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SEARCHING FOR GROUPED PATTERNS OF HETEROGENEITY IN THE CLIMATE-MIGRATION LINK

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

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Abstract

This paper uses international migration data and climate variables in a multi-country setting to investigate the extent to which international migration can be explained by changes in the local climate and whether this relationship varies between groups of countries. Moreover, the primary focus is to further investigate the differential effect found by Cattaneo and Peri (2016) for countries with different income levels using a high-frequency dataset. The idea being that country grouping is considered to be data driven, instead of exogenously decided. The estimation technique used to endogenously group the countries of origin is based on the group-mean fixed-effects (GFE) estimator proposed by Bonhomme and Manresa (2015), which allows us to group the origin countries according to the data generation process. The main results indicate that an increasing average local temperature is associated with an increase in that country's emigration rate, on average, but the effect differs between groups. The results are driven by a group of countries mainly located in Sub-Saharan Africa and Central Asia; however, no statistically significant association is found between the average amount of local precipitation and that country's rate of emigration.

JEL Codes: F22, Q54

Key Words: international migration, climate change, developing countries, GFE, group heterogeneity

1. Introduction

The impact of climate change on migration has been of concern since the early 1990s and different points of view have been presented by environmentalists, economists and political scientists. The discussion intensified with the publication of the fourth and fifth IPCC reports (IPCC, 2007; IPCC, 2014) and during the multilateral climate negotiations that lead to the Paris agreement and its implementation in November 2016. The IPCC (2007) report referred to the "potential for population migration" due to climate distress. Although the topic has received substantial media coverage, the academic research is still limited. While the standard statistical migration literature has traditionally placed heavy emphasis on the socioeconomic drivers of migration without considering climatic factors, a number of recent 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).

Very recently, a few economic studies have attempted to quantify the impacts on international migration not only of extreme events, but also of changes in local temperature and precipitation on a large scale (Backhaus et al., 2015; Beine and Parson, 2015; Cai et al., 2014; Coniglio et al, 2015 and Cattaneo and Peri, 2016). Whereas Beine and Parson (2015) focus mainly on extreme weather events and temperature anomalies and Coniglio et al. (2015) focus on rainfall variability in the sending countries, the other three papers focus on the effect of the average change in local temperature on international migration. The main findings indicate that international migration could be one of the responses to climate change, but the results vary by group of countries and depend on the climatic variables used and on the time-span considered. There is also an important difference in the approach of Cattaneo and Peri (2016) who focus on the global effect of temperature changes on international emigration rates, without controlling for the effect of the other determinants of international migration, and the remaining papers, which usually include the economic-related determinants of international migration. 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. The authors group the countries according to their income level and find that for middle-income countries, climatic warming is associated with significantly higher emigration rates, whereas it is associated with lower rates in poor countries where families cannot afford the cost of emigrating. We depart from Cattaneo and Peri (2016) in that we propose to use a data-driven alternative method of grouping countries.

The main focus of this paper is to further investigate the differential effect found by Cattaneo and Peri (2016) for high-frequency international migration data and for different country groups. The main contribution of the study is that the country grouping is not exogenously decided but 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, etc.). The main estimation technique to endogenously group the countries of origin is based on the group-mean fixed-effects estimator (GFE) proposed by Bonhomme and Manresa (2015) that allows us to group the origin countries according to the data generation process. After having found a suitable country grouping, a model for multi-origin countries augmented with climate variables is estimated. The main data are taken from Backhaus et al. (2015) and from Cattaneo and Peri (2016). We also replicate the results in Cattaneo and Peri (2016) with high-frequency international migration data from Backhaus et al. (2015) to see if the pattern they find is also valid for high-frequency data.

The results show that larger local temperature increases lead to an increase in emigration, on average, but the effect differs between groups. The positive link is driven by a group of countries located mainly in Sub-Saharan Africa and Central Asia, whereas no significant association is found between the average local precipitation and emigration. Moreover, changes in local precipitation levels also affect emigration differently between groups, but the effects are only weakly statistically significant or non-significant. In the replication, we find that similar results are obtained using yearly data and decadal data for the same sample of countries and using the same model specification and estimation technique.

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. Finally, Section 5 concludes.

2. Empirical Studies on Migration and Climatic Factors

In this section, we specifically focus on recent studies that consider domestic climatic factors to be explanatory variables of migration. We refer to Belasen and Polachek (2013) and Backhaus et al. (2015) 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, we refer to the literature survey presented in Lilleor and Van den Broeck (2011) and Choumert et al. (2015), 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 focus on internal and international migration, respectively. Both consider Sub-Saharan African (SSA) countries as the main target area. 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 1 presents a review of the studies focused on the climate-migration link including a summary of the main findings, the target climatic and migration variables used, the datasets and the methodology applied in each study. Among the more recent studies, we can distinguish between studies that use local average temperature and rainfall as the main climatic variables (Backhaus et al., 2015; Cai et al., 2016; and Cattaneo and Peri, 2016) and those that focus on the deviations of local rainfall and/or temperature from 'normal' levels (Beine and Parson, 2015; and Coniglio et al., 2016).

Table 1. Summary of the literature on the migration-climate link

A second important characteristic of the studies is related to the migration data used. Whereas some of them use data from 1960 to 2000 at ten-year intervals (Beine and Parson, 2015; and Cattaneo and Peri, 2016), three of the very recent studies use yearly data starting in the 1980s or 1990s until the mid-2000s (Backhaus et al., 2015; Cai et al., 2014; and Coniglio et al, 2015).

Concerning the methodology 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 to control for unobservable factors related to the destination country's migration policies, time-invariant origin country factors and to bilateral time-invariant factors (Backhaus et al., 2015; Beine and Parsons, 2015; Cai et al., 2016; and Coniglio et al., 2016).

Beine and Parsons (2015) consider both natural disaster and climatic variation as potential drivers of bilateral migration flows. Since their data provides information on migration in ten-year intervals, their analysis is oriented towards the medium- and 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 local average temperature and average precipitation levels as done by Cai et al. (2016) and Cattaneo and Peri (2016), who do find a direct effect of these climatic variables. Moreover, by using a large number of controls in the analysis of the migration-climate relationship, it could be difficult to investigate the indirect effects of the climatic variables on international migration. For this reason, as in Cattaneo and Peri (2016), we focus on the global effect of local temperature on the emigration rate, without controlling for the effect of other determinants of migration.

3. Theoretical Framework and Model Specification

We base our empirical model on the theoretical framework presented in Cattaneo and Peri (2016), which is a 'simple' two period model that delivers a 'hump-shaped' relation between migration rates and income per capita. Individuals work in the first period and earn the local wage and in the second period decide whether or not to emigrate. It is assumed that individuals cannot borrow; hence, they are only able to emigrate if they can pay for the monetary cost of emigrating. The main predictions of the model are twofold. First, an increase in the local average temperature is associated with an increase in the emigration rate in middle-income countries; and secondly, for poor countries an increase in the local average temperature is associated with a decrease in their emigration rate. The intuition behind this prediction is that in countries with income below the median, the liquidity constraint is binding and prevents migration, while individuals in countries with income above the median can afford the cost of migration and hence are able to respond to adverse climate change by migrating.

