natureresearch

https://doi.org/10.1038/s41558-020-0898-6

Supplementary information

A meta-analysis of country-level studies on environmental change and migration

In the format provided by the authors and unedited

Supplementary Materials

A Meta-Analysis of Country-Level Studies on Environmental Change and Migration

Roman Hoffmann, Anna Dimitrova, Raya Muttarak, Jesus Crespo Cuaresma, Jonas Peisker

Correspondence to: roman.hoffmann@pik-potsdam.de

This Supplementary Online Material contains 9 sections:

A. Literature Screening and Selection

The starting point in the meta-analysis process is a comprehensive and systematic search and screening of literature in the field, followed by the selection of relevant studies fulfilling a pre-defined set of selection criteria. Once the baseline sample of studies is identified, the information of interest is retrieved. The regression model coefficients, which are the key metric in our case, are standardized to obtain comparable average effect sizes for each study and its models, which form the basis for further analysis (see section B).[1]

The procedures of our literature search and screening, which was carried out in the period between November 2018 and June 2019, followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) recommendations and the Reporting Standards for Systematic Evidence Syntheses in Environmental Research (ROSES). Figure S1 shows a PRISMA flow diagram, which documents the different steps of our search and screening, and maps the number of records identified, included and excluded, and the reasons for exclusions.

We started with a broad systematic search for quantitative empirical studies related to environmental migration. The literature search included journal articles, book chapters, books and working papers and was carried out in Web of Science and Scopus, two multidisciplinary online databases with extensive bibliographic information. In particular, we searched for studies which contained terms related to (i) migration, (ii) environmental change and hazards, (iii) and quantitative analysis (e.g. data, relationship, effect, statistics) in their title, abstract, or keywords[1] .

[1] Search terms and keyword combinations used for Web of Science and Scopus search (exemplary for WoS search): (TS=((climat* OR weather OR environment* OR temperature OR flood OR drought OR "natural disaster" OR "natural disasters") AND (relationship* OR model* OR data* OR estimat* OR statistic* OR quantitative* OR econometric* OR empirical* OR equation* OR analys* OR panel) AND (migra* OR displace* OR refugee))) AND LANGUAGE: (English) AND DOCUMENT TYPES: (Article OR Book OR Book Chapter OR Data Paper OR Proceedings Paper)

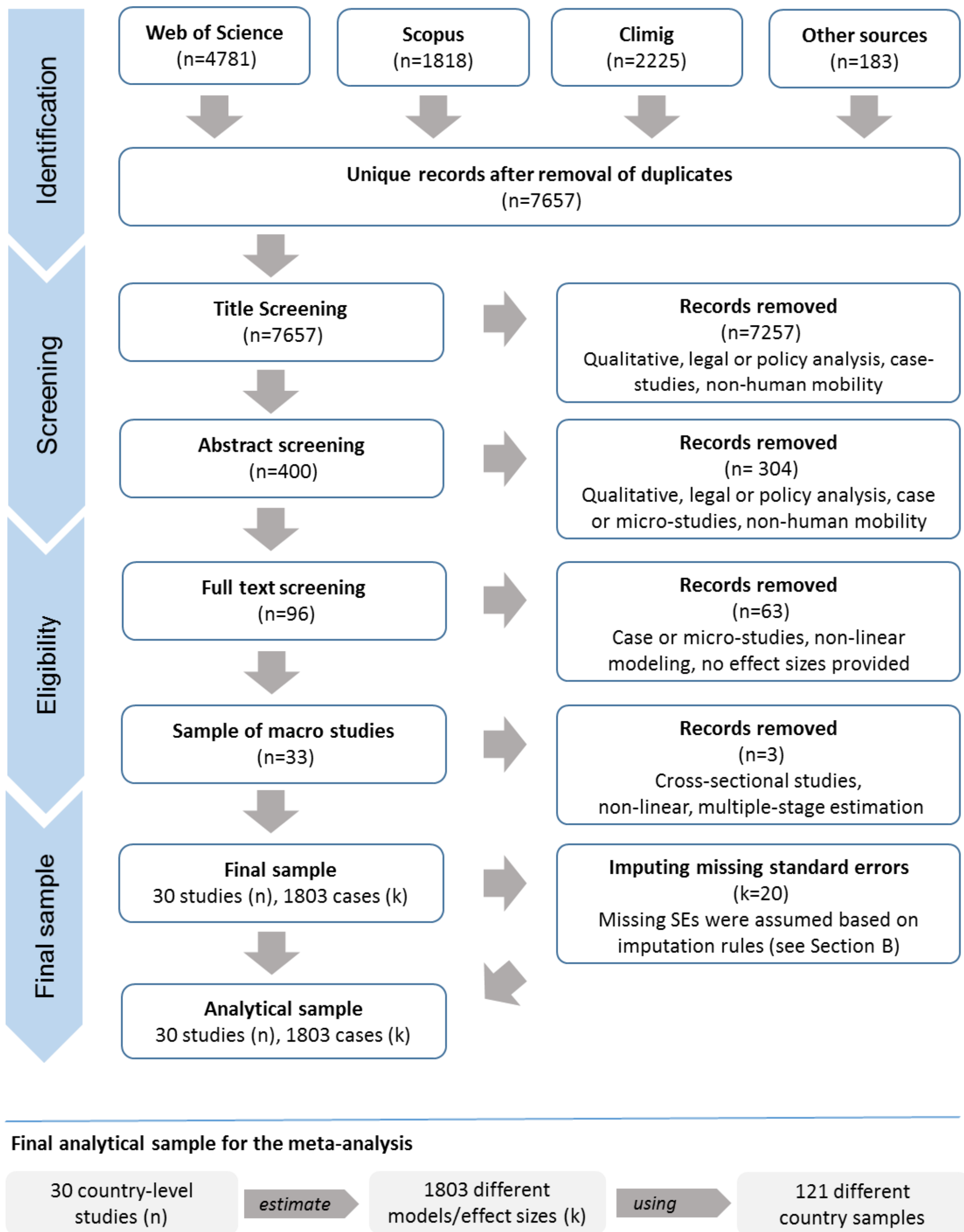

Figure S1 – PRISMA flow diagram. The graph displays the different phases of the literature search and screening. The bottom part shows the link between the selected country-level studies (n), the estimated effect sizes (k) and the different country samples used.

We restricted our search to social sciences, environmental or ecological studies, economics or multidisciplinary subject areas. We also used the CliMig bibliographic database, which provides a comprehensive collection of resources on migration, the environment, and climate change [2]. As an additional source, references provided in relevant papers and citation paths in Google Scholar were screened iteratively during the entire search process to complement the aforementioned databases and to identify any grey literature and working papers that were not captured by the Web of Science, Scopus and CliMig databases.

Our initial search resulted in 7,657 unique references, which were further screened for eligibility. First, we screened the titles of the identified records to exclude irrelevant articles, such as qualitative studies, legal or policy analyses or studies on animal mobility (n=7,257). As a next step, the abstracts of the remaining records were screened, followed by a full text screening to remove any further irrelevant records from the selection (304 and 63 articles were removed, respectively). Based on the full text screening, we derived a first selection of macro studies that analyzed the relationship between environmental factors and migration outcomes at the country level (n=33).

We chose to focus on macro-level studies for reasons of comparability, thus concentrating on studies that allow us to retrieve information on the distribution of the key input and outcome variables included in the analysis, which is required for the standardization of the coefficients (see Section B for the standardization procedure). Thanks to the standardization of the estimates, we can compare the effect sizes across studies and models despite differences in measurement and scaling of the key variables. Furthermore, focusing on macro studies provides a higher degree of comparability also from a methodological point of view, as the estimation frameworks are sufficiently similar to one another in terms of modeling approaches and empirical specifications.

We further restrict the sample to studies analyzing the relationships using longitudinal data, which can infer causal associations between environmental change and migration in a more reliable manner by exploiting variations in environmental variables over time. Two studies by Afifi and Warner (2008) [3] and Ragazzi (2012), [4] which were initially included in the selection of country-level studies, used cross-sectional estimation and were therefore excluded from the sample. Furthermore, the study of Abel et al. (2019),[5] albeit using country-level data and analyzing changes over time, was also excluded as the authors use a three-stage selection model to estimate the effect of climatic variable on conflict and the resulting impact of conflict on asylum seeker flows. The resulting estimates thus cannot be directly interpreted as linear effects of environmental conditions on migration outcomes.

The selection and screening process resulted in a total number of 30 eligible studies (n) estimating 1803 separable effects (k) in different models, which we use as cases for our analysis (see Figure 1 in the main text). In a final step, we imputed missing or incomplete standard errors for few effect coefficients (k=20, n=2) allowing us to also include those in our meta-analysis (see section B for a description of the imputation). The effect coefficients (k) from the single models are estimated based on different country samples with some models considering the relationship only for specific world regions or groups of countries (e.g. low-income economies). We make use of this variation in the sampling by constructing compositional shares indicating the percentage of countries belonging to certain categories (see section C).

