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Climate Variability and Transnational Migration: A Dyadic Analysis

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Abstract: This research builds upon and extends earlier research by studying whether people leave their homes and migrate to other states due to weather changes associated with climate variability. In particular, I examine how push and pull factors jointly influence emigration. Empirically, the theoretical arguments are analysed quantitatively with time-series cross-section data on transnational migration since the 1960s. The results suggest that climate indicators are strongly and robustly associated with transnational migration. The dyadic nature of the analysis allows for a close examination of patterns across pairs of countries by clearly distinguishing between "source" and "destination." Controlling for unobserved influences via country and year fixed effects, as well as a series of robustness checks, further increases the confidence in this finding. This research substantially improves our understanding of climate-induced migration and emphasizes that it is, in fact, a global phenomenon.

Keywords: climate variability; temperature; precipitation; transnational migration; dyadic analysis

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1. Introduction

The argument on climate variability inducing migration is usually based on individuals' capability and opportunity to leave their homes [1]. People look for life satisfaction in suitable and safe areas [2,3]. In the presence of an environmental event, people move from one area to another within their state (e.g., [4]). If environment factors have a major impact, e.g., to such an extent that the state is unable to respond to the adaptation needs of its population as a whole, they do influence the state as a whole as well. Under those circumstances, intrastate migration may not be a viable option, and people will then increasingly consider transnational emigration [5]. Thus, I stress the phenomenon of transnational migration with regards to climate variability, with a focus on asking: where does the environmentally affected individual go to? Considering the consequences of transnational migration, such as economic instability or diseases [6], finding evidence for transnational environmental migrants will highlight that climate-induced migration is, in fact, a global phenomenon.

Studies focusing on transnational migration flows due to variability in the weather are limited in both theory and empirics. For instance, Beine and Parsons [7] concentrate on the impact of temperature and rainfall averages on international migration, but only until the year 2000 (I use the terms "international" and "transnational" interchangeably). Backhaus et al. [8] analyze how temperature and precipitation affect migration flows with a dyadic setup and, thus, capture push and pull factors. However, they rely on a sample of 142 countries of origin and only 19 OECD destination countries, which implicitly assumes that migration only occurs from the "global South" to the "global North". Cattaneo and Peri [5] also study international migration due to low agricultural productivity that is affected by high temperatures in countries of origin, but thereby merely provide an analysis of indirect effects. While I build upon these works, I also seek to extend and go beyond them by offering an "inclusive study" of transnational migration not only on the countries of origin but also on the destination countries. Additionally, I examine direct effects of climate variability on transnational migration and I analyze a longer time period (from 1960 to 2010), and a larger set of countries (i.e., up to 186 states; not only OECD countries), which allows me to maximize the generalizability of my results over earlier work. This is important both from a scientific perspective and a policy point of view. Eventually, therefore, I circumvent the limitations of previous studies with regards to a narrow theoretical focus (mostly indirect effects) or the empirical analysis (small spatial and temporal coverage). My findings suggest that higher positive temperature shocks make people to migrate from their countries to lower-temperature countries, which is likely to have crucial implications globally—and not only within specific states as such.

2. The Links of Climate Variability to Transnational Migration

The causes of migration are complex and, to a large degree, context-specific [1]. People choose to migrate only as a last resort as substantial costs are usually associated with migration [4]. Hence, migration might be driven by a series of factors that are typically intertwined and generate less favorable living conditions. As a result, people deliberately decide or are somewhat "forced" to leave their homes, looking for a new place to live. In terms of the influences at the "source location," the literature usually focuses on push factors, distinguishing between willingness and opportunity aspects. Declining economic growth, low business activity, high levels of unemployment, and poverty are all (interlinked) determinants that push people to migrate out of their countries looking for employment and better living standards in other states. Opportunity and willingness define people's decision to move elsewhere [9]. Literature refers to the willingness factors as "stressors" that affect people's living satisfaction and could potentially impact on their willingness to emigrate [3,10–12]. On the other hand, opportunity factors at the destination define people's decision on where to migrate to, e.g., social and economic opportunities [13].

My main argument is twofold. First, climate variability is likely to affect a country in its entirety. Although within-country variation of climate variability clearly exists, it is usually not the case that only a few, remote areas within a nation experience the impact of an altered climate [14]. When the climate changes, this directly affects the country as a whole (stressors/"push" factors). Consider the case of smaller island nations, for example: Farbotko [15] and Farbotko and Lazrus [16], among others, highlight that inhabitants of low-lying atolls are simply forced to leave their "sinking" and "disappearing" countries. In the case of larger countries, the problem lies on adaptation that is either too expensive or it might require too much time to develop an effect [17]. For instance, McAdam and Loughry [18] focus on migration in the small islands of Kiribati and Tuvalu ("shrinking islands") and claim that climatic change along other socio-economic development has forced people to migrate. The authors argue that "the islands will be uninhabitable by the middle of this century whilst their people will be the world's first climate refugees" [18]. People are forced not only to domestically migrate from one area to another, but also to look for another country, e.g., Australia or New Zealand in this case. Second, people do not only consider the necessity of moving (defined by the current living conditions), but they also take into account the conditions that they will face in the new environment (opportunity or "pull" factors). Having experienced climate variability in the country of origin, individuals are looking for environmental quality, and a more stable environment with better living conditions. Emigration is therefore jointly influenced by "push" and "pull" factors.