We first replicate the results in Cattaneo and Peri (2016) with high-frequency migration data for OECD immigration flows originating from developing countries.

The baseline empirical model is given by:

$$\ln ln\, M_{it} = \alpha_o + \beta_1 ln\, wtemp_{it} + \beta_2 ln\, wpre_{it} + \beta_{j3}\, ln\, wtemp_{it} * \sum_j D_{ij} + \beta_{j4} ln\, wpre_{it} * \sum_j D_{ij} + \zeta_i + \delta_{rt} + \gamma_{pt} + u_{it} \quad (1)$$

where M_{it} is the immigration rate in 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 in year t. The population-weighted average annual temperature in degrees Celsius is denoted as $wtemp_{it}$, while $wpre_{it}$ denotes average annual precipitation in millimeters. 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, following the approach proposed by Dell et al. (2014). D_j is a set of dummies for each quartile of the distribution of income and j=1…4. Hence, four different coefficients are obtained for the variables of interest.

Alternatively, the variables are interacted with a dummy, d_{poor}, which takes the value of one if a country's income per capita is below the median. We include three sets of fixed effects (FE): country FE (ζ_i), region-year FE (δ_{rt}) and interactions between the dummy for poor countries and the year FE (γ_{pt}). Finally, u_{it} denotes a random error term that is clustered at the country level in the estimations.

In a second specification, we use the grouped fixed-effects (GFE) approach, which was recently proposed by Bonhomme and Manresa (2015), to study the relationship between climatic factors and migration flows over time and across countries. This statistical association has been recently investigated and could become an important stylized fact. Consequently, it is important to establish whether the relationship is heterogeneous across groups of countries. The GFE estimation introduces time-varying grouped patters 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 N big and T small 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. Both the group-specific time patterns and group membership are estimated from the data.

Our benchmark specification is a linear model that explains migration, M_{it}, with grouped patterns of heterogeneity and takes the form:

$$\ln M_{it} = x_{it}'\beta + \gamma_{g_i t} + u_{it} \qquad (2)$$

where x_{it}' 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, $\gamma_{g_i t}$. The countries in the same group share the same time profile and the number of groups is to be decided or estimated by the researcher and group membership remains constant over time.

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 our preferred specification[1]. We apply the within transformation 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 $\ddot{x}_{it} = (x_{it} - \bar{x}_i)\ and\ \ddot{M}_{it} = (M_{it} - \bar{M}_i), etc.$

The GFE in model (1) is the outcome of the minimization of the following expression:

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

$$\left(\hat{\beta}, \hat{\gamma}, \hat{\alpha}\right) = \underset{(\beta,\gamma,\alpha)\in\Theta \mathrm{x} \mathrm{A}^{\mathrm{GT}} \mathrm{x} \Gamma_{\mathrm{G}}}{argmin} \sum_{i=1}^{N}\sum_{t=1}^{T}(\ddot{M}_{it} - \ddot{x}_{it}'\beta - \ddot{\gamma}_{g_i t})^2 \quad (3)$$

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. The optimal group assignment for each country is given by:

$$\hat{g}_i(\beta,\gamma) = \underset{g\in\{1,\ldots,\mathrm{G}\}}{argmin} \sum_{t=1}^{T}(\ddot{M}_{it} - \ddot{x}_{it}'\beta - \ddot{\gamma}_{g_i t})^2 \quad (4)$$

Finally, the GFE estimates of beta and gamma are:

$$\left(\hat{\beta}, \hat{\gamma}\right) = \underset{(\beta,\gamma)\in\Theta \mathrm{x} \mathrm{A}^{\mathrm{GT}}}{argmin} \sum_{i=1}^{N}\sum_{t=1}^{T}(\ddot{M}_{it} - \ddot{x}_{it}'\beta - \ddot{\gamma}_{\hat{g}_i(\beta,\gamma)t})^2 \quad (5)$$

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

There are two algorithms available to minimize expression (5). 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. The former is used in this paper.

Following the related literature, the model includes the two aforementioned climatic variables, the average local temperature and precipitation rate. Meanwhile, the non-climate explanatory variables derived from neoclassical theory, namely economic, demographic, geographic and cultural controls as well as the trade-to-GDP ratio, are only included when investigating the transmission channels of the migration-climate link. With this aim the specification considered is:

$$\ln \ddot{M}_{it} = \alpha_o + \beta_1 wt\ddot{e}mp_{it} + \beta_2 w\ddot{p}re_{it} + \beta_3 ln\, G\ddot{D}P_{it} + \beta_4 (ln\, \ddot{G}DP)^2{}_{it} + \beta_5 Dem\ddot{P}res_{it} + \beta_6 \ln Popu\ddot{l}ation_{it} + \beta_7 \ddot{U}_{it} + \beta_8 ln\, Tr\ddot{a}de_{it} + \ddot{\gamma}_{g_i t} + u_{it} \quad (6)$$

where M_{it}, $wtemp_{it}$ and $wpre_{it}$ have already been described below equation (1). GDP_{it} denotes PPP-adjusted GDP in 1000 USD in the origin country in year t. A squared term of GDP_{it} is also included in all specifications to account for the non-linear effects of income in the origin country. $DemPres_{it}$ denotes the share of young people in the country of origin's working age population. 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, while $Trade_{it}$ denotes the openness ratio (Exports + Imports)/GDP in the country of origin at time t. The term $\gamma_{g_i t}$ captures time-variant group heterogeneity, while u_{it} is the error term.

4. Empirical Strategy

4.1 Data and Variables

In most of the estimations, the same dataset as Backhaus et al. (2015)[2] is used. The climatic variables used are yearly average temperature and precipitation in the countries of origin obtained from Dell et al. (2012). The data cover the period from 1995 to 2006, yielding 12 time periods for our analysis[3]. Both variables are population-weighted averages at the country-year level (using 1990 population figures for the weighting). The majority of the yearly changes appear to be rather subtle, as only 5.4% of the temperature changes in our sample fall outside of a one degree Celsius interval [-1, 1] and 1.65% of the changes in precipitation fall outside an interval of five millimeters [-5, 5].

[2] We also estimated some models using the dataset from Cattaneo and Peri (2016) to show the results for a different specification that includes climatic variables in levels, as done by Backhaus et al. (2015), instead of in natural logs.
[3] A list of variables and their sources are presented in Table A.1 in the Appendix.