B. Calculating Average Effect Sizes

Standardization of Coefficients and Standard Errors

One of the main challenges of meta-analysis is to make individual coefficients comparable across cases. The estimated effects of a variety of environmental factors on different migration outcomes result in different metrics depending on the definition of a particular variable used in the study. In order to make the linear coefficients comparable and to calculate 'average effect sizes', we employ an ex-post beta standardization approach. For this, we retrieve summary statistics on the distribution (i.e. the standard deviations) of the input and output variables used to model the relationships. The information is retrieved from the original papers, by contacting the authors, and from the original data sources used in the studies (e.g. World Bank Global Bilateral Migration Database, CRU-TS Climate Research Unit Data, etc.). Table S2 provides more detailed information on the respective data sources for each of the included papers.

Once the additional information is obtained, the ratio of the standard deviation of the environmental input variable to the standard deviation of the migration outcome serves as a 're-scaling factor'. The standardized coefficients β_{stan} are thus calculated as

$$\beta_{\text{stan,im}} = \beta_{\text{im}} \cdot \frac{\sigma_{\text{E,im}}}{\sigma_{\text{M,im}}} \tag{S1}$$

where $\sigma_{\text{E,im}}$ is the standard deviation of the environmental variable and $\sigma_{M,im}$ is the standard deviation of the migration variable used to estimate the coefficient β_{im} from model i in study m. The standardized standard errors SE are correspondingly computed as

$$SE_{\text{stan,im}} = SE_{\text{im}} \cdot \frac{\sigma_{\text{E,im}}}{\sigma_{\text{M,im}}} \tag{S2}$$

Weighting of Effect Sizes

For our meta-regressions, we employ a standard weighting approach to down-weigh imprecisely estimated coefficients. For a set of K standardized coefficients, we calculate a weighted estimate of the mean standardized effect across study-lines:

$$\widetilde{\beta}_{\text{stan}} = \sum_{i=1}^{K} \omega_{im} \beta_{\text{stan,im}} \tag{S3}$$

where w_{im} is the weight for model i derived from study m. Following a common approach, we use the variance of the estimated effects as a weighting factor [6–8]. Such a method ("precision-weighting”) is considered superior compared to other approaches, as it minimizes the variance of the average weighted effects.[9]

Figure S2 shows the distribution of the unweighted standardized effects in the sample. As can be seen from the graph, there is a substantial heterogeneity across studies, both in terms of the direction and size of the reported environmental effects on migration. Figure 2 in the Extended Data shows the aggregate distribution of the unweighted effect estimates overall, as well as between and within studies in the form of density plots. The between study standard deviation of effect sizes is 0.725.

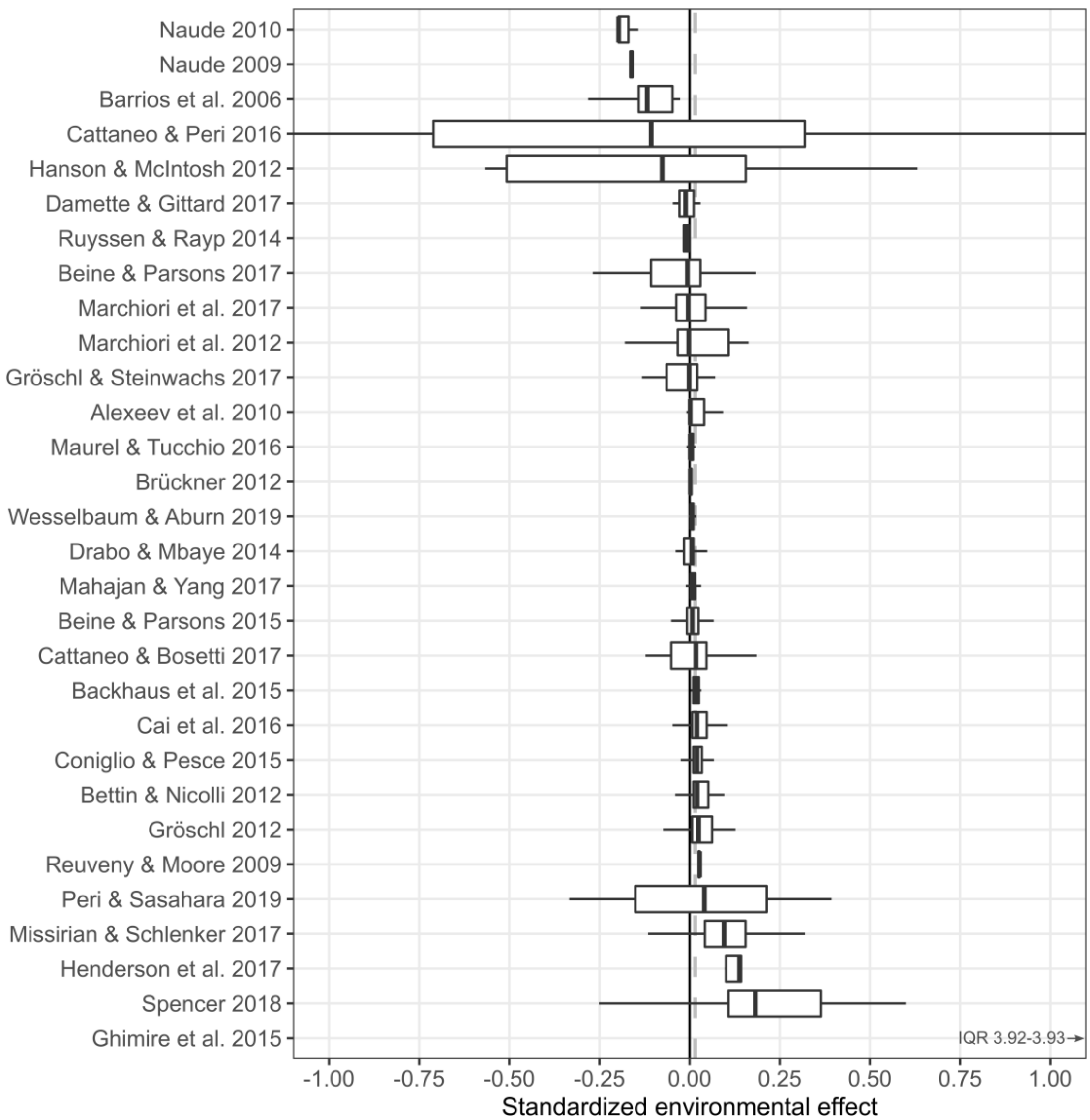

Figure S2 - Distribution of unweighted standardized environmental effects across studies. Boxplots display median and interquartile ranges (IQR) of effects across studies. Whiskers represent either the maximum value or +/- 1.5 of the IQR. Solid line shows zero effect values. Dashed line shows median effect size across all studies and estimates.

Imputing Missing Standard Errors

For few model cases (k=20, 2 studies) in our sample, information on the distribution of the estimated coefficients (standard errors, t-statistics) was missing or incomplete (e.g. studies reporting standard errors of "(0.00)"). To allow for the inclusion of these cases in our analysis, missing or incomplete standard errors were imputed based on two rules: For significant coefficients (significance levels were always provided), we conservatively assume an upper bound standard error, which takes a value such that the estimated coefficient is just significant at the indicated significance level (e.g. for $\alpha = 0.05, SE_{\mathrm{stan,im}} = \beta_{\mathrm{stan,im}}/1.96$). For insignificant coefficients where the p-values are larger than the lowest indicated significance level (mostly $\alpha = 0.1$), we assume a standard error that takes the value of the standardized coefficient ($SE_{\mathrm{stan,im}} = \beta_{\mathrm{stan,im}}$). All results remain fully robust to changes in the imputation rules (e.g. using $SE_{\mathrm{stan,im}} = 2\beta_{\mathrm{stan,im}}$ for insignificant coefficients) or to the exclusion of these effect estimates from the sample.

Non-Linear Transformations

Several of the studies included in the analysis estimate linear models but implement a non-linear transformation of the input and/or output variable in their specifications, such as applying logs. To calculate the standard deviations of the transformed variables, we retrieved the original data either from the original data sources or from the authors, since this information is commonly not reported in the summary tables in the papers. A few papers estimate gravity models making use of Poisson pseudo-maximum likelihood methods, delivering parameter estimates which are directly interpretable as elasticities and thus comparable to log-log gravity models (see for example: [10,11]). In those cases, all variables were log-transformed before calculating the standard deviations and standardizing the coefficients.

