwpreg1	−0.126 (0.126)	0.0359 (0.0915)	−0.0822 (0.110)	−0.261 (0.179)	0.0857 (0.117)	−0.0807 (0.108)	−0.0870 (0.106)
lnwpreg2	−0.0987 (0.0962)	−0.0836 (0.103)	−0.0997 (0.0980)	−0.119 (0.0998)	0.0509 (0.0425)	−0.0973 (0.0953)	−0.0989 (0.0963)
lnwpreg3	0.282 (0.182)	0.267^{*} (0.154)	0.259 (0.165)	0.308^{**} (0.120)	-2.206^{***} (0.0544)	0.259 (0.165)	0.263 (0.166)
lnwpreg4	−0.152 (0.144)	−0.116 (0.120)	−0.127 (0.122)	0.411^{**} (0.178)	0.0225 (0.160)	−0.120 (0.124)	−0.126 (0.122)
lnwpreg5	−0.0317 (0.109)	0.009 54 (0.101)	0.005 47 (0.0857)	0.0610 (0.0591)	0.133 (0.115)	0.006 26 (0.0882)	0.002 97 (0.0859)
lnwpreg6	0.0190 (0.164)	0.0673 (0.183)	0.0684 (0.181)	0.229 (0.210)	0.0676 (0.160)	0.0678 (0.180)	0.0677 (0.182)
lnwpreg7	−0.146 (0.109)	−0.175 (0.107)	−0.145 (0.109)	−0.344 (0.232)	0.0514 (0.201)	−0.138 (0.110)	−0.145 (0.108)
Log_gdpcap_origin	−0.128 (0.113)						
Trade_to_gdp		0.000 219 (0.000 753)					
Demographic_pressure			−0.004 07 (0.0125)				
Stability				−0.0258 (0.0378)			
Unemployment_origin					0.002 03 (0.004 83)		
Share_tsunami_deaths						-1.252^{***} (0.295)	
Floods						−0.131 (0.0808)	
Droughts						−0.003 12 (0.0286)	
Landslides						0.0308 (0.0286)	
Share_agricultural_land							−0.002 85 (0.006 10)
Obs	1484	1492	1573	1050	720	1573	1573
R^2	0.667	0.669	0.655	0.629	0.733	0.656	0.655
No. of countries	127	129	133	133	108	133	133

TABLE A1. Summary of cross-country macroeconomic studies on the migration–climate link. PPML is Poisson pseudomaximum likelihood.

Study	Countries	Period	Method	Migration type; *measure*	Climate variables	Main finding
Barrios et al. (2006)	78 countries	1960–90	Cross-country panel data with country and time FE	Internal; *urbanization* as a proxy	Rainfall level normalized by the mean	Rainfall shocks induce migration in SSA only
Marchiori et al. (2012)	43 SSA countries	1960–2000, yearly basis	Cross-country panel data with country and time–region FE	International; *net migration rate*	Precipitation and temperature anomalies	Positive effect of rainfall anomalies and negative effect of temperature anomalies via wage ratio
Backhaus et al. (2015)	142 sending countries to 19 OECD destinations	1995–2006, yearly basis	Gravity model with country pair and time FE, estimation in first differences	International; *bilateral migration inflows*	Population-weighted average temperature and precipitation	Average temperature is positively correlated with bilateral migration, mainly for agriculture-dependent countries
Beine and Parsons (2015)	226 origin and destination countries	1960–2000, 10-yr intervals (five waves)	Gravity model with origin and destination–time FE (PPML)	International; *bilateral migration rate*	Natural disasters and average deviations of decadal average temperature and rainfall and anomalies	No evidence of direct impacts of climate anomalies on international migration, only an indirect effect through wage differentials
Coniglio and Pesce (2015)	128 origin and 29 OECD destinations	1990–2001, yearly basis	Gravity model with origin and destination–time FE (PPML not reported)	International; *bilateral migration inflows*	Index of excess rainfall variability	An increase in rainfall variability (also in anomalies) is associated with an increase in average bilateral migration
Cai et al. (2016)	163 sending countries to 42 destinations	1980–2010, yearly basis	Gravity model with country pair and origin and destination linear trends	International; *bilateral migration rate*	Population-weighted average temperature and precipitation	Each 1°C increase in temperature generates a 5% increase in outmigration from the top 25% of agricultural countries (significant at the 1% level)
Cattaneo and Peri (2016)	115 sending and receiving countries (30 poor and 85 middle income)	1960–2000, 10-yr intervals (five waves)	Cross-country panel data with country and time–region FE	International; *net emigration flows* (difference between stocks in two consecutive censuses) from Özden et al. (2011)	Population-weighted average temperature and precipitation from Dell et al. (2012)	Climatic warming associated with significantly higher emigration rates in middle-income countries and significantly lower rates in poor countries

Table A2. List of variables, definitions, and sources. Source: author's elaboration. The International Disaster Database is available online (https://www.emdat.be).