3. Materials and Methods

3.1. Data and Dependent Variable

For the empirical test of my hypothesis, I use time-series cross-sectional data. The unit of analysis is dyad country-year between 1960 and 2010. The availability of data determines this spatio-temporal domain. For the outcome variable, data on migrants are taken from the World Bank over the last five decades, i.e., 1960–2010, and refer to "migrant stocks" (as defined by the World Bank), i.e., the total number of people born in a country other than that in which they live [19,20]. I transformed this information to the stock of migrants between two countries, i.e., the country of origin and the destination. The World Bank data are compiled from national census rounds, which are usually conducted in

10-year windows; missing data between two consecutive rounds are linearly interpolated (Note the robustness check in the appendix that omits all interpolated or imputed country years, and only relies on actually observed values of the migration item). The variable of emigrants is also logged transformed. This data allows a global empirical examination of transnational migration that aims to add to previous studies with a focus on either OECD countries (e.g., [8,21]) or developing countries [22].

Given the continuous dependent variable, I employ ordinary least squares (OLS) regression models to empirically test my hypothesis. I also cluster the standard errors by dyad to capture intra-group correlations. Serially correlated errors within countries might be possible; the temporally lagged dependent variable addresses this [23]. I also employ year-fixed effects to control for temporal shocks that are common for all states in a given year (e.g., economic crises, EU accession rounds). Country-fixed effects capture any time-invariant unit-level (domestic) influences.

3.2. Explanatory Variables

For the temperature and precipitation data, I follow Landis [24] and use the data from NOAA's NCEP/NCAR Reanalysis Monthly Means Dataset 1948–2011 (in degrees Celsius) and monthly precipitation data (mm/month) from the Global Precipitation Climatology Project Version 2.2, respectively. Following Landis [24], I aggregated these data at the country level and employ measures of temperature and precipitation shocks. A temperature/precipitation shock is a substantial (or extreme) deviation from a "normal" climate pattern, i.e., the standardized temperature/precipitation deviation (see [25]). Shocks in temperature and precipitation increase climate variability with immediate effects. For example, countries affected by low levels of precipitation suffer from various extreme conditions, including droughts. This "can cause disruptions in economic and social systems" [24] (p. 606) and [26], especially in vulnerable societies with low adaptability measures. Specifically, as described in detail in Landis [24] (p. 608), measures of temperature and precipitation shock use the monthly deviation from a country's long-term monthly mean. These can be either negative or positive deviations (not absolute values). More information on the explanatory variables can be found in the Appendix A.

Figure 1 illustrates the temperature shock rates (in Celsius) in the world between 1948 and 2010. Figure 2 illustrates precipitation shocks in each origin country between 1979 and 2011, measured in millimeters (mm).

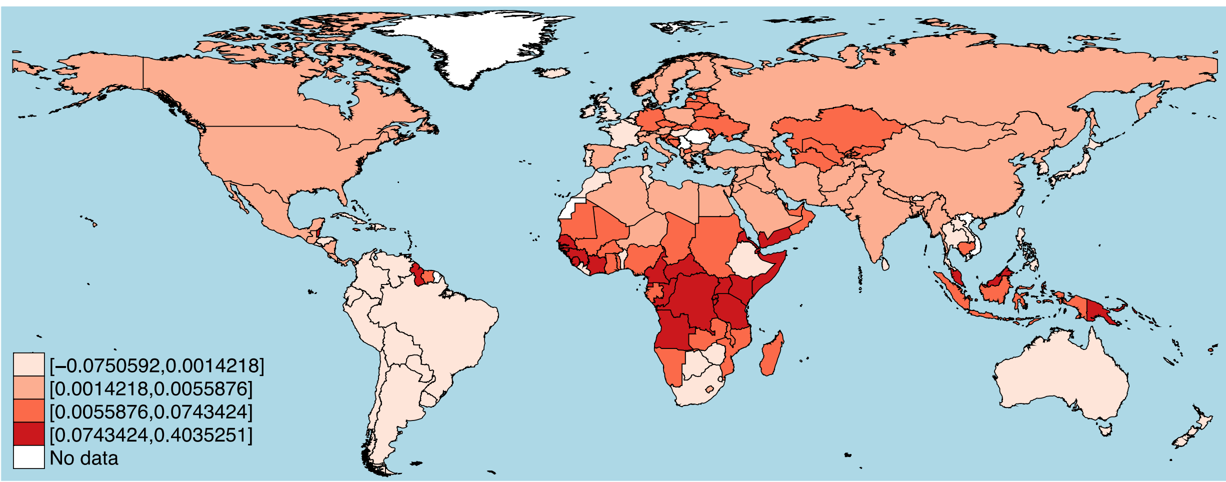

Figure 1. World map for yearly average temperatures shocks—origin country. To facilitate the illustration of the temperatures, I employed four different temperature shock categories where light red colour refers to low temperatures and dark red colour to high temperatures. White colour indicates no information. Temperature shock rates (in Celsius) in the world between 1948 and 2010 (averaged across years for each origin country).