Interaction Effects: Binary Interaction Variable

How environmental factors influence migration under different conditions and contexts is a key question addressed in several of the studies considered in our meta-analysis. While some studies test for heterogeneities in effect sizes by analyzing the relationship separately for different sub-samples, others use interaction terms. Typically, the environmental variable is interacted with a binary variable $\mathrm{I_{ct}}$ indicating whether a country c belongs to a specific group in the year t, such as agriculturally dependent or low- and middle-income countries [12,13].

$$\mathrm{M_{ct}} = \alpha + \mathrm{E_{ct}}\beta + \mathrm{E_{ct}} \cdot \mathrm{I_{ct}}\delta + \mathrm{C_{ct}}\gamma + \theta_{\mathrm{c}} + \tau_{\mathrm{t}} + \epsilon_{\mathrm{ct}} \tag{S4}$$

In our analysis, we are interested in differences in the effect size given the composition of the samples underlying the estimated models. In case of an interaction with a country classifying variable (e.g. whether a country is agriculturally dependent or not), we decompose the interaction effect into the main effect β (for $I = 0$) and a combined effect $\beta + \delta$ (for $I = 1$). The two estimates capture the relationship for different sub-samples of countries, e.g. agriculturally dependent ($\beta + \delta$) vs. agriculturally independent (β) countries. From one interaction model i, we can thus derive two separable coefficients, which we generically classify here as model coefficients j and k derived from the same study m. The standardized coefficients can be calculated for the sub-samples, using the standard deviation of the outcome and input variables for the countries included in the sub-samples of the two derived coefficients (e.g. restricting the country samples to only agriculturally dependent vs. agriculturally independent countries).

$$\beta_{stan,jm} = \beta_{im} \cdot \frac{\sigma_{E,jm}}{\sigma_{M,jm}} \tag{S5}$$

$$\beta_{stan,km} = (\beta_{im} + \delta_{im}) \cdot \frac{\sigma_{E,km}}{\sigma_{M,km}} \tag{S6}$$

While the standardization of the standard error of the main effect SE_β is straightforward, the calculation for the combined effect is more complex. Standard errors of interactions are calculated as

$$SE_{\beta+\delta} = \sqrt{SE_\beta^2 + SE_\delta^2 + 2Cov(\beta, \delta)} \tag{S7}$$

where $SE_{\beta+\delta}$ is the standard error of the combined effect. For few cases (<1%), the covariance between the coefficients is unknown and was assumed to be zero. Based on the transformation above, the standardized standard error of the combined effect $SE_{\beta+\delta}$ can be calculated as follows, using information of the output and input variables for the restricted sub-sample of countries:

$$SE_{stan,km} = SE_{\beta+\delta} \cdot \frac{\sigma_{E,km}}{\sigma_{M,km}} \tag{S8}$$

Interaction Effects: Continuous Interaction Variable

While most interaction models in our sample are estimated using binary interaction variables I_{ct} as a country classifier (formula S4), 190 specifications include a continuous variable in the interaction term. For these models, we calculate the average effect of the environmental factor on migration at the mean of the interaction variable I_{ct}, i.e. the interaction effect δ is multiplied by the mean of the interaction variable $\bar{I}$ and added to the main effect β. The standardization is done using the distributional information for the environmental and migration variables for the entire sample of countries.

$$\beta_{\text{stan,im}} = (\beta_{\text{im}} + \delta_{\text{im}} \cdot \bar{\text{I}}) \cdot \frac{\sigma_{\text{E,im}}}{\sigma_{\text{M,im}}} \quad \text{(S9)}$$

Linearization of Quadratic Terms

Some studies estimate non-linear effects of the environmental variable by including quadratic terms in their models [14,15]. In order to include the derived estimates as separate coefficients, the non-linear functions are re-estimated and approximated with a linear functional form. For this, in a first step, we simulate 1000 coefficient combinations based on the coefficient estimates of the linear and quadratic terms, taking the point estimates of the parameters as the mean and the standard error as the standard deviation of the corresponding normal distributions. The resulting 1000 non-linear functions are then fitted with linear models by minimizing the deviations to the curves. The average of the slopes obtained is used as the estimator and the standard deviations of the slopes as its corresponding standard error.

C. Exploring Mechanisms and Context Influences

This section explains the intuition behind our tests of mechanism and sample composition effects. When exploring mechanisms, we are interested in mediating factors explaining how environmental conditions may have an effect on migration outcomes. Sample composition effects refer to the moderating role of certain factors, amplifying or suppressing a relationship.

Mechanisms

The exploration of mechanisms is challenging in meta-analysis, as the basis for the analysis is not primary data but instead the findings from existing empirical studies. We employ a mediation method approach, which builds on differences in the specification of the models used in the studies to infer information about how different factors potentially influence the environment-migration nexus. The approach used mainly yields explorative results, which can be indicative of important patterns and relationships but should not be interpreted as a clear causal inference.

When assessing whether migration depends on environmental change and shocks, we are interested in the total effect of an environmental factor on migration outcomes. Environmental effects on migration can either be direct, for example if they represent an existential threat, such as in the case of displacement due to a rapid-onset disaster, or indirect if they are mediated through another channel. For this analysis, we are interested in the mediating role of income and conflict, which are commonly recognized as important mechanisms explaining environmental effects on migration and are also considered in several of the studies included in our meta-sample. For example, environmental shocks can lead to a reduction in income, subsequently forcing households to migrate in order to sustain their livelihood [12,13]. At the same time, resource scarcity due to environmental change can trigger conflict, which can in turn drive migration [5,8].

Assuming a hypothetical baseline model which regresses a migration outcome on an environmental factor, the estimated relationship between the two variables represents the total effect of a change in the environmental variable on the outcome (Figure S3, Panel A). If a variable X is a mediating factor or mechanism explaining the environmental effect, then controlling for X in the model would reduce the size of the estimated environmental coefficient, which now only captures the direct effect on migration, net of the indirect effect running through the mediator X (Figure S3, Panel B.). We account for this mediator effect by including a variable in our meta-regressions indicating whether an original model controlled for either income/wealth or conflict, the two central channels considered in our analysis.

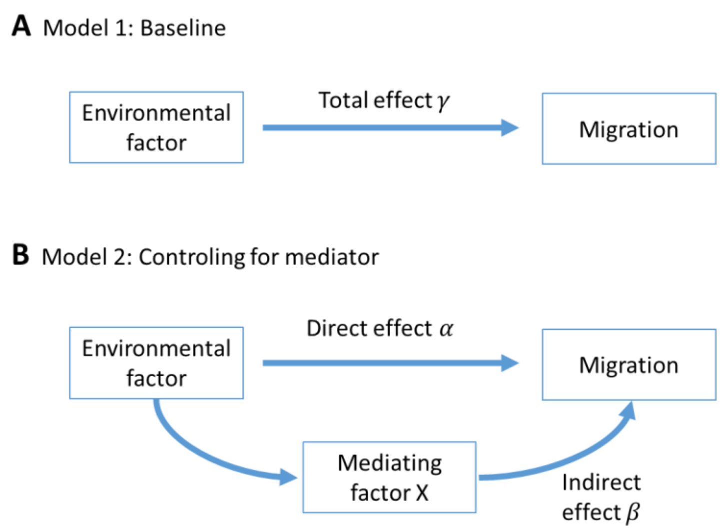

Figure S3 – Conceptual framework. Conceptual framework showing the intuition behind the indirect exploration of mechanisms in the meta-analysis explaining the relationship between environmental factors and migration

Context Effects and Compositional Shares

While we explore differences in the model specification to learn about the potential mechanisms underlying the environmental effects, we use differences in the composition of study samples to analyze the role of context effects. As described above, studies commonly calculate effects separately for different sub-samples or use interaction terms to obtain different effect estimates. The studies included in our analysis base their findings on 121 country samples, consisting of different combinations of countries. We retrieve for each model (k=1803) in the considered studies (n=30) the exact list of countries used to obtain the estimates and calculate the share of countries in each sample belonging to a certain category, namely non-OECD countries, countries in Asia, Sub Saharan Africa, Latin America and the Caribbean, and Middle-East and North Africa, as well as low-income or lower/upper-middle-income countries, agriculturally dependent countries, and countries which experienced major episodes of political conflict since 1960, the mode starting year of most panels considered in our analysis. The general intuition behind this approach is that if countries' characteristics, such as their income level, matter for environmental migration, then a higher or smaller share of countries in the respective sample with high or low income levels should change the estimated effect size.

D. Descriptive Statistics

Our meta-regressions include a variety of variables which were constructed based on information from the individual study cases (k=1803). Table S1 provides information on the categorization of the migration and environmental variables, including details on how they were measured in the original studies. Table S2 shows further details on the migration and environmental data used by each one of the original studies included in the meta-analysis, as well as the modeling strategies used. Table S3 provides an overview of the key variables used in our meta-analysis and presents selected summary statistics on their range and distribution.

Table S1 – Overview of categorization of migration and environmental variables

Our category	Measurement in original studies
Environmental variables	
Precipitation level change	Annual normalized rainfall, log average rainfall, average rainfall, change in average rainfall over longer time horizons, changes in moisture levels
Precipitation variability/anomaly	Anomalies as deviations from the country's long-term mean, divided by its long-run standard deviation, rainfall variability/fluctuation measures (e.g. standard deviation of rainfall), simple deviation/differences from mean levels, variability indices and coefficient of variation, occurrence of droughts
Temperature level change	Annual average temperature, occurrence of extreme or excess temperature levels (dummies), change in temperature level over longer time horizons
Temperature variability/anomaly	Anomalies as deviations from the country's long-term mean, divided by its long-run standard deviation, simple deviation/differences from mean levels, temperature variability/fluctuation measures (e.g. standard deviation of rainfall), variability indices and coefficient of variation
Rapid-onset events	Weather-related, geophysical, climatic or hydrological disaster event (following the EM-DAT classification)
Migration variables	
Internal migration	Share of population living in cities relative to total population, growth of urbanization rate, net internal migration rates (in-migration minus out-migration) per 1km² grid cell
International migration, worldwide	Global bilateral international migration estimates, mostly using data for all countries of the world
International migration, only low/middle-income destinations	International migration to low or middle-income countries, countries in SSA, "Global South", non-OECD countries
International migration, only high-income destinations	International migration to OECD, high-income countries, US, Canada and Spain, Europe and US, EU, "Global North"
International migration, ambiguous destinations	Australia and Asia, "mostly OECD countries" (~22 out of 40 destination countries)

Note: The measurement descriptions are based on the terminologies used in the original studies, OECD, Organization for Economic Co-Operation and Development; EM-DAT; Emergency Events Database by the Centre for Research on the Epidemiology of Disasters (CRED))