Variable	Definition	Source
Weighted temperature (wtemp)	Population-weighted average annual temperature in degrees Celsius in country *i*; constant 1990 population weights	Dell et al. (2012)
Weighted precipitation (wpre)	Population-weighted average annual precipitation in millimeters in country *i*; constant 1990 population weights	Dell et al. (2012)
Emigration rate (emigrants per inhabitants)	Inflow of population from sending country *i* divided by population in the sending country	OECD (2014): OECD International Migration Database; Eurostat (2014): immigration
GDP per capita	PPP-adjusted GDP per capita in sending country in current U.S. dollars	World Bank (2019): World Development Indicators Database
Demographic pressure	Percentage of young population as a share of working-age population in the sending country	World Bank (2019): World Development Indicators Database
Unemployment rate	Unemployment rate in the country of origin (share of total labor force)	World Bank (2019): World Development Indicators Database
Trade to GDP	Sum of exports and imports of goods and services as a share of the sending country's gross domestic product	World Bank (2019): World Development Indicators Database
Share of agricultural land	Share of sending country *i*'s land area that is arable, under permanent crops, or under permanent pastures	World Bank (2019): World Development Indicators Database
State fragility index	Ordinally scaled (0–25) measure of sending country *i*'s state fragility	Center for Systemic Peace (2019): state fragility index
Share of tsunami deaths	Tsunami deaths as a share of total population	The International Disaster Database (EM-DAT 2020)
Droughts	Dummy variable that takes the value of 1 if a drought has occurred in a given year and 0 otherwise	The International Disaster Database (EM-DAT 2020)
Floods	Dummy variable that takes the value of 1 if a flood has occurred in a given year and 0 otherwise	The International Disaster Database (EM-DAT 2020)
Landslides	Dummy variable that takes the value of 1 if a landslide has occurred in a given year and 0 otherwise	The International Disaster Database (EM-DAT 2020)
Political stability	Political stability and absence of violence/terrorism (ranges from −2.5 to 2.5)	World Bank (2019): world governance indicators

as a measure of openness in column 2, demographic pressure in column 3, political stability in column 4,[14] unemployment in column 5, and share of agricultural land in the origin countries as regressors in column 7. Moreover, in column 6 I considered as controls a number of proxy variables for the occurrence of natural disasters (floods, droughts, landslides, and tsunamis). The only variable that presents a statistically significant coefficient is the share of tsunami deaths, which is negatively signed. This could be due to the fact that tsunamis prevent families from sending one of their members abroad, since help is required at home to cope with the disaster, and also because the funds required to be able to migrate could be needed at home. This is consistent with the findings summarized in Kaczan and Orgill-Meyer (2020) indicating that severe shocks may affect a household's capability to migrate to a greater extent than its vulnerability does.

Furthermore, in the model incorporating natural disasters, the results concerning average temperature remain unchanged. The fact that floods, droughts, and landslides do not seem to have any effect on international emigration is not surprising; according to the literature climate disasters seem to be more closely linked to long-distance domestic displacements rather than international ones (Kaczan and Orgill-Meyer 2020).

In summary, the addition of other controls does not alter the relationship between the climatic variables and emigration rate; when it does, it is mainly due to the reduction of the sample size and not to the inclusion of additional regressors. The reason why the country-specific variables included to proxy potential channels are not showing any effects could be that time-invariant controls (the so-called country fixed effects) and the time effects (which vary per group in the GME) are absorbing the variability of the country-of-origin determinants.

The mechanisms through which the climate variables are expected to trigger migration could be related to

[14] As an alternative to political stability, for which there are many missing observations, I considered a state fragility index, but again the coefficient was not statistically significant. Results are available upon request.

TABLE A3. List of countries. Note that this is the author's elaboration.