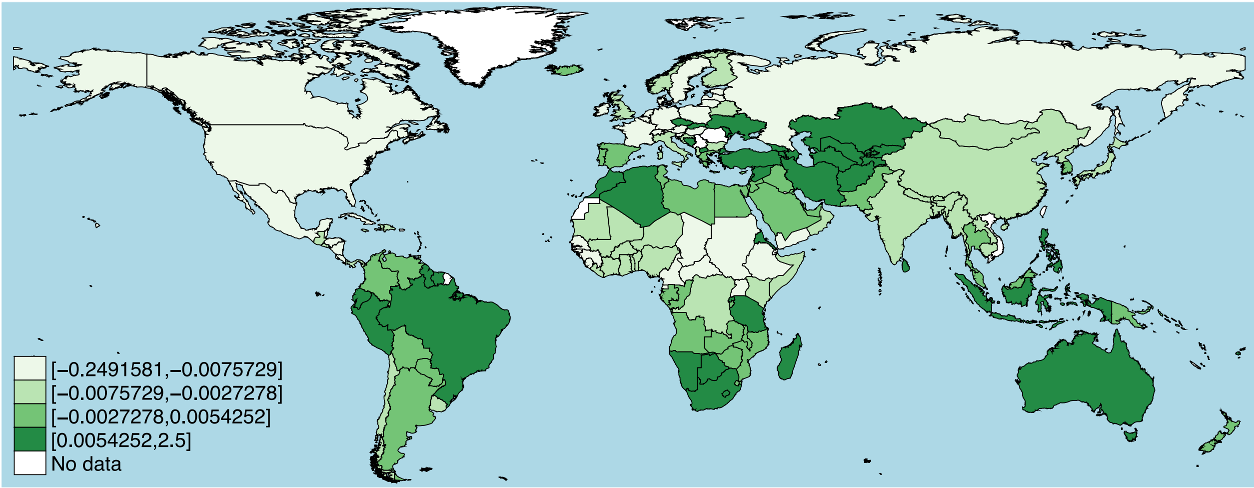

Figure 2. World map for yearly average precipitation shocks—origin country. To facilitate the illustration of the precipitation levels, I employed four different precipitation shocks categories. Dark green pertains to high levels of precipitation, while lighter greens pertain to lower levels of precipitation. White colour indicates no information. Precipitation shocks in each country between 1979 and 2009, measured in millimeters (mm) (averaged across years for each origin country).

In terms of the control variables described in Table 1, I consider a set of indicators that have been identified as possible influences of the willingness and opportunity for translational migration [12,27,28]. In order to address issues of simultaneity bias, all explanatory variables are lagged by one year.

Table 1. Control variables.

	Definition	Source
Cultural distance $_{\ln}$	Standardized measure of cultural differences	Kandogan's [29] revised variable of Kogut and Singh's [30]
Civil war	At least 25 battle deaths	Armed Conflict Database [31]
Democracy	State's regime (polity 2)	Polity IV data set [32]
GDP per capita $_{\ln}$	Log-transformed Countries' economic output	[33]
Population $_{\ln}$	Log-transformed total number of humans living in a country	[33]

Note: Refer to the Appendix A for a detailed explanation of the control variables.

Table 2 summarizes the descriptive statistics of all variables discussed so far as well as the variation inflation factors (VIFs) of the explanatory factors. According to the VIFs, multicollinearity is unlikely to be a major issue, since all VIFs are well below the common threshold value of 5 [34].

Table 2. Descriptive statistics and VIF.