Table S2 – Overview of methods and data sources used by original studies

#	Study	Climate data/measurement	Migration data/ measurement	Modeling	Transfor-mation	Standard errors	Inter-actions
1	Barrios et al. 2006	log of normalized precipitation, IPCC	share of population living in cities, UN World Urbanization Prospects	OLS	loglog	robust	binary
2	Naude 2009	disaster occurrence, EMDAT	net migration rate, UN Population Division	FD (System GMM)	linlin	robust	--
3	Reuveny & Moore 2009	log of the total number of people affected by weather-related natural disasters, GEO Data Portal (2005)	log of bilateral migration, OECD Statistics Portal (2006), 1996 and 2003 Statistical Yearbooks of the U.S. Citizenship and Immigration Services Office	OLS, Tobit	loglog	robust	--
4	Alexeev et al. 2010	number/share of affected, number of occurances and fatalities of weather and non-weather related disasters, EM-DAT	migration flow from origin to destination (thousand), OECD, SOPEMI and USINS	OLS	loglog	clustered on directed dyad	con-tinuous
5	Naude 2010	disaster occurrence, EMDAT	net migration rate, UN Population Division	System GMM	linlin	--	--
6	Bettin & Nicolli 2012	Temperature & precipitation anomalies, TYN CY 1.11 CRU University of East Anglia; occurrence of disaster (dummy) in previous 5 years, EM-DAT	change in the stock of migrants in country j from country i between two periods, World Bank GBMD	Zero-Inflated Negative Binomial	loglin	--	con-tinuous
7	Brückner 2012	annual rainfall and precipitation: 1900–2006 Gridded Monthly Time Series, Version ll; data are from Terrestrial Air Temperature 1.01 (Matsuura and Willmott, 2007).	urbanization rate, measured as the share of the population living in urban areas), WDI	OLS	linlin	robust	--
8	Gröschl 2012	number occurrence of geophysical, climatic, meteorological, and hydrological disasters, EMDAT	bilateral decennial migration, World Bank	OLS	loglin	country pair clustered	con-tinuous
9	Hanson & McIntosh 2012	disaster occurrence, EMDAT	census data, birth cohorts in the origin country, WDI	FE	linlin	clustered on orig./dest. region	binary & con-tinuous
10	Marchiori et al. 2012	rainfall and temperature levels and anomalies	net migration rate, share of urban population in total population	FE2SLS	linlin, loglin	robust	binary
11	Drabo & Mbaye 2014	dummy for hydrological disaster, climatological disaster, meteorological disaster, EMDAT; level of temperature and precipitation	bilateral international migration of Schiff and Sjöblom (2008) (World Bank Databases)	OLS, System GMM	linlin	robust	binary
12	Ruyssen & Rayp 2014	log of population affected by disasters, EMDAT; log of temperature deviations from the century average, IPCC	foreign residents in each destination in 1970 and 1980, disaggregated by country of origin, World Bank GBMD	Spatial Durbin model	linlog	bootstrap	none

13	Backhaus et al. 2015	temperature and precipitation levels, Dell et al. (2008)	migration flows, OECD's International Migration Database	FE, FD	loglin	robust	con-tinuous
14	Beine & Parsons 2015	temperature & precipitation anomalies, TS3.0 dataset CRU University of East Anglia; number of disaster events, EM-DAT	bilateral migration rates as the number of migrants from country i in country j as a ratio of natives from i who have stayed in the origin country, Özden et al. (2011)	PPML	loglog	robust	binary& con-tinuous
15	Coniglio & Pesce 2015	disaster, EMDAT; rainfall, excess temperature, temperature level, excess rainfall, rainfall shortage, TYN CY 1.1 database	bilateral migration flows towards OECD countries	PPML	loglin	Clustered by country of destination	con-tinuous
16	Ghimire et al. 2015	rainfall variability, TYN database	flood-induced displacement, Dartmouth Flood Observatory	Random Effects	linlin	Boot-strapped	none
17	Cai et al. 2016	mean temperature and total precipitation, NASA Modern Era Retrospective Analysis for Research and Applications (Rienecker et al.,2011)	outmigration rate (based on bilateral stocks of foreigners in 42 destination countries), Pedersen et al (2008), Adsera and Pytlikova (2015).	OLS	loglin	robust, clustered by origin countries	binary& con-tinuous
18	Cattaneo & Peri 2016	temperature and precipitation levels, Dell et al. (2012)	net emigration rate, Özden et al. (2011)	OLS	loglog, linlog	cluster by country of origin	binary
19	Maurel & Tucchio 2016	coefficient of variation, anomalies, and standard deviation of temperature and rainfall		OLS, 3SLS	loglin	--	-
20	Beine & Parsons 2017	temperature & precipitation anomalies, TS3.0 dataset CRU University of East Anglia; number of disaster events, EM-DAT	bilateral migration rates as the number of migrants from country i in country j as a ratio of natives from i who have stayed in the origin country, Özden et al. (2011)	PPML	loglog	robust	-
21	Cattaneo & Bosetti 2017	mean temperature and total precipitation, Dell et al. (2012); occurence of floods, storms, droughts, EM-DAT	net emigration flows as differences between stocks of foreigners (divided by 1000), Özden et al. (2011)	OLS	linlin	robust	binary
22	Damette & Gittard 2017	precipitation and temperature deviation from long-run mean	net migration rate, corrected for refugee movement	FE2SLS	linlin	--	binary
23	Gröschl & Steinwachs 2017	disaster index, vulcano, drought, earthquake, storm occurrence; rainfall, temperature deviation from mean	bilateral decennial migration rates, World Bank	Gravity	loglog, loglin	robust	--
24	Henderson et al. 2017	2 year change in precipitation and moisture, UDEL data	urban and rural population measures, census reports	OLS	linlin	robust	con-tinuous
25	Mahajan & Yang 2017	hurricane index	confidential immigration data provided by the U.S. Census Bureau, Department of Homeland Security	OLS	linlin	clustered at country level	con-tinuous
26	Marchiori et al. 2017	rainfall and temperature anomalies	net migration rate, share of urban population in total population	FE2SLS	loglin, linlin	robust	binary

27	Missirian & Schlenker 2017	temperature and precipitation levels, TYN CY 1.1	bilateral international migration; share of urban working population, FAOSTAT	FE	loglin	robust	binary
28	Spencer 2018	hurricane wind damage index (occurence and strenght), Strobl (2012)	immigration to the USA, Statistical Yearbook of the United States Immigration and Naturalization Service, Yearbook of Immigration Statistics	FE	loglin	--	--
29	Peri & Sasahara 2019	temperature change	net migration per one-kilometer grid cell, aggregated to country level (de Sherbinin et al., 2015).	OLS	linlin	Clustered at country-level	binary
30	Wesselbaum & Aburn 2019	temperature anomaly, Berkeley Earth Database; disaster occurrence, EMDAT	net migration flow, UN Population Division	OLS	loglin	Clustered at country-pair level	binary& con-tinuous

Note: OECD, Organization for Economic Co-Operation and Development; SOPEMI, Continuous Reporting System on Migration/Système d'observation permanente des migrations; USINS, U.S. Immigration and Naturalization Service; IPCC, Inter-Governmental Panel on Climate Change; CRU, Climatic Research Unit of the University of East Anglia; EM-DAT, Emergency Events Database by the Centre for Research on the Epidemiology of Disasters (CRED); World Bank GBMD, Global Bilateral Migration Database; WDI, World Development Indicators; FD, first differences estimation; FE, fixed effects estimation; Özden et al. (2011)[16]; Dell et al. (2009)[17]; Matsuura and Willmott, (2007)[18]; Rienecker et al (2011)[19]; Pedersen et al (2008)[20]; Adsera and Pytlikova (2015)[21]; Dell et al. (2012)[22]; de Sherbinin et al. (2015)[23].

Table S3 – Summary statistics of all relevant variables used in the meta-analysis