	Destination countries	
Australia	France	Portugal
Austria	Germany	South Korea
Belgium	Italy	Spain
Canada	Japan	Sweden
Denmark	Netherlands	Switzerland
Finland	Norway	United Kingdom
		United States
	Origin countries	
Afghanistan	Gabon	Oman
Albania	Gambia	Pakistan
Algeria	Georgia	Panama
Angola	Ghana	Papua New Guinea
Argentina	Guatemala	Paraguay
Armenia	Guinea	Peru
Azerbaijan	Guinea-Bissau	Philippines
Bahamas	Guyana	Poland
Bangladesh	Haiti	Puerto Rico
Belarus	Honduras	Qatar
Belize	Hungary	Republic of the Congo
Benin	India	Romania
Bhutan	Indonesia	Russian Federation
Bolivia	Iran	Rwanda
Bosnia and Herzegovina	Iraq	Samoa
Botswana	Jamaica	São Tomé and Príncipe
Brazil	Jordan	Saudi Arabia
Brunei	Kazakhstan	Senegal
Bulgaria	Kenya	Sierra Leone
Burkina Faso	Kuwait	Slovenia
Burundi	Kyrgyzstan	Solomon Islands
Cambodia	Laos	Somalia
Cameroon	Latvia	South Africa
Cape Verde	Lebanon	Sri Lanka
Central African Republic	Lesotho	Sudan
Chad	Liberia	Suriname
Chile	Libya	Swaziland
China	Lithuania	Syria
Colombia	Macedonia [former Yugoslavian republic (FYR)]	Tajikistan
Comoros	Madagascar	Tanzania
Democratic Republic of the Congo	Malawi	Thailand
Costa Rica	Malaysia	East Timor
Côte d'Ivoire	Mali	Togo
Croatia	Mauritania	Trinidad and Tobago
Cuba	Mauritius	Tunisia
Cyprus	Mexico	Turkey
Czech Republic	Moldova	Turkmenistan
Djibouti	Mongolia	Uganda
Dominican Republic	Morocco	Ukraine
Ecuador	Mozambique	United Arab Emirates
Egypt	Myanmar	Uruguay
El Salvador	Namibia	Uzbekistan
Equatorial Guinea	Nepal	Vanuatu
Eritrea	New Zealand	Venezuela
Estonia	Nicaragua	Vietnam
Ethiopia	Niger	Yemen
Fiji	Nigeria	Zambia
		Zimbabwe

TABLE A4. List of countries by group (G1–G7; the colors used in Fig. 2: are given in parentheses).

G1 (dark yellow)	G2 (red)	G3 (yellow)	G4 (brown)	G5 (green)	G6 (blue)	G7 (black)
Argentina	Afghanistan	Bahamas	Botswana	Algeria	Benin	El Salvador
Armenia	Albania	Belize	Fiji	Bangladesh	Bhutan	Guatemala
Azerbaijan	Angola	Comoros	Liberia	Burkina Faso	Bosnia and Herzegovina	Guyana
Bolivia	Cape Verde	Croatia	Oman	Democratic Republic of the Congo	Brunei	Haiti
Brazil	Chile	Iraq	Panama	Costa Rica	Cambodia	Jamaica
Bulgaria	Colombia	Niger	Qatar	Côte d'Ivoire	Central African Republic	Kuwait
Burundi	Czech Republic	São Tomé and Príncipe	Saudi Arabia	Cuba	Chad	Laos
Belarus	Ecuador	Solomon Islands	Trinidad and Tobago	Djibouti	Dominican Republic	Nicaragua
Cameroon	Egypt	Suriname	Uruguay	Eritrea	Gabon	Tajikistan
China	Equatorial Guinea			Estonia	Honduras	United Arab Emirates
Georgia	Gambia			Ethiopia	Jordan	Yemen
India	Hungary			Ghana	Lesotho	
Kyrgyzstan	Indonesia			Guinea	Libya	
Latvia	Iran			Guinea-Bissau	Madagascar	
Lithuania	Kazakhstan			Kenya	Mali	
Moldova	Macedonia			Lebanon	Mauritania	
Nepal	Malawi			Malaysia	Mauritius	
Nigeria	Morocco			Mexico	Republic of the Congo	
Poland	Peru			Mozambique	Rwanda	
Puerto Rico	Philippines			Myanmar	Sri Lanka	
Romania	Russia			Namibia	Tanzania	
Thailand	Samoa			New Zealand	Togo	
East Timor	Senegal			Pakistan	Turkmenistan	
Ukraine	Sierra Leone			Papua New Guinea		
	Swaziland			Paraguay		
	Tunisia			Slovenia		
	Turkey			Somalia		
	Vanuatu			South Africa		
	Venezuela			Sudan		
				Syria		
				Uganda		
				Uzbekistan		
				Vietnam		
				Côte d'Ivoire		
				Zambia		
				Zimbabwe		

degradation of land use for agriculture, disruption of fragile ecosystems and depletion of natural resources, including freshwater, which will directly impact individuals' lives and productive activities. Most of the mechanisms are expected to operate heterogeneously across countries. In particular, water scarcity will mostly affect agriculture-dependent countries. A more detailed evaluation of these mechanisms is beyond the scope of this paper.

c. *Sensitivity analysis*

I perform a series of sensitivity checks and explore some modifications of the basic model. In each specification in Table 2, which presents the results of the GFE model, I estimated the model by varying the number of groups in order to find the optimal number.