The corresponding data on yearly migration flows from the countries of origin to the destination countries, originate primarily from the OECD's International Migration Database (IMD, 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. Some of the latter are members of the OECD as well, e.g. Mexico, Chile and New Zealand. Although these countries might be important destinations from the perspective of less developed countries, its role as a sending country is also important. A complete list of the source and destination countries together with their respective share of non-missing migration flow observations can be found in Table A.2 in the Appendix. The IMD is constructed on the basis of statistical reports of the OECD member countries, which implies that the data might not be fully comparable across countries, as the criteria for registering an immigrant population and the conditions for granting residence permits varies by country[4]. Regarding the European destination countries, data on inflows into Italy are missing for many source countries and is completely unavailable for the years 1995-1997 and 2003. Observations from the Eurostat online database (Eurostat, 2014) were used to fill some of the gaps. For Austria, Switzerland and the UK, numerous non-European source countries could be added. Moreover, some rounded and inaccurate figures for the UK could be replaced. Adding and replacing rounded observations was only done if the figures from the OECD and Eurostat databases coincided for countries in which data was available in both databases. In this way, the same definitions of immigration are used in both data sources and the consistency of the dataset is not compromised by combining them. The data are mostly complete for France, Spain and Germany, which together account for about sixty percent of the migratory flows to Europe in our

[4] Illegal migration flows are only partially covered as data are only obtained through censuses. Furthermore, the majority of the destination countries did not record immigrants from the full set of source countries during the first few years of our period of analysis, as missing data are most frequent in this period. In the cases of Japan and the Republic of Korea, only the inflows from the most important regional sending countries have been recorded over a longer period of time.

sample; as well as for Australia, Canada and the United States, which reflects the long history of immigration in these countries. With 12 years, 142 countries of origin and 19 countries of destination, a dataset that is as comprehensive as possible on the immigration to OECD countries is obtained by combining OECD and Eurostat information when possible.

Data for the economic and demographic variables are obtained from the World Bank's World Development Indicators (WDI, 2016) database. Table 1 presents summary statistics of the main variables included in our model.

Table 2. Summary Statistics

4.2 Main Results

The migration models introduced in Section 3 are estimated for a wide sample of countries of origin using yearly data from 1995 to 2006 from Backhaus et al. (2015). The first empirical model (specification (1)) is also estimated using data from Cattaneo and Peri (2016), covering a sample of 115 countries with information every ten years from 1990 to 2000.

Table 3 shows the results obtained from estimating specification (1). The first and second columns present estimations obtained with Backhaus et al. (2016) data[5] with the target variables in levels and in natural logs, respectively. The results in the first column mostly present non-significant coefficients at conventional levels, whereas the results in column 2 show different signs and significance levels for the coefficients of the different income quartiles. More specifically, for countries in the third quartile (fourth quartile), a 1 percent higher average temperature in the countries of origin is associated with a 1.9 (1.6) percentage increase in the emigration rate over one year, whereas countries in the first quartile who had a 1 percent higher average temperature are associated with a decrease in the emigration rate of 4.5 percent.

[5] We restrict the sample to developing countries, excluding high-income countries.

Furthermore, a decrease in the average precipitation rate in the countries of origin by 1 percent corresponds to a 0.3 percentage increase in the emigration rate for the first quartile, whereas it corresponds to a 0.2 percent decrease in the emigration rate in the second quartile. However, the coefficient estimates for precipitation are imprecisely estimated. In column 3, the sample is restricted to the 115 countries for which decade migration-stock data is available[6]. The results stay similar to those in column 2, with the only difference being that the coefficients for the weighted precipitation are statistically significant at the 5 percent level and therefore become more accurate. Results for decade-data are presented in column (4), which is a replication of the results found by Cattaneo and Peri (2016) –page 135, Table 2 (column 1) –. Although the coefficients are not directly comparable, it is remarkable that the sign and statistical significance of the estimates remain very similar in columns 3 and 4 for the coefficients of the weighted temperature in each quartile and for the weighted precipitation. The only exception being for the first quartile of the weighted precipitation, which is not statistically significant in column 4, but it was at the 5% level in column 3. As expected, the coefficients are higher in magnitude using the second sample, since they refer to changes over decades instead of to annual changes.

Overall, we obtain similar conclusions using high frequency data (annual) and decadal data.

Table 3. Parameter Estimates for the Benchmark Model

Next, we estimate a similar model using interactions of the climatic variables with a dummy variable for countries with low income levels, using the definition from Cattaneo and Peri (2016) of poor countries[7]. The results are presented in Table 4 for the specification with the climatic

[6] This is done to compare the results using the same origin countries in both datasets.

[7] Afghanistan, Benin, Burkina Faso, Burundi, Cambodia, the Central African Republic, the Democratic Republic of Congo, Equatorial Guinea, Ethiopia, Gambia, Ghana, Guinea-Bissau, Lao People's Democratic Republic, Lesotho,

variables in natural logarithms. Also in this case, the results for the weighted temperature variables remain similar for both samples. However, for average precipitation, the interaction with the poor dummy presents a negative coefficient, which is statistically significant in columns 2 and 3 for the yearly-data (sample B) but not for the decade-data (column 3). However, the results for the average temperature are not robust to changes in the specification[8].

Table 4. Determinants of Emigration Rates. Poor versus Non-Poor Countries

In Table 5, the relevance of non-linearity in the climatic variables is examined for the yearly-data sample and compared with the decadal-data sample. The results in columns 1 to 3 show that there is a non-linear relationship between the average temperature and the migration rate for all countries (column 1), which vary by income level. While the relationship has an inverted-U shape for middle-income countries (column 2), a U-shape curve is found for poor countries. Using the C&P sample, the square terms are not statistically significant.

Table 5. Determinants of Emigration Rates with Non-Linearity

In our main empirical model, we allow the time-variant group effects $\gamma_{g_i t}$ to be correlated with the explanatory variables[9]. Possible reasoning behind this assumption is that each group has its own unobservable, time-varying mentality towards emigration that affects actual emigration rates

Liberia, Madagascar, Malawi, Mali, Mozambique, Nepal, Niger, Nigeria, Rwanda, Somalia, Sudan, the United Republic of Tanzania, Togo, Uganda, Yemen and Zambia.

[8] When the model with the climatic variables in levels is estimated (Table A.4 in the Appendix), the weighted temperature variable is only statistically significant at the 10 percent level and only for poor countries (column 2) and for the low-frequency data the weighted temperature variable is only significant at the 10 percent level (column 3).

[9] We only estimated this model with the low-frequency dataset, given that the GFE is more suitable for a panel with a time dimension that is not very small.

or that there exist specific relations between some source countries. The results are presented in Table 6.

Table 6. Group Fixed Effects Estimation Results. Sample: Annual Data

The baseline GFE specification is presented in columns 1 and 2 of Table 6. The results in column 1 are obtained with the local climatic variables in levels[10] and in column 2 in natural logs. In both columns, the coefficient for average temperature is positive and statistically significant indicating that higher average temperatures are associated with higher migration rates from developing countries to OECD countries. The results for average 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 percent level for the model in natural logs. Two additional specifications with non-linearity 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* dummy variable, as was done in Table 4. With the GFE estimator, the results 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 average local temperature. Concerning the precipitation variable, while decreasing precipitation induces migration in less-poor countries, in poor countries decreasing precipitation is associated with decreasing emigration. This second outcome is consistent with the 'poverty trap' argument.

The results in column 4 come from a model that includes the squared terms of the climatic variables, as was done in Table 5. The results show that the squared term is only weakly relevant for the average local temperature and precipitation. This could be the result of having specified unobserved patterns of time-variant heterogeneity.