Variables	Mean	St. Dev.	Min	Median	Max
Effect sizes					
Unweighted standardized coefficient	-0.010	0.652	-13.727	0.015	10.861
Standardized standard error	0.183	1.016	0.0001	0.035	38.357
Weighted standardized coefficient	0.835	1.887	-6.146	0.714	17.110
Environmental variables					
Effect of precipitation level change	0.271	0.444	0	0	1
Effect of precipitation variability/anomaly	0.122	0.327	0	0	1
Effect of rapid-onset events	0.216	0.412	0	0	1
Effect of temperature level change	0.303	0.460	0	0	1
Effect of temperature variability/anomaly	0.088	0.283	0	0	1
Environmental event-migration lag>0(in years)	0.174	0.379	0	0	1
Specification controls for other env. Factors (0/1)	0.902	0.297	0	1	1
Measurement timeframe > 1 year	0.285	0.451	0	0	1
Temperature controlled for (0/1)	0.456	0.498	0	0	1
Precipitation controlled for (0/1)	0.501	0.500	0	1	1
Rapid-onset controlled for (0/1)	0.237	0.426	0	0	1
Migration variables					
Internal migration (0/1)	0.120	0.325	0	0	1
International migration, worldwide (0/1)	0.223	0.416	0	0	1
International migration, only low-inc. destinations (0/1)	0.134	0.341	0	0	1
International migration, only high-inc. destinations (0/1)	0.216	0.412	0	0	1
International migration, destination is ambiguous (0/1)	0.307	0.461	0	0	1
Compositional shares					
% non-OECD countries in sample (0-1)	0.910	0.135	0.276	1.000	1.000
% low-income-countries in sample (0-1)	0.483	0.300	0.000	0.417	1.000
% lower-middle-income-countries in sample (0-1)	0.261	0.155	0.000	0.259	0.875
% upper-middle-income-countries in sample (0-1)	0.135	0.112	0.000	0.141	0.571
% agriculturally dependent countries in sample (0-1)	0.428	0.295	0.000	0.333	0.972
% conflict countries in sample (0-1)	0.432	0.113	0.111	0.441	0.857
% countries from Europe/North America in sample (0-1)	0.165	0.152	-0.000	0.151	1.000
% countries from SSA in sample (0-1)	0.390	0.281	0.000	0.309	1.000
% countries from MENA in sample (0-1)	0.105	0.085	0.000	0.112	1.000
% countries from LAC in sample (0-1)	0.164	0.155	0.000	0.169	1.000
% countries from Asia in sample (0-1)	0.177	0.118	0.000	0.172	1.000
Mechanisms controlled					
Income channel controlled for (0/1)	0.505	0.500	0	1	1
Conflict channel controlled for (0/1)	0.324	0.468	0	0	1
Other control variables					
Political environment (0/1)	0.233	0.423	0	0	1
Population size/density (0/1)	0.286	0.452	0	0	1
Past migration levels/flows (0/1)	0.152	0.359	0	0	1
Level of economic development (0/1)	0.520	0.500	0	1	1
Cultural factors (0/1)	0.250	0.433	0	0	1
Geographical factors (0/1)	0.259	0.438	0	0	1
Sum of control variables (0/1)	2.661	2.320	0	1	8

Sample size					
Countries in sample	85.707	57.501	5	67	205
Years covered	30.389	9.727	10	30	50
Start year of time series/panel	1974	11.1	1960	1980	1998
End year of time series/panel	2004	5.2	1990	2001	2015
Fixed effects					
Spatial fixed effects (0/1)	0.921	0.269	0	1	1
Temporal fixed effects (0/1)	0.957	0.204	0	1	1
Other modeling features					
Model uses weights (0/1)	0.281	0.450	0	0	1
Linear specification (ref: log-lin, log-log spec) (0/1)	0.138	0.345	0	0	1
Robustness check (0/1)	0.333	0.472	0	0	1
Publication					
Paper was published in listed scientific journal (0/1)	0.87	0.34	0	1	1

E. Sensitivity Tests

The following section presents additional results and robustness checks, testing for the sensitivity of the findings presented in the main text. All estimations are based on the baseline models presented in Table 1 in the main text. The additional tests indicate that our findings are not sensitive to different specifications and estimations of our meta-regressions.

Table S4 and S5 show the results of meta-regressions only for those estimations, which control for spatial fixed effects (k=1661) and time period fixed effects (k=1725) in their models. The results remain fully robust to these variations in our sample. Table S6 shows the results of mixed effects/random effects meta-regression models, which do not control for study-specific intercepts and allow for a greater influence of between-study variation in the estimation. Also when using this different modeling approach, our main results remain fully robust.

Table S7 shows meta-regression models, which include the 15 additional control variables displayed in Table S14. These are related to the specification of the original models and estimation procedures. Except for minor changes in the migration factor variables, controlling for the additional factors does not alter the results from our main models. The models in Table S8 are estimated removing coefficient estimates with very large effect sizes (>2 standard deviations) from the analysis (k=1767) and Table S9 shows our main meta-regressions considering only international migration estimates (k=1587). The estimated effects remain fully consistent, except for a weakening of the conflict effect in the latter sampling variation (Table S9, Model 5).

Finally, Table S10 shows meta-regression models, which use alternative conflict measures. Aside of the MEPV data, we use data from the Uppsala Conflict Data Base (UCDP) here. All models reproduce Model 5 in Table 1 in the main text. Model 1 in Table S10 shows the results from the main text as benchmark. Here, a country exposed to several conflicts is defined as a country which has experienced at least 5 years of violence in the period 1960-2000. Model 2 in Table S10 considers only civil conflicts in the calculation. Model 3 extends the definition of conflict countries to countries which have experienced at least 10 years of violence in the period 1960-2000. Model 4 and 5 use the UCDP data, which is available for the period 1989 until today. To achieve comparability, we use the years 1989 – 2000 as reference period and define a country as prone to conflict, which has seen in most of the years in this period a conflict (Model 4) or which has seen a conflict with at least 25 fatalities in most of the years in this period (Model 5). Despite the use of different data sets and measurements, the main findings on the role of conflict as a moderator of environmental migration processes holds.

Table S4 – Meta-regression models with precision weighting and study-specific intercepts: Only models controlling for spatial fixed effects

	Outcome Standardized environmental effect				
	Model 1	Model 2	Model 3	Model 4	Model 5
Environmental drivers *(ref: prec. level change)*					
Precipitation variability/anomaly	0.016**	0.016*	0.016**	0.016**	0.016**
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)
Rapid-Onset event	0.015*	0.015*	0.015*	0.015*	0.015*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)
Temperature level change	0.018**	0.017*	0.018**	0.018**	0.017**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Temperature variability/anomaly	0.015*	0.014*	0.014*	0.014*	0.014*
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)
Further environmental controls					
Environment-migration lag in years		-0.001	-0.0004	-0.0005	-0.001
		(0.001)	(0.001)	(0.001)	(0.001)
Measurement timeframe > 1 year [a]		(0.000)	(0.000)	(0.000)	(0.000)
Other environmental factors controlled for		-0.002**	-0.003***	-0.003***	-0.003***
		(0.001)	(0.001)	(0.001)	(0.0005)
Migration destination (*ref: international, worldwide*)					
Internal migration			0.006**	0.006**	0.006**
			(0.002)	(0.002)	(0.002)
International, destination only low/middle-income countries			0.069**	0.067**	0.062**
			(0.031)	(0.029)	(0.027)
International, destination only high-income countries			0.005	0.005*	0.003
			(0.003)	(0.003)	(0.003)
International, destination ambiguous			-0.008**	-0.007**	-0.010***
			(0.003)	(0.003)	(0.003)
Sample composition					
% non-OECD countries in sample				0.007**	
				(0.003)	
% low-income-countries in sample					-0.084***
					(0.022)
% lower middle-income-countries in sample					0.020***
					(0.006)
% upper middle-income-countries in sample					0.048***
					(0.006)
% agriculturally dependent countries in sample					0.117***
					(0.024)
% conflict countries in sample					-0.028***
					(0.003)
# of case observations (k)	1,661	1,661	1,661	1,661	1,661
# of studies (n)	24	24	24	24	24
R-squared	0.273	0.273	0.296	0.302	0.337
Adj. R squared	0.258	0.258	0.279	0.285	0.319

Notes: Meta-regression coefficients with cluster robust standard errors in parentheses. Clustering of standard errors on study level (n=30). The dependent variable is the weighted standardized coefficient derived from the original models (k=1803). All models are based on equation (3) in the Methods section. They control for study-specific intercepts (fixed effects). Additional omitted controls capturing whether the estimate was derived from an interaction term, whether the original study controls for time fixed effects, and the sum of all control variables included in the model. [a] Variable was omitted because of too high collinearity. P-values: * 0.1 ** 0.05 *** 0.01

Table S5 – Meta-regression models with precision weighting and study-specific intercepts: Only studies controlling for time period fixed effects

	Outcome Standardized environmental effect				
	Model 1	Model 2	Model 3	Model 4	Model 5
Environmental drivers *(ref: prec. level change*)					
Precipitation variability/anomaly	0.017**	0.016*	0.016**	0.016**	0.015*
	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)
Rapid-Onset event	0.015*	0.015*	0.015*	0.015*	0.014*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Temperature level change	0.018**	0.017**	0.018**	0.018**	0.017**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Temperature variability/anomaly	0.016*	0.014*	0.014*	0.014*	0.013*
	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)
Further environmental controls					
Environment-migration lag in years		-0.001	-0.0004	-0.0004	-0.001
		(0.001)	(0.0005)	(0.0005)	(0.001)
Measurement timeframe > 1 year		-0.016***	-0.016***	-0.017***	-0.011***
		(0.0004)	(0.0003)	(0.0003)	(0.002)
Other environmental factors controlled for		-0.002**	-0.003***	-0.003***	-0.003***
		(0.001)	(0.0005)	(0.0005)	(0.0005)
Migration destination (*ref: international, worldwide*)					
Internal migration			0.006**	0.006**	0.006**
			(0.002)	(0.002)	(0.003)
International, destination only low/middle-income countries			0.069**	0.068**	0.063**
			(0.031)	(0.029)	(0.027)
International, destination only high-income countries			0.005	0.005*	0.003
			(0.003)	(0.003)	(0.003)
International, destination ambiguous			-0.008**	-0.007**	-0.010***
			(0.003)	(0.003)	(0.003)
Sample composition					
% non-OECD countries in sample				0.006**	
				(0.002)	
% low-income-countries in sample					-0.070***
					(0.020)
% lower middle-income-countries in sample					0.013**
					(0.006)
% upper middle-income-countries in sample					0.042***
					(0.008)
% agriculturally dependent countries in sample					0.101***
					(0.022)
% conflict countries in sample					-0.023***
					(0.002)
# of case observations (k)	1,725	1,725	1,725	1,725	1,725
# of studies (n)	26	26	26	26	26
R-squared	0.278	0.292	0.313	0.318	0.348
Adj. R squared	0.264	0.276	0.297	0.301	0.330