	Obs.	Mean	Std. Dev.	Min	Max	VIF
Emigrants $_{\ln}$ (lag)	307,614	−5.25	17.16	−34.54	16.27	
Temperature shock (lag)—Origin	307,614	0.08	0.25	−0.87	1.76	1.06
Temperature shock (lag)—Destination	307,614	0.09	0.26	−1.83	1.79	1.07
Precipitation shock (lag)—Origin	307,614	0.01	0.23	−1.04	1.62	1.00
Precipitation shock (lag)—Destination	307,614	0.01	0.22	−1.04	1.65	1.01
Cultural distance $_{\ln}$ (lag)	307,614	9.85	0.63	6.00	11.50	1.36
Civil war (lag)—Origin	307,614	0.05	0.23	0.00	1	1.04

Table 2. *Cont.*

	Obs.	Mean	Std. Dev.	Min	Max	VIF
Civil war (lag)—Destination	307,614	0.06	0.24	0.00	1	1.03
Democracy (lag)—Origin	307,614	4.57	6.81	−10	10	1.29
Democracy (lag)—Destination	307,614	1.68	7.26	−10	10	1.20
GDP per capita $_{ln}$ (lag)—Origin	307,614	8.89	1.09	5.45	10.77	1.58
GDP per capita $_{ln}$ (lag)—Destination	307,614	8.22	1.26	4.51	10.97	1.24
Population $_{ln}$ (lag)—Origin	307,614	10.01	1.90	6.78	21.01	1.32
Population $_{ln}$ (lag)—Destination	307,614	9.24	1.98	5.37	21.01	1.23

Notes: Data on precipitation only available for 1979 to 2009; all other items are available for 1960 to 2010.

4. Results

Model 1 in Table 3 omits control variables as they may actually increase the bias instead of decreasing it [35]. Model 2 constitutes my full model, i.e., all control variables are included.

Table 3. The impact of climate change on emigration (dyadic setting).

	Model 1	Model 2
Temperature shock (lag)—Origin	0.16 ***	0.11 ***
	(0.02)	(0.03)
Temperature shock (lag)—Destination	−0.17 ***	−0.19 ***
	(0.02)	(0.03)
Precipitation (lag)—Origin	−0.11 ***	−0.17 ***
	(0.02)	(0.03)
Precipitation (lag)—Destination	0.07 ***	0.01
	(0.02)	(0.03)
Cultural distance$_{\text{ln (lag)}}$		0.06
		(0.07)
Civil war (lag)—Origin		−0.03
		(0.03)
Civil war (lag)—Destination		0.01
		(0.03)
Democracy (lag)—Origin		−0.00
		(0.00)
Democracy (lag)—Destination		−0.01 ***
		(0.00)
GDP per capita$_{ln}$ (lag)—Origin		−0.20 ***
		(0.04)
GDP per capita$_{ln}$ (lag)—Destination		0.35 ***
		(0.04)
Population (lag)—Origin		−0.01
		(0.11)
Population (lag)—Destination		−1.93 ***
		(0.11)
Constant	−0.58 ***	22.40 ***
	(0.00)	(2.15)
Obs.	931,760	307,614
Lagged dependent variable	Yes	Yes
Country fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Clustered standard errors (dyad)	Yes	Yes
R^2	0.96	0.95
RMSE	4.09	3.97

Notes: Table entries are coefficients; standard errors clustered by countries are in parentheses; *** $p < 0.01$.

Due to the temporally lagged dependent variable, the coefficient estimates of all other explanatory variables only reflect the short-term effect, i.e., the impact in a current year (left panel in Figure 3). To estimate the asymptotic, long-term impact of the independent variables, I re-estimate the individual coefficients by taking into account the coefficient of the lagged dependent variable [36] (p. 336), Accordingly, I estimate asymptotic long-term effects (in addition to short-term effects) for the main explanatory variables of Model 2 and summarize them in Figure 3.