[10] The estimated coefficient for the weighted temperature variable (in levels) was obtained by Backhaus et al. (2015) with a model for bilateral migration using a FE estimator. A number of control variables are also positive and statistically significant. The dependent variable in this case is the natural log of the migration bilateral flow.

The GFE model presents the lowest RSME and the higher adjusted R-squared 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. The list of countries in each group is shown in Table A.3 in the Appendix.

In Table 7, we present results showing the group-specific coefficients for the climatic variables, assuming that the groups remain constant over time. In column 1 of Table 7, only the average temperature and the time group-specific variables are included in the model. Column 2 includes only precipitation as a control variable while both sets of variables are included in column 3. The results indicate that the positive relationship found for the average local temperature, and migration from developing to developed countries, is driven by countries in group six, most of which are located in Sub-Saharan Africa and Asia (see Table A.3 for a list of countries by group). For group two, the coefficient for the average local temperature is negative and statistically significant at the ten percent level. In this group, higher local 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.

Table 7. Group-Specific Coefficients for Climatic Variables

Finally, we investigate the channels through which temperature operates on migration. We add a number of controls to the model to see if the statistical significance of the climate variables remains similar. In most cases, the addition of other controls does not alter the relationship, and when it does, it is mainly due to the reduction of the sample size and not to the inclusion of additional regressors.

Table 8. Transmission Channels

4.3 Sensitivity Analysis

We perform a series of sensitivity checks and explore some modifications of our basic model. In each specification of Table 7 (in columns 1 to 4), we have estimated the model by varying the number of groups. Table 9 presents an example of the estimations corresponding to the model in column 2 (Table 7). Table 9 presents the results of applying the GFE estimator assuming a different number of groups. We started with two groups (column 1) and increased the number until the RMSE did not decrease any longer and the adjusted R-squared did not add any additional explanatory power to the model. It can be observed that the results in columns 5 and 6, which corresponds to groups six and seven, show very similar coefficients for the two target variables. Furthermore, by increasing to 8 groups (not-shown), the results do not vary and the additional group is very small in size[11].

Secondly, we have estimated the GFE model restricting the sample to the countries considered by Cattaneo and Peri (2016) and the country-grouping stays similar for the 115 remaining countries.

Finally, we 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[12].

Table 9. Migration Rate and Climatic Variables. Sensitivity Analysis

5. Concluding Remarks

[11] Similar results, which are not reported, are obtained for the model in levels, with interaction and squared terms. In all cases, groups 7-8 provide the most suitable grouping according to statistical criteria (RMSE and adjusted R-squared).

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

This paper documents a robust relationship between climatic variables and international migration. In particular, increases in the average local temperature, and sometimes decreases in the 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, our preferred method, indicates that the effect is moderate, especially in relation to the actual climatic variations in the high-frequency data. On average, a one percent increase in the local temperature is associated with a 0.5 percent increase in the emigration rate for all countries, whereas an increase of one percent in local precipitation is associated with a decrease in the emigration of 0.07 percent. 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 Sub-Saharan Africa and Central Asia. More detailed studies of the countries in this group, exploiting finer spatial variation in local precipitation and temperature, should be further investigated.

FIGURES

Figure 1. Emigration by Source

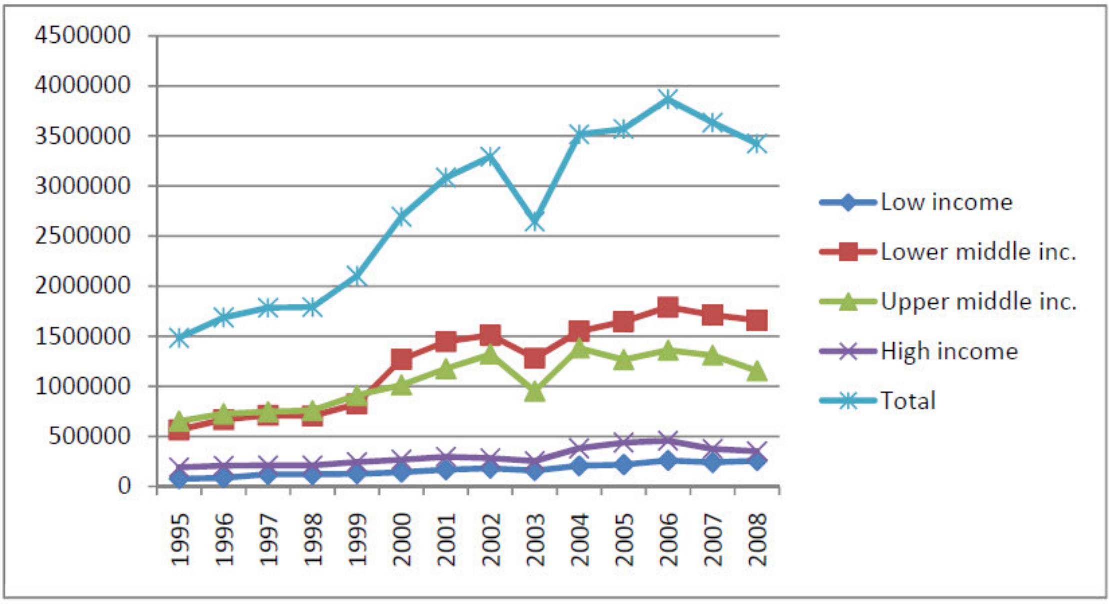
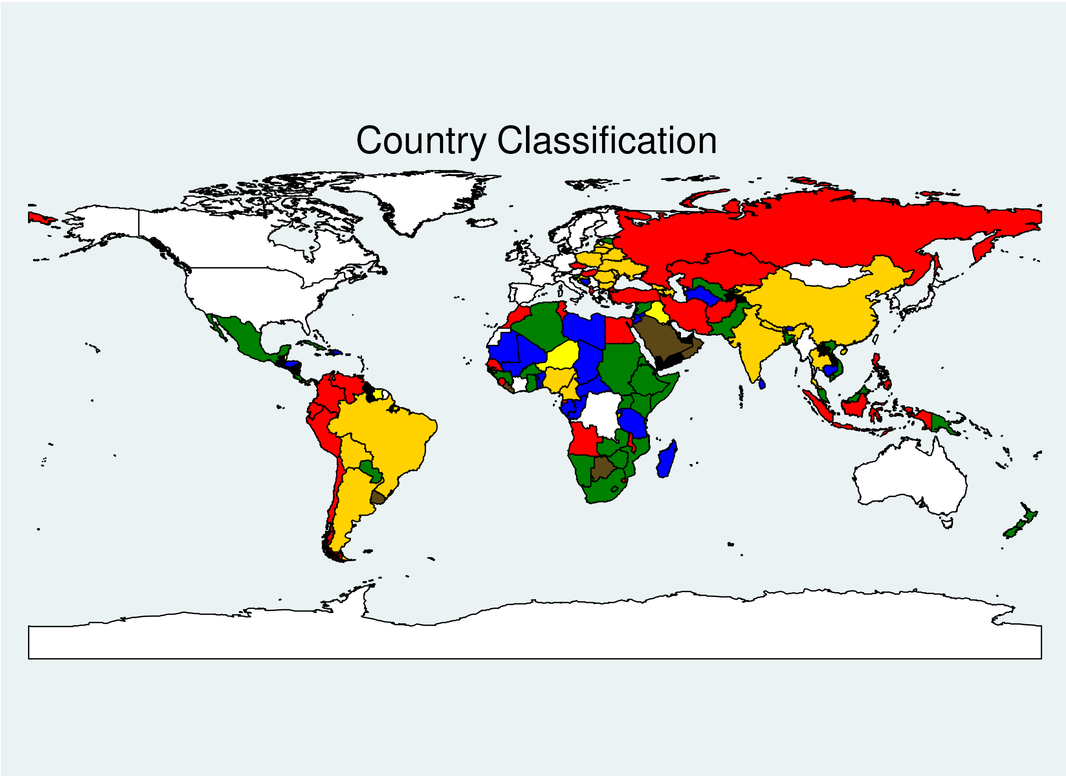