Notes: Meta-regression coefficients with cluster robust standard errors in parentheses. Clustering of standard errors on study level (n=30). The dependent variable is the weighted standardized coefficient derived from the original models (k=1803). All models are based on equation (3) in the Methods section. They control for study-specific intercepts (fixed effects). Additional omitted controls capturing whether the estimate was derived from an interaction term, whether the original study controls for spatial fixed effects, and the sum of all control variables included in the model. P-values: * 0.1 ** 0.05 *** 0.01

Table S6 – Mixed effects meta-regression models with precision weighting (no study specific intercepts)

	Outcome Standardized environmental effect				
	Model 1	Model 2	Model 3	Model 4	Model 5
Environmental drivers *(ref: prec. level change)*					
Precipitation variability/anomaly	0.017***	0.015***	0.015***	0.015***	0.015***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Rapid-Onset event	0.015***	0.015***	0.015***	0.015***	0.014***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Temperature level change	0.018***	0.017***	0.018***	0.018***	0.017***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Temperature variability/anomaly	0.015***	0.014***	0.014***	0.014***	0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Further environmental controls					
Environment-migration lag in years		-0.001	-0.0004	-0.0005	-0.001
		(0.001)	(0.001)	(0.001)	(0.001)
Measurement timeframe > 1 year		-0.016***	-0.016***	-0.017***	-0.011***
		(0.003)	(0.003)	(0.003)	(0.003)
Other environmental factors controlled for		-0.002	-0.003	-0.003	-0.003
		(0.002)	(0.002)	(0.002)	(0.002)
Migration destination (*ref: international, worldwide*)					
Internal migration			0.005**	0.005**	0.006***
			(0.002)	(0.002)	(0.002)
International, destination only low/middle-income countries			0.061***	0.060***	0.057***
			(0.010)	(0.010)	(0.009)
International, destination only high-income countries			0.022**	0.022**	0.020**
			(0.009)	(0.010)	(0.010)
International, destination ambiguous			0.011	0.011	0.008
			(0.014)	(0.014)	(0.014)
Sample composition					
% non-OECD countries in sample				0.006***	
				(0.002)	
% low-income-countries in sample					-0.073***
					(0.011)
% lower middle-income-countries in sample					0.014***
					(0.005)
% upper middle-income-countries in sample					0.044***
					(0.007)
% agriculturally dependent countries in sample					0.103***
					(0.013)
% conflict countries in sample					-0.023***
					(0.006)
Constant	-0.001	0.009	-0.031*	-0.036**	-0.036**
	(0.015)	(0.014)	(0.016)	(0.017)	(0.017)
# of case observations (k)	1,803	1,803	1,803	1,803	1,803
# of studies (n)	30	30	30	30	30
Akaike Information Criterion	-4,551.427	-4,548.674	-4,554.277	-4,552.526	-4,592.184
Bayesian Information Criterion	-4,479.963	-4,460.719	-4,444.333	-4,437.084	-4,454.753

Notes: Meta-regression coefficients with cluster robust standard errors in parentheses. Clustering of standard errors on study level (n=30). The dependent variable is the weighted standardized coefficient derived from the original models (k=1803). All models are based on equation (3) in the Methods section. Omitted controls capturing whether the estimate was derived from an interaction term, whether the original study controls for spatial fixed effects and time fixed effects, and the sum of all control variables included in the model. P-values: * 0.1 ** 0.05 *** 0.01

Table S7 – Meta-regression models with precision weighting and study-specific intercepts: All controls included

	Outcome Standardized environmental effect				
	Model 1	Model 2	Model 3	Model 4	Model 5
Environmental drivers *(ref: prec. level change)*					
Precipitation variability/anomaly	0.018**	0.016*	0.016*	0.016**	0.016*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Rapid-Onset event	0.015*	0.016*	0.016*	0.016*	0.015*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Temperature level change	0.018**	0.018**	0.018**	0.018**	0.017**
	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)
Temperature variability/anomaly	0.016**	0.014*	0.014*	0.014*	0.014*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Further environmental controls					
Environment-migration lag in years		-0.001	-0.001	-0.001	-0.001
		(0.001)	(0.001)	(0.001)	(0.001)
Measurement timeframe > 1 year		-0.018***	-0.018***	-0.018***	-0.010***
		(0.0005)	(0.0004)	(0.001)	(0.002)
Other environmental factors controlled for		-0.003***	-0.003***	-0.003***	-0.003***
		(0.001)	(0.001)	(0.001)	(0.001)
Migration destination (*ref: international, worldwide*)					
Internal migration			0.001	0.001	0.002
			(0.009)	(0.009)	(0.009)
International, destination only low/middle-income countries			0.062	0.062	0.053
			(0.042)	(0.042)	(0.035)
International, destination only high-income countries			0.005	0.005	0.005
			(0.003)	(0.004)	(0.003)
International, destination ambiguous			-0.008**	-0.008*	-0.008**
			(0.003)	(0.004)	(0.004)
Sample composition					
% non-OECD countries in sample				0.0004	
				(0.005)	
% low-income-countries in sample					-0.074***
					(0.022)
% lower middle-income-countries in sample					0.014*
					(0.007)
% upper middle-income-countries in sample					0.046***
					(0.015)
% agriculturally dependent countries in sample					0.106***
					(0.023)
% conflict countries in sample					-0.024***
					(0.007)
# of case observations (k)	1,803	1,803	1,803	1,803	1,803
# of studies (n)	30	30	30	30	30
R-squared	0.289	0.306	0.316	0.316	0.344
Adj. R squared	0.268	0.284	0.292	0.292	0.320

Notes: Meta-regression coefficients with cluster robust standard errors in parentheses. Clustering of standard errors on study level (n=30). The dependent variable is the weighted standardized coefficient derived from the original models (k=1803). All models are based on equation (3) in the Methods section. They control for study-specific intercepts (fixed effects). Additional omitted controls capturing whether the estimate was derived from an interaction term, whether the original study controls for spatial fixed effects and time fixed effects, and the sum of all control variables included in the model. In addition, all controls displayed in Table S14 are included in the models as additional control variables.P-values: * 0.1 ** 0.05 *** 0.01

Table S8 – Meta-regression models with precision weighting and study-specific intercepts: outlier cases (effect > 2 standard deviations) removed

	Outcome Standardized environmental effect				
	Model 1	Model 2	Model 3	Model 4	Model 5
Environmental drivers *(ref: prec. level change)*					
Precipitation variability/anomaly	0.017**	0.016*	0.016**	0.016**	0.015*
	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)
Rapid-Onset event	0.015*	0.015*	0.015*	0.015*	0.014*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Temperature level change	0.018**	0.017*	0.018**	0.018**	0.017**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Temperature variability/anomaly	0.016*	0.014*	0.014*	0.014*	0.013*
	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)
Further environmental controls					
Environment-migration lag in years		-0.001	-0.0004	-0.0004	-0.001
		(0.001)	(0.0005)	(0.001)	(0.001)
Measurement timeframe > 1 year		-0.016***	-0.016***	-0.017***	-0.010***
		(0.0004)	(0.0003)	(0.0003)	(0.002)
Other environmental factors controlled for		-0.002**	-0.003***	-0.003***	-0.003***
		(0.001)	(0.0005)	(0.0005)	(0.001)
Migration destination (*ref: international, worldwide*)					
Internal migration			0.006**	0.006**	0.006**
			(0.002)	(0.002)	(0.003)
International, destination only low/middle-income countries			0.070**	0.069**	0.064**
			(0.031)	(0.030)	(0.028)
International, destination only high-income countries			0.005*	0.006**	0.004
			(0.003)	(0.003)	(0.002)
International, destination ambiguous			-0.007**	-0.007**	-0.010***
			(0.003)	(0.003)	(0.003)
Sample composition					
% non-OECD countries in sample				0.006**	
				(0.002)	
% low-income-countries in sample					-0.073***
					(0.020)
% lower middle-income-countries in sample					0.013**
					(0.006)
% upper middle-income-countries in sample					0.044***
					(0.008)
% agriculturally dependent countries in sample					0.104***
					(0.022)
% conflict countries in sample					-0.022***
					(0.003)
# of case observations (k)	1,767	1,767	1,767	1,767	1,767
# of studies (n)	30	30	30	30	30
R-squared	0.283	0.296	0.318	0.322	0.354
Adj. R squared	0.267	0.279	0.300	0.304	0.335

Notes: Meta-regression coefficients with cluster robust standard errors in parentheses. Clustering of standard errors on study level (n=30). The dependent variable is the weighted standardized coefficient derived from the original models (k=1803). All models are based on equation (3) in the Methods section. They control for study-specific intercepts (fixed effects). Additional omitted controls capturing whether the estimate was derived from an interaction term, whether the original study controls for spatial fixed effects and time fixed effects, and the sum of all control variables included in the model. P-values: * 0.1 ** 0.05 *** 0.01

Table S9 – Meta-regression models with precision weighting and study-specific intercepts: only international migration