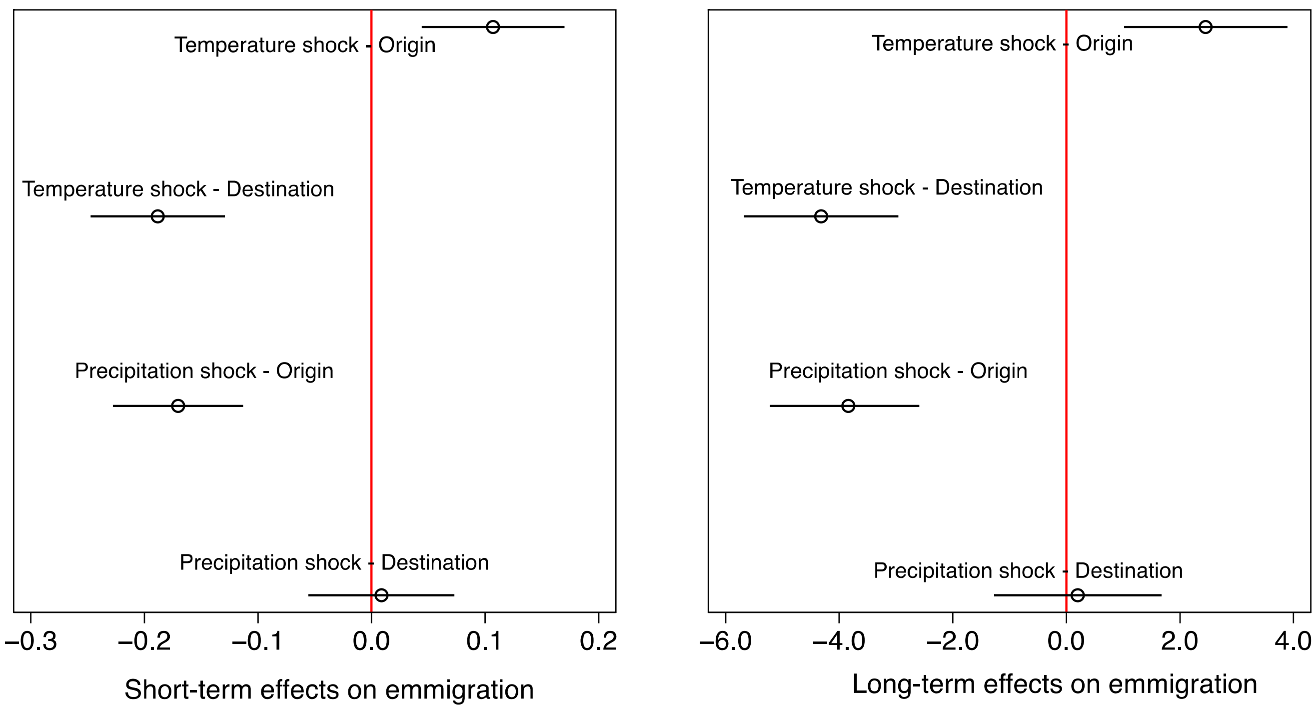

Figure 3. Short and asymptotic long-term effects on emigration Model 2. Horizontal bars are 90 percent confidence intervals; vertical red line represents a marginal effect of 0; estimates are based on Model 2 (Table 3). Marginal effect estimates are presented in the Appendix A in Tables A2 and A3.

The dyadic nature of the analysis allows for a detailed examination of the motivation for emigration—not only in the country of origin, but also in the destination state. Put differently, the results show what climatic conditions in the origin and destination country drive emigration. Overall the results confirm the impact of climate variation and specifically of higher positive temperature shocks on transnational migration. At the same time, migrants are more likely to migrate to those countries with colder temperature shocks. The coefficient estimate of temperature shock (lag)—origin is 0.11 (Model 2). Given that the outcome variable is log-transformed, the substantive short-term effect of temperature shock is exp(0.11), i.e., for a one-unit increase in that variable, the geometric mean of emigrants increases by 11.6 percent. Given the mean value of emigrants $_{\ln}$ (lag) and the distribution ranging in (−34.54; 16.27), an increase of 11.6 percent refers to about 363 people leaving. The asymptotic long-term effect is 2.45. Although the short-term effect is, in fact, rather small, the substantive long-term impact of temperature shocks highlights that an increase in temperature is very high, considering that the size of a small-islanded country such as the Republic of Nauru is just over 10,000 people.

The coefficient estimate of temperature shock (lag)—destination is −0.19 (Model 2), the substantive short-term effect of temperature shock is −21 percent, i.e., for a one-unit increase in that variable, the geometric mean of emigrants decreases by 21 percent, and the asymptotic long-term effect is −4.32. This means that individuals from warmer-temperature countries migrate to colder countries. Regarding the climate indicator of precipitation, the coefficient estimate of the precipitation shock (lag) at the origin is −0.17, the substantive short-term effect of precipitation shock at the origin is −18.5 percent, i.e., for a one-unit increase in that variable, the geometric mean of emigrants decreases by 18.5 percent, and the asymptotic long-term effect is −3.84. This reflects previous findings on precipitation that are, in general, ambiguous [37]. The precipitation shock indicator at the destination does not have a significant impact on emigration though. These estimates are statistically significant at the 1 percent level. Given that I control for a large set of alternative explanations, including year- and country-fixed effects, there is strong confidence in the validity of my findings.

Moving to the rest of the explanatory variables of the analysis, the results show that more democratic states do not attract migrants as they may have more restrictive policies towards migration [38], while income levels play a significant role "at home" and "abroad:" lower income levels in the source country lead to more emigration, while it is precisely the other way around in the destination country, i.e., economically wealthier states attract migrants more strongly than poorer nations (in the appendix, I offer an analysis interacting temperature shock at the origin with unemployment rates at the destination country) [39,40]. Moreover, population in the destination country is linked to Emigration in a significant way. To further examine the robustness of this model, I examined the predictive power of the main explanatory variables of interest via in-sample predictions techniques in the Appendix A. The specifications employed perform well in predicting transnational migration and clarifying the robustness of this empirical analysis.

5. Discussion and Conclusions

This note attempts to identify countries' characteristics that determine environmental migrants' origin and destination. Among other drivers, environmental migrants look for environmentally safe countries, i.e., not affected by temperature shocks. There are several studies on the relationship between environmental change and migration, particularly at the domestic, within-country level (e.g., [1,4]), and some at the international level with limited coverage of countries and years (e.g., [6–8]). In this study, I took a different approach by examining climate change induced transnational migration in a dyadic analysis.