Figure 1: Emigration by source country income classification over time

Figure 2. Map and Graph for Seven Groups (Model 2, Table 6)



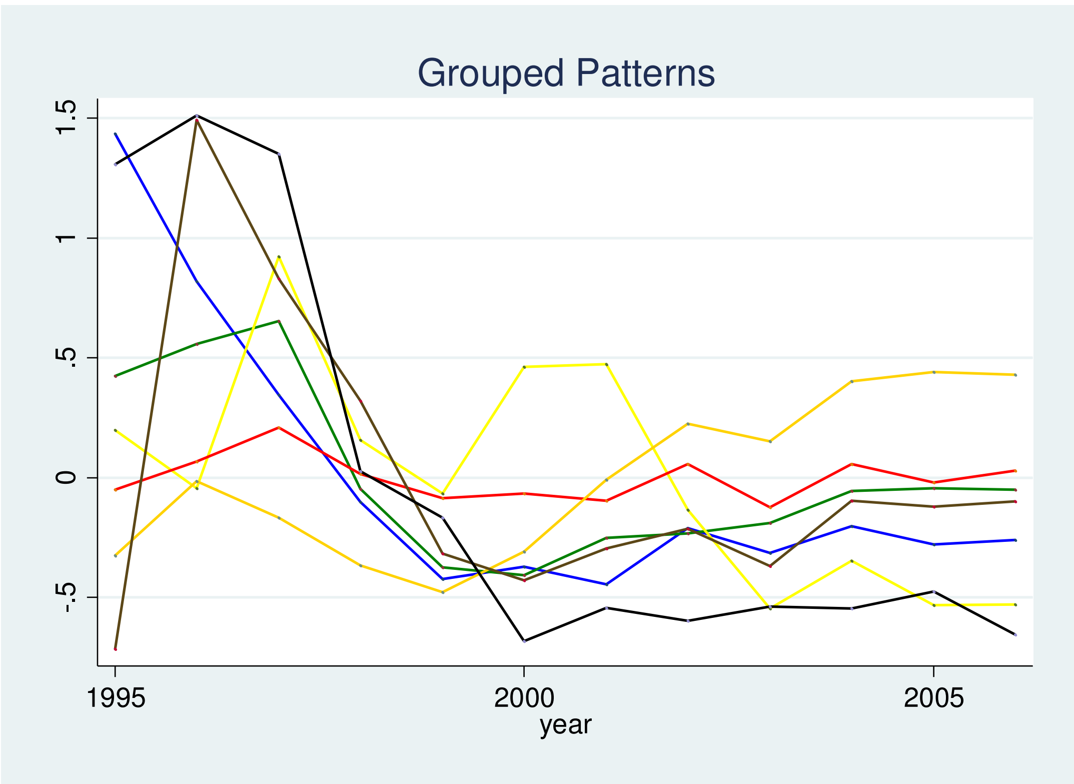
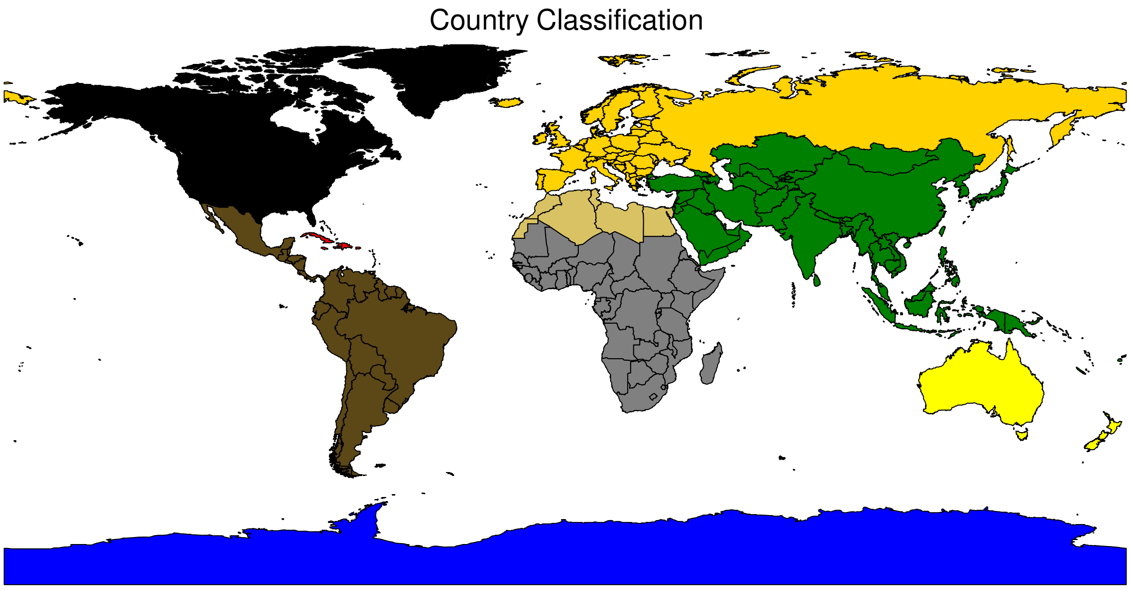


Figure 3. Regional Classification



Colors	Region	
Blue	Antarctica	2
Green	Asia	55
Yellow	Australia	2
Red	Caribbean	17
Gold	Europe	45
Olive	Latin America	22
Black	North America	4
Sand	North Africa	6
Cranberry	Pacific	7
Gray	Sub-Saharan Africa	49

TABLES

Table 1. Summary of the Literature on the Migration-Climate Link

Study	Countries	Period	Method	Migration type and measure	Climate variables	Main Finding
Barrios et al. (2006)	78 countries	1960-1990	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 (negative) effect of rainfall (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 agricultural-depending countries
Beine and Parson (2015)	226 origin and destination countries	1960-2000, ten year intervals (5 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 but only an indirect effect through wage differentials
Coniglio and Pesce (2015)	128 origin and 29 OECD destinations (Listed in online Appendix)	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 implies a 5% increase in out migration from the top 25% agricultural countries (significant at the 1% level)
Cattaneo and Peri (2016)	115 sending and receiving countries (30 poor and 85 middle-income) (Data in online Appendix)	1960-2000, ten year intervals (5 waves)	Cross-country panel data with country and time-region FE	International, Net emigration flows (diff between stocks in two consecutive census) from Ozden 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

Note: Author's elaboration.