	Outcome Standardized environmental effect				
	Model 1	Model 2	Model 3	Model 4	Model 5
Environmental drivers *(ref: prec. level change)*					
Precipitation variability/anomaly	0.017**	0.014*	0.014*	0.014*	0.013
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Rapid-Onset event	0.015*	0.015*	0.015*	0.015*	0.014*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Temperature level change	0.018**	0.018**	0.018**	0.018**	0.017*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Temperature variability/anomaly	0.016**	0.014*	0.014*	0.014*	0.014*
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
Further environmental controls					
Environment-migration lag in years		-0.0001	-0.00005	-0.00004	-0.00001
		(0.001)	(0.001)	(0.001)	(0.001)
Measurement timeframe > 1 year		-0.017***	-0.017***	-0.017***	-0.017***
		(0.002)	(0.002)	(0.002)	(0.002)
Other environmental factors controlled for		-0.002***	-0.002***	-0.002***	-0.002**
		(0.001)	(0.001)	(0.001)	(0.001)
Migration destination (*ref: international, worldwide*)					
International, destination only low/middle-income countries			-0.003	-0.003	-0.006
			(0.004)	(0.004)	(0.005)
International, destination only high-income countries			-0.001	-0.001	-0.001
			(0.004)	(0.004)	(0.004)
International, destination ambiguous			-0.013***	-0.013**	-0.013***
			(0.004)	(0.005)	(0.004)
Sample composition					
% non-OECD countries in sample				-0.002	
				(0.009)	
% low-income-countries in sample					-0.043***
					(0.013)
% lower middle-income-countries in sample					0.021***
					(0.006)
% upper middle-income-countries in sample					0.116***
					(0.026)
% agriculturally dependent countries in sample					0.096***
					(0.011)
% conflict countries in sample					-0.008
					(0.019)
# of case observations (k)	1,587	1,587	1,587	1,587	1,587
# of studies (n)	26	26	26	26	26
R-squared	0.319	0.336	0.336	0.336	0.370
Adj. R squared	0.304	0.321	0.320	0.319	0.352

Notes: Meta-regression coefficients with cluster robust standard errors in parentheses. Clustering of standard errors on study level (n=30). The dependent variable is the weighted standardized coefficient derived from the original models (k=1803). All models are based on equation (3) in the Methods section. They control for study-specific intercepts (fixed effects). Additional omitted controls capturing whether the estimate was derived from an interaction term, whether the original study controls for spatial fixed effects and time fixed effects, and the sum of all control variables included in the model. P-values: * 0.1 ** 0.05 *** 0.01

Table S10 – Meta-regression models with precision weighting and study-specific intercepts: Alternative conflict measures

	Outcome Standardized environmental effect				
	Model 1	Model 2	Model 3	Model 4	Model 5
Environmental drivers *(ref: prec. level change)*					
Precipitation variability/anomaly	0.015*	0.015*	0.015*	0.015*	0.015*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Rapid-Onset event	0.014*	0.014*	0.014*	0.014*	0.014*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Temperature level change	0.017**	0.017**	0.017**	0.017**	0.017**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Temperature variability/anomaly	0.013*	0.013*	0.013*	0.013*	0.014*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Further environmental controls					
Environment-migration lag in years	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Measurement timeframe > 1 year	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Other environmental factors controlled for	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.001)	(0.0005)	(0.001)	(0.001)	(0.001)
Migration destination (*ref: international, worldwide*)					
Internal migration	0.006**	0.006**	0.006**	0.006**	0.006**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
International, destination only low/middle-income countries	0.063**	0.063**	0.063**	0.063**	0.063**
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
International, destination only high-income countries	0.003	0.003	0.003	0.003	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
International, destination ambiguous	-0.010***	-0.011***	-0.011***	-0.011***	-0.011***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Sample composition					
% low-income-countries in sample	-0.074***	-0.073***	-0.077***	-0.072***	-0.071***
	(0.021)	(0.021)	(0.021)	(0.022)	(0.022)
% lower middle-income-countries in sample	0.014**	0.010*	0.011	0.009	0.014**
	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)
% upper middle-income-countries in sample	0.044***	0.045***	0.041***	0.044***	0.045***
	(0.008)	(0.007)	(0.008)	(0.009)	(0.008)
% agriculturally dependent countries in sample	0.104***	0.102***	0.103***	0.100***	0.104***
	(0.022)	(0.021)	(0.023)	(0.022)	(0.021)
Sample composition: Alternative conflict measures					
Conflict at least 5 years, MEPV, 1960-2000	-0.022***				
	(0.003)				
Civil conflict at least 5 years, MEPV, 1960-2000		-0.021			
		(0.014)			
Conflict at least 10 years, MEPV, 1960-2000			-0.019*		
			(0.010)		
Conflict with fatalities for >7 years, UCDP, 1989-2000				-0.023***	
				(0.008)	
Conflict with >25 fatalities for >7 years, UCDP, 1989-2000					-0.036***
					(0.011)
# of case observations (k)	1,803	1,803	1,803	1,803	1,803
# of studies (n)	30	30	30	30	30
R-squared	0.340	0.337	0.338	0.340	0.341
Adj. R squared	0.321	0.318	0.318	0.321	0.322

Notes: Meta-regression coefficients with cluster robust standard errors in parentheses. Clustering of standard errors on study level (n=30). The dependent variable is the weighted standardized coefficient derived from the original models (k=1803). All models are based on equation (3) in the Methods section. They control for study-specific intercepts (fixed effects). Additional omitted controls capturing whether the estimate was derived from an interaction term, whether the original study controls for spatial fixed effects and time fixed effects, and the sum of all control variables included in the model. P-values: * 0.1 ** 0.05 *** 0.01

F. Extended Models and Further Results

Interactions Between Environmental Factors

In this section, the main models presented in Table 1 are extended to further explore underlying factors influencing the environment-migration relationship. Typically, studies consider the effect of several environmental factors at once, which may depend on one another and simultaneously influence migration. These potential interrelations among environmental factors have to be taken into account in the modeling exercise to avoid biases in the estimation [24]. In our main meta-regressions, we control for whether or not the original study simultaneously estimates the effects of different environmental factors. The models in Table S11 test further whether the inclusion of additional environmental variables in the original study changes the estimated migration effects separately for precipitation and temperature (variability/anomalies or level) changes, as well as rapid-onset events.

Table S11 – Weighted meta-regression models: Exploring environmental interactions

	Outcome					
	Standardized effect			Absolute standardized effect		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Standardized coefficient captures:	prec. effect	temp. effect	rapid-onset effect	prec. effect	temp. effect	rapid-onset effect
Additional factors controlled for in models:						
Precipitation controlled	-0.001** (0.001)	0.015*** (0.005)	-0.003 (0.003)	-0.002*** (0.0004)	0.015*** (0.004)	-0.002 (0.003)
Temperature controlled	-0.018*** (0.003)	-0.015*** (0.005)	0.004 (0.004)	0.005*** (0.001)	-0.015*** (0.004)	0.004 (0.003)
Rapid-onset controlled	0.007** (0.003)	-0.001 (0.001)	-0.010*** (0.002)	-0.012*** (0.001)	-0.001 (0.001)	-0.009*** (0.002)
# of case observations (k)	708	705	390	708	705	390
R^2	0.231	0.361	0.528	0.380	0.477	0.600
Adjusted R^2	0.199	0.337	0.496	0.355	0.457	0.573

Notes: Meta-regression coefficients with cluster robust standard errors in parentheses. Clustering of standard errors on study level (n=30). The dependent variable is the weighted standardized coefficients derived from the original study (1-3) and the absolute standardized coefficient (4-6). All models control for study-specific intercepts (fixed effects) and all baseline controls: whether the estimate is derived from an interaction term, whether the original study controls for spatial fixed effects and time fixed effects, and the sum of all control variables included in the original specification. P-values: * 0.1 ** 0.05 *** 0.01

We separate the cases into categories based on whether the coefficients in the original models were estimated for precipitation changes (k=708, Model 1 and 4), temperature changes (k=705, Model 2 and 5), or rapid-onset events (k=390, Model 3 and 6). We test for differences in the estimated coefficients resulting from the inclusion of additional environmental factors in the original model.

Here, we consider both the original coefficients (Models 1-3), which can be positive or negative, and their absolute values (Models 4-6), which are only positive and which serve as a measure of the strength of the relationship irrespective of whether it is positive or negative. Some of the original studies simultaneously estimate the effects of a set of environmental factors falling in the same category, i.e. precipitation change, temperature change or rapid-onset events, which we also account for in our models.

The results presented in Table S11 show that the effects sizes are on average smaller if additional environmental factors falling in the same category are controlled for in the model (see negative effect size changes along the main diagonal of the table). We also find that the effect size and direction depend on the inclusion of environmental factors from other categories in the models. For example, standardized effects of precipitation changes (Table S11, Model 1) are by 0.018 standard deviations weaker if temperature changes are controlled for, whereas temperature effects are estimated larger if precipitation changes are controlled for (Table S11, Model 2). The results suggest important interrelations among the environmental factors, which influence the estimation of the effects.

Environmental Conditions as a Pull Factor

Environmental conditions may not only play a role as a push factor of migration but may also influence the choice of destination. A few cases (k=225), which are not part of our main analytical sample (k=1803 cases), use bilateral migration data (origin-destination country pairs) and test whether environmental conditions in destination countries had an impact on migration flows from the countries of origin. We add the additional coefficients to our meta-sample and construct an additional dummy variable measuring whether the estimated environmental effects on migration reflects changes in the country of origin or destination (Table S12).