The results strongly and robustly suggest that if a country experiences high positive temperature shocks, migration is likely to occur across countries. The findings further highlight a significant difference between the short- and long-term effects of temperature shocks on transnational migration. In particular, individuals will be migrating from countries with warmer shocks to countries with colder shocks. Meanwhile, the results for precipitation shocks are rather mixed reflecting previous findings [37]. Higher precipitation at the origin decreases migration whilst precipitation shock at the destination country is not related to emigration. Given the consequences of migration at larger scales, many countries will face adaptation and mitigation challenges not only due to the large migration flows, but also as my results suggest, indirectly due to climate variability as well.

Based on this research and the analyses presented, future studies will identify conditions under which climate variability effects are stronger or weaker, and what are other climate indicators that could impact transnational migration. A question raised here is whether the absence of adaptability measures in certain countries is already a driver for people to preemptively migrate fearing for disastrous environmental consequences. Moreover, internal migration for social, economic, and political reasons is strongly linked to people's return, while transnational migration is frequently associated with lower rates of return [41]. In terms of climate-induced migration, the conditions of return might look even more different. A country that is affected by climatic changes will not be able to recover due to the severity of the climate variability consequences (e.g., as demonstrated by the challenges of small island states). That is, further research could move beyond the consequences of climate-induced internal migration and examine further climate-induced transnational migration and its consequences, e.g., grievances and conflicts.

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Appendix A

I begin this appendix by presenting further information on the explanatory and control variables included in the main analysis. The information on temperature comes from the NOAA's NCEP/NCAR Reanalysis Monthly Means Dataset 1948–2011 (in degrees Celsius) [42]. These data provide surface or near surface air temperatures (at a 0.995 sigma level) with spatial coverage of a 2.5 × 2.5-degree longitude native resolution (144 × 72). Specifically, as described in detail in Landis [24] (p. 608), the temperature shock measure "uses the monthly deviation from a country's long-term monthly mean, indicated by $(X_{itz} - X_{it\text{-}bar})/a_{it}$ where X_{itz} is the mean temperature of country i in month t in year z, $X_{it\text{-}bar}$ is the panel mean of country i's long-term monthly (*t-bar*) mean temperature for the period 1948–2011, and a_{it} is the standard deviation of that panel." According to Landis [24], this approach is adopted from Hendrix and Salehyan's [25] (pp. 40–41) measure of rainfall deviation, as the latter study argues that deviations from the panel mean are an optimal operationalization of the "eco-shock" mechanism. Additionally, I employ standardized precipitation deviations (see also [25]) using monthly precipitation data (mm/month) from the Global Precipitation Climatology Project Version 2.2. These data have a spatial coverage of 2.5 × 2.5-degrees with a longitude resolution (144 × 72) for 1979–2011.

Regarding the control variables, first, there is some evidence linking climate to conflict and, thus, migration [43,44]. Hence, I include a civil war onset indicator (based on at least 1000 battle deaths). This information is taken from the Armed Conflict Database [31]. Second, a variable for a state's (i.e., the state sending/receiving migrants) regime captures whether people's choice of leaving their country is also affected by domestic politics in the source location. Additionally, the regime the destination controls for people's choices based on political-related factors. This factor also captures influences like state repression or human rights violations. I include the polity 2 item taken from the Polity IV data set, which covers basically all countries in my sample over the entire period [32]. The polity 2 measure ranges between −10 and +10, with higher values standing for more democratic countries. High unemployment might also push people to leave their countries looking for better life conditions. At the same time, low levels of unemployment should be attracting more migrants. I thus include an indicator for unemployment from the World Bank Development Indicators. The measure for unemployment refers to the share of the labor force that is without work but available for and seeking employment. For example, in 2000, Greece was affected by 11.1% of unemployment. The original variable of unemployment suffers from missing values. To address this issue, I linearly interpolate these missings. This interpolation explains why some states in the sample then have an unemployment rate of 0. To address any concerns stemming from this treatment, I also present models that omit the unemployment variable. I also control for population size and GDP per capita using data from Gleditsch [33]. These measures are log-transformed to reduce their distributions' skewness, because some countries are much wealthier and larger than others. Finally, in light of the dyadic nature of this analysis, I also add a measure on the cultural distance between states. The rationale behind this item is to capture a truly dyadic influence on emigration, i.e., whether cultural similarities impact on emigrants' choice of the destination country. To this end, I adopt Kandogan's [29] revised variable of Kogut and Singh's [30] standardized measure of cultural differences.

In Table A1 of this appendix, I examine the impact of climate variability on transnational migration, as discussed in the main analysis (Table 3), while excluding the variable on precipitation shocks. When including this item as done in Table 2 of the main text, I only capture the period between 1979 and 2009 because of the limited data availability for the precipitation variable. Omitting the precipitation item, and increasing the number of observations as a consequence, does not change the main finding.