Table 2. Summary Statistics for the Dataset 1996-2008

Variable	Obs.	Mean	Std. Dev.	Min	Max
Emigration rate	1,704	0.137	0.247	0	3.296
Ln emigration rate	1,693	-4.441	1.301	-8.238	-0.233
Weighted temperature	1,704	20.643	6.888	-1.562	29.583
Weighted Precipitation	1,704	10.910	7.415	0.066	40.567
GDP per capita 1000USD	1,605	5.580	7.922	0.123	65.182
Ln population	1,704	15.814	1.689	11.759	20.994
Demographic pressure	1,704	59.478	6.487	47.724	81.718
Stability	1,134	-0.369	0.925	-3.079	1.426
State fragility index	1,613	11.777	5.942	0	25
Unemployment rate	778	10.023	6.454	0.6	39.3
Max temperature	1,704	21.294	6.742	0.212	29.583
Min temperature	1,704	19.940	7.088	-1.562	28.495
Share_agriulture land	1,704	41.107	22.445	0.467	91.160
Steady wtemp change	1,278	0.128	0.335	0	1
Steady wpre change	1,278	0.095	0.293	0	1
Migration outflows	1,704	1370.405	2640.830	0	27828.830
Ln migration flows	1,693	4.474	1.614	0	8.652

Note: See Table A.1 in the Appendix for the definition of variables. 'Weighted' indicates that the corresponding variable is population-weighted.

Table 3. Parameter Estimates for the Benchmark Model with Two Samples

Dep. Variable: ln_emigration rate	(1) FE (Sample B)	(2) FE (Sample B)	(3) FE (Sample countries C&P)	(4) FE (Sample countries & decades C&P)
Exp. Variables:	no_ln	ln	ln	ln
wtemp_initxtilegdp1	-0.162	-4.527**	-4.842**	-16.476***
	[0.105]	[2.154]	[2.430]	-6.25
wtemp_initxtilegdp2	-0.0247	0.828	1.564	7.474
	[0.0924]	[1.368]	[1.198]	-6.824
wtemp_initxtilegdp3	0.124*	1.947***	2.086***	8.614*
	[0.0700]	[0.734]	[0.751]	-5.143
wtemp_initxtilegdp4	0.0633	1.595***	1.980***	2.840**
	[0.0639]	[0.435]	[0.527]	-1.391
wpre_initxtilegdp1	-0.0157	-0.273*	-0.335**	-1.643
	[0.0127]	[0.156]	[0.162]	-1.902
wpre_initxtilegdp2	0.0204	0.256*	0.343**	-1.684**
	[0.0153]	[0.142]	[0.142]	-0.658
wpre_initxtilegdp3	0.0163	0.0994	0.0474	0.097
	[0.0163]	[0.137]	[0.137]	-0.404
wpre_initxtilegdp4	0.00848	0.032	0.0182	0.434
	[0.0124]	[0.175]	[0.207]	-0.642
Country FE	Yes	Yes	Yes	Yes
Year (decade)-quartile FE	Yes	Yes	Yes	Yes
Year3 (decade)-region FE	Yes	Yes	Yes	Yes
Observations	1,522	1,511	1,367	458
R-squared	0.294	0.306	0.335	0.249
Number of countries	127	127	115	115

Note: Sample B denotes the sample of countries and years from Backhaus et al. (2015) and Sample C&P denotes the sample from Cattaneo and Peri (2016). ***, **, * denote significance levels at the one, five and ten percent level, respectively. Robust standard errors are reported in parentheses.

Table 4. Determinants of Emigration Rates Poor versus Non-Poor Countries

Dep. Variable: ln_emig rate	(1) FE (Sample B)	(2) FE (Sample B)	(3) FE (Sample C&P)
Ln wtem	1.706***	1.946***	3.755**
	[0.408]	[0.425]	-0.661
Ln wtempoor	-6.540***	-6.799***	-19.967***
	[2.459]	[2.468]	-6.607
Ln wpre	0.0977	0.105	-0.223
	[0.0946]	[0.108]	-0.325
Ln wprepoor	-0.433**	-0.440**	-1.399
	[0.187]	[0.194]	-1.912
FE (as in Table 3)	yes	yes	yes
Observations	1511	1,367	458
R-squared	0.315	0.334	0.202
Number of cid	127	115	115

Note: Sample B denotes the sample of countries and years from Backhaus et al. (2015) and Sample C&P denotes the sample of countries and decades from Cattaneo and Peri (2016). ***, **, * denote significance levels at the one, five and ten percent level, respectively. Robust standard errors are reported in parentheses.

Table 5. Determinants of Emigration Rates with Non-Linearity

VARIABLES	(1) FE (Sample B)	(2) FE (Sample B)	(3) FE (Sample B)	(4) FE (Sample C&P)
Countries:	All	MIC	Poor	All
Ln wtem	7.317***	7.194***	-27.45***	9.280
	[1.834]	[2.209]	[8.012]	[5.889]
Ln wtem squared	-1.380***	-1.838***	3.520**	−1.737
	[0.435]	[0.542]	[1.613]	[1.455]
Ln wpre	-0.0392	0.0800	-2.225*	−0.182
	[0.122]	[0.136]	[1.152]	(0.380)
Ln wpre squared	0.0287	0.0184	0.391	−0.030
	[0.0273]	[0.0324]	[0.273]	(0.109)
Country FE	yes	yes	yes	yes
Year3-region FE	yes	yes	yes	yes
Observations	1,367	1,072	384	458
R-squared	0.321	0.034	0.134	0.175
Number of cid	115	91	32	115

Note: ***, **, * denote significance levels at the one, five and ten percent level, respectively. Robust standard errors are reported in parentheses.

Table 6 Group Fixed Effects Estimation Results Sample Annual Data

VARIABLES	(1) GFE_no ln	(2) GFE_ln	(3) GFE_ln	(4) GFE_ln
(ln) wtem_dm	0.0643***	0.490**	0.390	-1.341
	[0.0231]	[0.237]	[0.290]	[1.145]
(Ln) wpre_dm	0.00175	-0.0729*	-0.183***	-0.114*
	[0.00501]	[0.0467]	[0.0558]	[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	0.671***	-0.203*	1.912***
	[0.156]	[0.145]	[0.107]	[0.216]
FE Group 3	-0.299***	0.382**	1.196***	-0.771***
	[0.0846]	[0.161]	[0.122]	[0.155]
FE Group 4	-0.976***	1.955***	0.0631	0.225**
	[0.142]	[0.232]	[0.282]	[0.0884]
FE Group 5	-0.588***	2.105***	0.125	-0.312***
	[0.111]	[0.179]	[0.110]	[0.108]
FE Group 6	0.969***	0.481***	1.921***	0.922***
	[0.196]	[0.153]	[0.205]	[0.135]
FE Group 7	1.001***	1.060***	0.206	1.197***
	[0.127]	[0.146]	[0.130]	[0.119]
FE Group 8				0.143
				[0.157]
Observations	1,693	1,681	1,681	1,681
R-squared	0.676	0.655	0.660	0.679
R-squared Adjusted	0.657	0.637	0.639	0.659
RMSE	0.312	0.321	0.327	0.311

Note: ***, **, * denote significance levels at the one, five and ten percent level, respectively. Robust standard errors are reported in parentheses. Group-year dummy variables are included in all columns, coefficients not reported.