Table A5 of the appendix presents the estimations using the model in column 2 of Table 2. The results indicate that the best model according to the RMSE (lowest value) and the adjusted R^2 (highest value) is the model presented in column 6, where the optimal number of country groups is seven. I started with two groups (column 1) and increased the number to the point where the RMSE no longer decreased and the adjusted R^2 did not add any additional explanatory power to the model. It can be

TABLE A5. Sensitivity analysis: different number of groups for the baseline GFE estimator. Three asterisks, two asterisks, and one asterisk denote significance levels at the 1%, 5%, and 10% levels, respectively. Robust standard errors are reported in parentheses. Group-year dummy variables are included in all columns; coefficients are not reported. The dataset is from Backhaus et al. (2015).

GFE baseline	Column 1	Column 2	Column 3	Column 4	Column 5	Column 6
			Dependent variable			
ln emigration rate						
			Explanatory variables			
Ln wtem_dm	0.478 (0.344)	0.336 (0.267)	0.275 (0.290)	0.102 (0.236)	0.483** (0.234)	0.490** (0.237)
Ln wpre_dm	−0.0419 (0.0668)	−0.0659 (0.0444)	−0.0605 (0.0499)	−0.0697* (0.0410)	−0.0574 (0.0443)	−0.0729* (0.0467)
FE group 2	−1.046*** (0.101)	1.510*** (0.113)	−1.090*** (0.113)	−0.231* (0.137)	0.871*** (0.206)	0.671*** (0.145)
FE group 3		0.264*** (0.0918)	−1.832*** (0.214)	1.041*** (0.150)	2.029*** (0.175)	0.382** (0.161)
FE group 4			−1.577*** (0.116)	−0.389*** (0.129)	0.966*** (0.145)	1.955*** (0.232)
FE group 5				0.941*** (0.239)	1.955*** (0.232)	2.105*** (0.179)
FE group 6					0.487*** (0.146)	0.481*** (0.153)
FE group 7						1.060*** (0.146)
Obs	1681	1681	1681	1681	1681	1681
R^2	0.439	0.516	0.557	0.594	0.626	0.655
R^2 adjusted	0.431	0.505	0.544	0.579	0.609	0.637
RMSE	0.402	0.375	0.360	0.346	0.333	0.321

observed that the results in columns 5 and 6, which correspond to groups 6 and 7, show very similar coefficients for the two climatic variables. Furthermore, when increasing the number to eight groups (not shown), the results do not vary and the additional group is very small.[15]

Second, I have estimated the GFE model restricting the sample to the countries considered by Cattaneo and Peri (2016), and the country grouping remains similar for the 115 remaining countries.

Last, I have also estimated the model with the climatic variables in levels using the GFE model, and the results show slightly lower significance levels for the estimates. However, the country grouping remains very similar.[16]

5. Concluding remarks

This paper documents a robust relationship between climatic variables and international migration over the period 1995–2006. In particular, increases in the weighted average local temperature, and sometimes decreases in the weighted average local precipitation in a sending country, are associated with increases in international migration flows, especially for certain groups of countries. The main results obtained using the GFE estimator indicate that the effect is moderate, especially in relation to the actual climatic variations in the yearly data. On average, a 1% increase in the local temperature is associated with a 0.5% increase in the emigration rate for all countries, whereas a 1% increase in local precipitation is associated with a decrease in emigration of 0.07%. However, the effects are heterogeneous across country groups. The endogenous grouping of the countries suggests that the reaction of emigration due to local temperature changes might be driven by a group of sending countries mainly located in Africa and central Asia.

More detailed studies of the countries in this group are needed, exploiting finer spatial variation in local precipitation and temperature. This should be done to ascertain the extent to which these countries differ notably from others concerning climate variations and also whether particular areas in the countries in question are more affected than others. More specifically, it would be worth investigating migration flows related to weather changes between neighboring countries in these regions using gridded datasets.

Further research should also examine the mechanisms through which the climate variables are expected to trigger international migration. These variables are expected to exert a heterogeneous influence across countries and could be related to degradation of agricultural land, disruption of fragile ecosystems, and depletion of natural resources.

[15] Similar results, which are not reported, are obtained for the model in levels, with interaction and squared terms. In all cases, the estimation with seven groups provides the most suitable grouping according to statistical criteria (RMSE and adjusted R^2).

[16] Results from the second and third robustness checks are available upon request.

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APPENDIX

Summary of the Related Studies, Data Description, and Sensitivity Analysis

Table A1 presents a review of the cross-country macroeconomic studies that focus on the climate–migration link, including a summary of the main findings, the target climate and migration variables used, the datasets, and the method applied in each study. A list of variables and their sources are presented in Table A2. Table A3 gives a complete list of the source and destination countries. The list of countries in each group is shown in Table A4. Table A5 presents estimations using the model in column 2 of Table 2.

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