Table A1. The impact of climate variability on emigration—Omitting precipitation.

	Model 1	**Model 2**
Temperature shock (lag)—Origin	0.14 ***	0.10 ***
	(0.02)	(0.02)
Temperature shock (lag)—Destination	−0.23 ***	−0.20 ***
	(0.02)	(0.02)
Precipitation (lag)—Origin		
Precipitation (lag)—Destination		
Constant	3.42 ***	16.29 ***
	(0.00)	(1.20)
Obs.	1,218,626	446,279
Lagged dependent variable	Yes	Yes
Country fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Clustered standard errors (dyad)	Yes	Yes
R^2	0.96	0.95
RMSE	3.90	3.73

Notes: Table entries are coefficients; standard errors clustered by countries are in parentheses; *** $p < 0.01$; the results are based on a sample for the 1960–2009 period as I omit the precipitation variable; control variables are included in Model 2 for the estimation but omitted from presentation.

Table A2 shows the short-term effects of climate variability on transnational migration (based on Figure 3 in the main text). For example, the results indicate that the coefficient estimate of Temperature shock (lag)-origin is 0.12 (based on specifications of Model 2 in Table 3 of the main analysis). While this is a rather small impact, it does not come unexpectedly; the fact remains that the variable is highly statistically significant. In addition, due to the temporally lagged dependent variable included as a predictor, the coefficient estimates of all explanatory variables only reflect the short-term effect, i.e., the impact in a current year (i.e., the short-term effects). Hence, I have calculated the long-term effects of climate variability on transnational migration. Table A3 shows that the coefficient estimate of Temperature shock (lag)-origin is 2.61 (based on specifications of Model 2 in Table 3 of the main analysis).

Table A2. Short-term effects of climate variability.

	Marginal Effect Estimate	**Lower Bound**	**Upper Bound**
Temperature shock (lag)—Origin	0.11	0.04	0.17
Temperature shock (lag)—Destination	−0.19	−0.25	−0.13
Precipitation shock (lag)—Origin	−0.17	−0.23	−0.11
Precipitation shock (lag)—Destination	0.01	−0.05	0.07

Note: Figures are based on Figure 3 (left panel) in the main text.

Table A3. Asymptotic long-term effects of climate variability.

	Marginal Effect Estimate	**Lower Bound**	**Upper Bound**
Temperature shock (lag)—Origin	2.45	1.01	3.89
Temperature shock (lag)—Destination	−4.31	−5.67	−2.96
Precipitation shock (lag)—Origin	−3.83	−5.22	−2.59
Precipitation shock (lag)—Destination	0.20	−1.27	1.67

Note: Figures are based on Figure 3 (right panel) in the main text.

I linearly interpolated missing values in the outcome variable, which only reports values per decade. While this addresses the issue of missing values, it may increase the risk of inducing another problem: cointegration, particularly since temperature rises on average more or less linearly as well (but note: temperature shocks do not). Cointegration may lead to spurious findings. As described by Toll [45]:

> "a regression analysis seeks to explain as much as possible of the observed variation in the dependent variable by the variations in the independent variables. The variance of a trending variable is dominated by its trend. If an independent variable has a trend as well, then its variance too is dominated by the trend. More importantly, the trend in any independent variable can explain a large share of the trend in the dependent variable. This implies that, in a regression analysis, the confidence in the parameter estimates is overstated. That is, a regression analysis will find a statistically significant relationship even when there is none."

For examining whether cointegration might be an issue, I re-run the analysis only with the actually observed data, i.e., I drop the linearly interpolated values (Table A4). The results remain qualitatively the same as in the main analysis (Model 2 in Table 3): I still obtain evidence for a significantly positive relationship between temperature shocks and transnational migration. An increase in temperature shocks at home increases the amount of emigrants whilst and a decrease in temperature shocks in the destination country attracts more migrants. Additionally, precipitation shocks in the destination country decrease the number of emigrants whereas this was insignificant in the main analysis.

Table A4. The impact of climate variability on emigration—without linearly interpolated data.

	Model 1
Temperature shock (lag)—Origin	0.57 **
	(0.25)
Temperature shock (lag)—Destination	−5.01 ***
	(0.27)
Precipitation (lag)—Origin	−0.37
	(0.27)
Precipitation (lag)—Destination	−1.03 ***
	(0.24)
Constant	64.32 ***
	(14.66)
Obs.	36,369
Lagged dependent variable	No
Country fixed effects	Yes
Year fixed effects	Yes
Clustered standard errors (dyad)	Yes
R^2	0.52
RMSE	12.89

Notes: Table entries are coefficients; standard errors clustered by countries are in parentheses; control variables are included in Model 2 for the estimation but omitted from presentation; ** $p < 0.05$; *** $p < 0.01$.