Table 7. Group-Specific Coefficients for Climatic Variables

VARIABLES	(1) FE	(2) FE	(3) FE
Ln wtem g1	0.0411		0.00883
	[0.310]		[0.325]
Ln wtem g2	-0.693*		-0.733*
	[0.399]		[0.403]
Ln wtem g3	2.536		0.533
	[8.313]		[9.632]
Ln wtem g4	3.343		2.670
	[2.715]		[2.603]
Ln wtem g5	0.752		0.760
	[0.688]		[0.777]
Ln wtem g6	2.284**		2.410**
	[1.004]		[0.960]
Ln wtem g7	-1.526		-1.922
	[1.271]		[1.437]
Ln wpre g1		-0.0488	-0.0808
		[0.102]	[0.107]
Ln wpre g2		-0.0935	-0.0970
		[0.0990]	[0.0952]
Ln wpre g3		0.262**	0.259
		[0.103]	[0.165]
Ln wpre g4		-0.166	-0.126
		[0.122]	[0.122]
Ln wpre g5		-0.0119	0.00418
		[0.0770]	[0.0859]
Ln wpre g6		-0.00904	0.0669
		[0.176]	[0.182]
Ln wpre g7		-0.113	-0.142
		[0.104]	[0.108]
Observations	1,573	1,584	1,573
R-squared	0.654	0.652	0.655
Number of cid	133	133	133

Note: ***, **, * denote significance levels at the one, five and ten percent level, respectively. Robust standard errors are reported in parentheses. Group-year dummy variables are included in all columns, coefficients not reported.

Table 8. Transmission Channels

VARIABLES	(1) FE	(2) FE	(3) FE	(4) FE	(5) FE	(6) FE	(7) FE
lnwtemg1	0.217	0.242	0.0117	-0.0963	0.123	0.00843	-0.0155
	[0.299]	[0.300]	[0.325]	[0.370]	[0.397]	[0.326]	[0.317]
lnwtemg2	-0.703*	-0.621*	-0.742*	-1.113**	**-0.0618**	-0.733*	-0.767*
	[0.417]	[0.344]	[0.407]	[0.437]	[0.276]	[0.403]	[0.420]
lnwtemg3	1.435	-0.554	0.509	9.256	-47.53***	0.533	0.490
	[9.465]	[9.464]	[9.634]	[6.361]	[0.0808]	[9.635]	[9.608]
lnwtemg4	2.369	2.477	2.675	6.224**	1.851	2.670	2.685
	[2.838]	[2.580]	[2.617]	[2.721]	[2.034]	[2.604]	[2.610]
lnwtemg5	0.189	0.334	0.754	0.553	0.0591	0.762	0.756
	[0.623]	[0.688]	[0.780]	[0.949]	[0.557]	[0.777]	[0.777]
lnwtemg6	2.485**	2.405**	2.429**	**1.750**	5.600***	2.384**	2.401**
	[1.003]	[0.964]	[0.972]	[1.140]	[1.610]	[0.959]	[0.962]
lnwtemg7	-1.819	-2.219	-1.900	-4.081**	0.242	-1.922	-1.923
	[1.450]	[1.432]	[1.437]	[1.666]	[8.538]	[1.437]	[1.430]
lnwpreg1	-0.126	0.0359	-0.0822	-0.261	0.0857	-0.0808	-0.0870
	[0.126]	[0.0915]	[0.110]	[0.179]	[0.117]	[0.107]	[0.106]
lnwpreg2	-0.0987	-0.0836	-0.0997	-0.119	0.0509	-0.0986	-0.0989
	[0.0962]	[0.103]	[0.0980]	[0.0998]	[0.0425]	[0.0952]	[0.0963]
lnwpreg3	0.282	0.267*	0.259	0.308**	-2.206***	0.259	0.263
	[0.182]	[0.154]	[0.165]	[0.120]	[0.0544]	[0.165]	[0.166]
lnwpreg4	-0.152	-0.116	-0.127	0.411**	0.0225	-0.126	-0.126
	[0.144]	[0.120]	[0.122]	[0.178]	[0.160]	[0.122]	[0.122]
lnwpreg5	-0.0317	0.00954	0.00547	0.0610	0.133	0.00506	0.00297
	[0.109]	[0.101]	[0.0857]	[0.0591]	[0.115]	[0.0860]	[0.0859]
lnwpreg6	0.0190	0.0673	0.0684	0.229	0.0676	0.0635	0.0677
	[0.164]	[0.183]	[0.181]	[0.210]	[0.160]	[0.182]	[0.182]
lnwpreg7	-0.146	-0.175	-0.145	-0.344	0.0514	-0.142	-0.145
	[0.109]	[0.107]	[0.109]	[0.232]	[0.201]	[0.108]	[0.108]
log_gdpcap_origin	-0.128						
	[0.113]						
trade_to_gdp		0.000219					
		[0.000753]					
demographic_pressure			-0.00407				
			[0.0125]				
stability				-0.0258			
				[0.0378]			
unemployment_origin					0.00203		
					[0.00483]		
share_tsunami_deaths						-1.236***	
						[0.296]	
share_agricultural_land							-0.00285
							[0.00610]
Observations	1,484	1,492	1,573	1,050	720	1,573	1,573
R-squared	0.667	0.669	0.655	0.629	0.733	0.656	0.655
Number of cid	127	129	133	133	108	133	133

Table 9. Sensitivity. Different Number of Groups for the Baseline GFE Estimator

GFE Baseline Dep. Var: ln emigration rate	(1)	(2)	(3)	(4)	(5)	(6)
Ind. VARIABLES						
Ln wtem_dm	0.478	0.336	0.275	0.102	0.483**	0.490**
	[0.344]	[0.267]	[0.290]	[0.236]	[0.234]	[0.237]
Ln wpre_dm	-0.0419	-0.0659	-0.0605	-0.0697*	-0.0574	-0.0729*
	[0.0668]	[0.0444]	[0.0499]	[0.0410]	[0.0443]	[0.0467]
FE Group 2	-1.046***	1.510***	-1.090***	-0.231*	0.871***	0.671***
	[0.101]	[0.113]	[0.113]	[0.137]	[0.206]	[0.145]
FE Group 3		0.264***	-1.832***	1.041***	2.029***	0.382**
		[0.0918]	[0.214]	[0.150]	[0.175]	[0.161]
FE Group 4			-1.577***	-0.389***	0.966***	1.955***
			[0.116]	[0.129]	[0.145]	[0.232]
FE Group 5				0.941***	1.955***	2.105***
				[0.239]	[0.232]	[0.179]
FE Group 6					0.487***	0.481***
					[0.146]	[0.153]
FE Group 7						1.060***
						[0.146]
Observations	1,681	1,681	1,681	1,681	1,681	1,681
R-squared	0.439	0.516	0.557	0.594	0.626	0.655
R-squared 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

Note: ***, **, * denote significance levels at the one, five and ten percent level, respectively. Robust standard errors are reported in parentheses. Group-year dummy variables are included in all columns, coefficients not reported. Dataset from Backhaus et al. (2015).