I also examined the predictive power of the main explanatory variables of interest via in-sample predictions techniques. That is, I analyze how accurate "conditional statements about a phenomenon for which the researcher actually has data, i.e., the outcome variable has been observed" [46] (p. 311) are. I rely on one measure for assessing the in-sample prediction power: Theil's U According to Böhmelt and Bove [47] (p. 3), "Theil's U is the square root of the ratio between the sum of squared prediction errors of a baseline model and the sum of squared prediction errors of a naïve model; that is, a no-change prediction. If Theil's U is larger than 1, the model actually performs worse than the naïve model; values for Theil's U smaller than 1 indicate that the "theoretically informed model" performs better than the naïve specification."

For my baseline model (Model 1 in Table 3 in the main analysis), Theil's U is at 0.83798313. Table A5 below gives an overview of the model's in-sample prediction power and the individual contribution each of the variables employed in Model 2 makes. The contributions of each variable is measured by calculating the difference between the value of the baseline model's Theil's U values on one hand and, on the other hand, the corresponding goodness-of-fit measure's value calculated for a model that discards that particular item. For example, excluding Temperature shock-origin (lag) from the baseline model leads to an increase in Theil's U from 0.83680681 to 0.83682049. Therefore, Temperature shock at the origin country does contribute to the model's overall prediction power by 0.001368 units according to Theil's U. Finally, note that none of these predictors included in Model 2 diminishes the predictive power. In other words, Theil's U n decrease when leaving out an item from the model specification. Ultimately, the specifications used in the main analysis perform well in predicting transnational migration and clarifying the robustness of this empirical analysis.

Table A5. In-sample prediction power.

Excluded Variables	Mean U	ΔU
None (baseline model)	0.83680681	–
Temperature shock (lag)—Origin	0.83682049	0.001368
Temperature shock (lag)—Destination	0.83684651	0.00397
Precipitation shock (lag)—Origin	0.83684564	0.003883
Precipitation shock (lag)—Destination	0.8368069	0.000009

Notes: Results are based on Model 1 in Table 3 of the main analysis; difference in Theil's U multiplied by 100 to facilitate reading. Control variables included for estimation but omitted from presentation.

To further examine whether unemployment rates play a significant role for the choice of the destination country, I interact temperature shock at the origin country and unemployment rate at the destination country (Figure A1 in this appendix). The information on unemployment comes from the World Bank indicators and it show the percentage of total labour force that is unemployed. The results show that emigration increases at high levels of temperature shock at the origin country and low levels of unemployment in the destination country. This means that emigrants do consider the economic characteristics of the country they are migrating, also while taking into account the climatic influences I focus on.

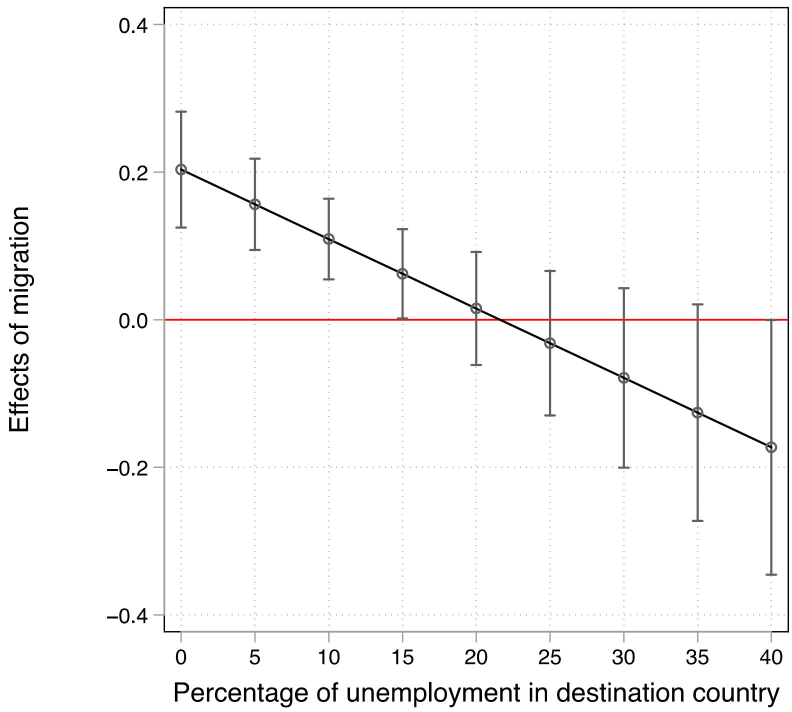

Figure A1. Average marginal effects of temperature shock in origin country and unemployment in destination country. Vertical bars are 90 percent confidence intervals; horizontal red line represents a marginal effect of 0; estimates are based on Model 2 (Table 3 in the main analysis). The values of the unemployment variable are linearly interpolated due to missing values.

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