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APPENDIX

Table A.1. List of Variables, Definitions and Sources

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. (2014)
Migration flow	Inflow of population from sending country *i*	Organization for Economic Co-operation and Development (2014): OECD International Migration Database. Eurostat (2014): Immigration.
GDP per capita	PPP-adjusted GDP per capita in sending country at current US$	World Bank (2014): World Development Indicators Database.
Population	Population in the sending country	World Bank (2014): World Development Indicators Database.
Demographic pressure	Percentage or young population as a share of working age population in the sending country	World Bank (2014): World Development Indicators Database.
Unemployment rate	Unemployment rate in the country of destination, total (share of total labor force)	World Bank (2014): World Development Indicators Database.
Trade to GDP	Sum of exports and imports of goods and services measured as a share of the sending country's gross domestic product	World Bank (2014): World Development Indicators Database.
Share of agricultural land	Share of sending country *i*'s land area that is arable, under permanent crops, and under permanent pastures	World Bank (2014): World Development Indicators Database.
State fragility index	Ordinally scaled (0-25) measure of sending country *i*'s state fragility	Center for Systemic Peace (2014): State Fragility Index.

Table A.2. List of Countries

Destination Countries

Australia	0.76	France	0.82	Norway	0.84
Austria	0.6	Germany	0.88	Portugal	0.08
Belgium	0.11	Italy	0.28	Spain	0.69
Canada	0.86	Japan	0.13	Sweden	0.57
Denmark	0.57	Korea	0.03	Switzerland	0.7
Finland	0.5	Netherlands	0.69	United Kingdom	0.39
				United States	0.82

Countries of Origin

Afghanistan	0.64	Fiji	0.45	Nigeria	0.64
Albania	0.61	Gabon	0.37	Oman	0.45
Algeria	0.65	Gambia	0.56	Pakistan	0.74
Angola	0.61	Georgia	0.57	Panama	0.52
Argentina	0.62	Ghana	0.64	Papua New Guinea	0.29
Armenia	0.57	Guatemala	0.54	Paraguay	0.49
Azerbaijan	0.57	Guinea	0.54	Peru	0.64
Bahamas	0.36	Guinea-Bissau	0.46	Philippines	0.83
Bangladesh	0.67	Guyana	0.49	Poland	0.78
Belarus	0.57	Haiti	0.46	Puerto Rico	0.02
Belize	0.36	Honduras	0.54	Qatar	0.28
Benin	0.44	Hungary	0.62	Romania	0.76
Bhutan	0.4	India	0.79	Russian Federation	0.85
Bolivia	0.57	Indonesia	0.69	Rwanda	0.57
Bosnia & Herzegovina	0.69	Iran	0.7	Samoa	0.2
Botswana	0.46	Iraq	0.67	Sao Tome&Principe	0.22
Brazil	0.8	Jamaica	0.6	Saudi Arabia	0.52
Brunei Darussalam	0.3	Jordan	0.6	Senegal	0.6
Bulgaria	0.68	Kazakhstan	0.57	Sierra Leone	0.54
Burkina Faso	0.48	Kenya	0.6	Slovenia	0.57
Burundi	0.53	Kuwait	0.43	Solomon Islands	0.11
Cambodia	0.55	Kyrgyzstan	0.53	Somalia	0.68
Cameroon	0.61	Laos	0.51	South Africa	0.59
Cape Verde	0.46	Latvia	0.59	Sri Lanka	0.68
Central African Rep.	0.32	Lebanon	0.66	Sudan	0.57
Chad	0.36	Lesotho	0.31	Suriname	0.37
Chile	0.6	Liberia	0.54	Swaziland	0.37
China	0.86	Libya	0.56	Syria	0.63
Colombia	0.63	Lithuania	0.6	Tajikistan	0.47
Comoros	0.2	Macedonia FYR	0.56	Tanzania	0.59
Congo, Dem. Rep.	0.55	Madagascar	0.5	Thailand	0.82
Congo, Rep.	0.5	Malawi	0.5	Timor-Leste	0.08

Costa Rica	0.52	Malaysia	0.61	Togo	0.54
Côte d'Ivoire	0.58	Mali	0.46	Trinidad and Tobago	0.57
Croatia	0.64	Mauritania	0.46	Tunisia	0.66
Cuba	0.56	Mauritius	0.59	Turkey	0.79
Cyprus	0.57	Mexico	0.63	Turkmenistan	0.43
Czech Republic	0.61	Moldova	0.61	Uganda	0.57
Djibouti	0.43	Mongolia	0.54	Ukraine	0.69
Dominican Republic	0.58	Morocco	0.6	United Arab Emirates	0.44
Ecuador	0.62	Mozambique	0.55	Uruguay	0.52
Egypt	0.64	Myanmar	0.51	Uzbekistan	0.57
El Salvador	0.53	Namibia	0.5	Vanuatu	0.14
Equatorial Guinea	0.22	Nepal	0.57	Venezuela	0.68
Eritrea	0.54	New Zealand	0.62	Viet Nam	0.79
Estonia	0.6	Nicaragua	0.54	Yemen	0.5
Ethiopia	0.64	Niger	0.49	Zambia	0.57
				Zimbabwe	0.56

Note: The numbers denote the share of non-missing observations.

Table A.3 Country Grouping from Model (1) in Table 6

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

Table A.4. Determinants of Emigration Rates: Poor versus Non-Poor Countries with Climatic Variables in Levels

Dep. Variable: ln_emig rate	(1) FE (Sample B)	(2) FE (Sample B)	(3) FE (Sample C&P)
Exp. Variables:			
wtemp	0.0548	0.0553	0.267*
	[0.0450]	[0.0479]	[0.155]
wtempoor	-0.198*	-0.217*	-1.127***
	[0.117]	[0.120]	[0.336]
wpre	0.0182**	0.0192*	0.013
	[0.00890]	[0.00987]	[0.024]
wprepoor	-0.0301**	-0.0387**	0.841
	[0.0132]	[0.0156]	[0.116]
FE (as in Table3)	yes	yes	yes
Observations	1522	1378	458
R-squared	0.34	0.318	0.05
Number of cid	127	115	115

Note: Sample B denotes the sample of countries and years from Backhaus et al. (2015) and sample C&P denotes sample of countries and decades from Cattaneo and Peri (2016). ***, **, * denote significance levels at the one, five and ten percent level, respectively. Robust standard errors are reported in parentheses.