Table S12 – Weighted meta-regression models: Environment as pull factor (bilateral migration flows)

	Outcome Standardized effect	
	Model 1	Model 2
Location of environmental shock/change		
Location in destination countries	-0.005*** (0.001)	-0.005*** (0.002)
Environmental drivers *(ref: precipitation level change*)		
Precipitation variability/anomaly		0.006 (0.007)
Rapid-Onset event		0.013* (0.008)
Temperature level change		0.016** (0.008)
Temperature variability/anomaly		0.005 (0.007)
Further environmental controls		
Environment-migration lag in years		0.005*** (0.001)
Other environmental factors controlled for		-0.0001 (0.001)
Measurement timeframe > 1 year		-0.024*** (0.001)
Migration destination (*ref: international, high & low-income*)		
Internal migration		0.004** (0.002)
International, destination only low-income countries		0.064** (0.031)
International, destination only high-income countries		0.003 (0.005)
International, destination ambiguous		-0.008 (0.005)
# of case observations (k)	2,028	2,028
# of studies (n)	30	30
R^2	0.171	0.277
Adjusted R^2	0.156	0.260

Notes: Meta-regression coefficients with cluster robust standard errors in parentheses. Clustering of standard errors on study level (n=30). The dependent variable is the weighted standardized coefficients derived from the original study. All models control for study-specific intercepts (fixed effects) and the baseline controls: whether the estimate was derived from an interaction term, whether the original study controls for spatial fixed effects and time fixed effects, and the sum of all control variables included in the original specification. P-values: * 0.1 ** 0.05 *** 0.01

We find a negative association between this dummy variable and the standardized effects, i.e. a reduction in migration, if the considered environmental factor refers to changes in the potential destination region (Model 1 and 2). This result suggests that environmental change in destination regions also plays a role as a determinant of migration and that worsening environmental conditions can have a negative impact on migration to these regions. All other estimated effects from the main model remain robust to this change in the sample of coefficients considered and the inclusion of the additional dummy variable.

Testing for the Influence of Different Regional Sample Compositions

Table S13 complements the results from Table 1 (Model 4) in the main text, distinguishing study samples by regional composition. It shows that differences in effects are not only explained by the share of non-OECD countries, but also depend on the regional composition of the samples. While we find that a higher share of countries from Europe and North America in the sample significantly reduces the estimated effects on average, a higher share of countries from Sub Saharan Africa

(SSA) and Latin America and the Caribbean (LAC) increases them. Study samples consisting only of SSA countries and samples consisting only of LAC countries find on average 0.011 and 0.015 standard deviation larger effects compared to samples with a share of zero countries from SSA and LAC, respectively.

Table S13 – Weighted meta-regression models: Testing for region sample composition effects

	Outcome				
	Standardized effect				
	Model 1	Model 2	Model 3	Model 4	Model 5
	Europe/NA	SSA	MENA	LAC	Asia
Sample compositions by regions					
% countries from Europe/North America in sample	-0.005*** (0.0004)				
% countries from SSA in sample		0.011** (0.005)			
% countries from MENA in sample			0.005 (0.011)		
% countries from LAC in sample				0.015*** (0.003)	
% countries from Asia in sample					0.002 (0.007)
# of case observations (k)	1,803	1,803	1,803	1,803	1,803
# of studies (n)	30	30	30	30	30
R^2	0.310	0.311	0.305	0.310	0.305
Adjusted R^2	0.291	0.293	0.286	0.291	0.286

Notes: Meta-regression coefficients with cluster robust standard errors in parentheses. Clustering of standard errors is based on study level (n=30). The dependent variable is the weighted standardized coefficients. The models complement Model 4 in Table 1 in the main text. They control for study-specific intercepts (fixed effects), the environmental and migration controls used in Table 1 (Model 4), and all baseline controls: whether the estimate was derived from an interaction term, whether the original study controls for spatial fixed effects and time fixed effects, and the sum of all control variables included in the original specification.
P-values: * 0.1 ** 0.05 *** 0.01

Exploring the Income and Conflict Mechanisms

The strength of the environmental effect can depend on the model specification, particularly if the model controls for potential mediators which are influenced by the environmental factor and also have an impact on migration. If this is the case, the mediator would capture part of the total environmental effect on migration (see Section C above). The models presented in Table S14 test for such changes in the estimated standardized effect sizes depending on whether the original study include potential mediating variables.

We are particularly interested in the role of income and conflict as two potential mediators in the environment-migration pathway. We only consider income and conflict variables as potential mediators if these refer to the same time period as the environmental change variable, or some later period. Other control variables that measure the general level of economic development of the countries or their economic condition prior to measuring the environmental change are grouped under "level of economic development" in Table S14 below.

The models consider the absolute standardized coefficients as an outcome, which reflect the strength of the relationship, regardless if it is positive or negative. We choose not to use the regular (positive or negative) standardized coefficients as an outcome, since controlling for potential mediators may both reduce or increase the size of the original coefficient, depending on whether the relationship between the environmental factor and the migration outcome is estimated to be positive or negative. Using the absolute standardized coefficients allows us to avoid this issue and to test whether the effect size is attenuated upon the inclusion of mediators in the model (Table S14, Model 1). We additionally test for other modeling features which might influence the absolute effect size, such as whether the original study controlled for spatial and temporal fixed effects (Model 2), the sample size (Model 3), other modeling characteristics (Model 4), and information on the temporal distribution of the panel country observation (Model 5), which we capture with two variables measuring the start and end year of each study's country panel.

The results in Table S14 show that absolute standardized effect sizes are considerably reduced in the models that control for income and conflict, by 0.012 and 0.026, respectively. Although we are not able to directly test for the role of both factors, this finding suggests that income changes and conflict risks may be two of the mechanisms explaining how environmental factors influence migration outcomes. Model 1 also assesses the effect of controlling for other variables related to sociopolitical conditions and geographical factors on the standardized coefficients. Several of these variables reduce the estimated environmental effects if controlled for in the model. As it becomes clear from these findings, the specification of the models matters for the estimation of environmental effects on migration.

We find that the use of temporal and spatial fixed effects play a role for the estimation of environmental effects on migration (Model 2). Temporal fixed effects are found to strongly reduce the estimated effect sizes, suggesting that the effect of environmental factors on migration may be influenced by factors which have common trends over time. The use of spatial fixed effects, on the other hand, only slightly changes the absolute effect sizes and has only a marginal effect on the size of the environmental effect as considered in our main models in Table 1. All of our meta-regression models control for whether the original study used temporal and spatial fixed effects to capture their influence on the estimation. As a robustness check (Table S4 and S5), we removed the cases that do not control for unobserved heterogeneity in the form of spatial or time fixed effects from our meta-regressions. All our results are fully robust to this variation in our sample.

Table S14 - Weighted meta-regression models: Testing for model specification and estimation effects

	Outcome Absolute standardized effect				
	Model 1	Model 2	Model 3	Model 4	Model 5
Mechanisms controlled					
Income channel controlled for	-0.012** (0.005)				
Conflict channel controlled for	-0.026*** (0.009)				
Other control variables					
Political environment	-0.001 (0.010)				
Population size / density	-0.026** (0.011)				
Past migration	0.001*** (0.00003)				
Level of economic development	-0.015*** (0.005)				
Cultural factors	-0.018 (0.011)				
Geographical factors	-0.026*** (0.006)				
Sum of control variables	0.014** (0.006)				
Fixed effects					
Temporal fixed effects		-0.022*** (0.0002)			
Spatial fixed effects		0.001*** (0.000)			
Sample size					
Countries in sample			-0.00002** (0.00001)		
Years covered			0.003 (0.003)		
Other modeling features					
Model uses weights				-0.002 (0.004)	
Linear specification (ref: log-lin, lin-log, log-log spec)				0.057*** (0.001)	
Robustness check				0.001 (0.004)	
Time period effects					
Start year of panel					0.013*** (0.005)
End year of panel					0.001 (0.003)
# of case observations (k)	1,803	1,803	1,803	1,803	1,803
# of studies (n)	30	30	30	30	30
R^2	0.389	0.380	0.377	0.377	0.216
Adjusted R^2	0.375	0.369	0.365	0.364	0.201

Notes: Meta-regression coefficients with cluster robust standard errors in parentheses. Clustering of standard errors on study level (n=30). The dependent variable is the weighted standardized coefficient derived from the original models (k=1803). All models are based on equation (3) in the Methods section. They control for study-specific intercepts (fixed effects) and for whether the estimate was derived from an interaction term. P-values: * 0.1 ** 0.05 *** 0.01

Testing for sample size effects, we find that studies which focus on a larger number of countries report significantly lower absolute environmental effects, although the differences are very small (Model 3). In Model 4, we consider the role of modeling choices as determinants of the absolute effect sizes. If the original model is based on a linear (lin-lin) specification as opposed to a logarithmic one (log-log, log-lin, lin-log), the size of the environmental coefficients is larger. While we do not judge which approach is more suitable for estimating environmental migration, we note that design and modeling choices may affect the results. We also find that models which use a more recent country panel (larger panel start year), find on average larger effect sizes, suggesting that the relationship between environmental factors and migration outcomes has become stronger in more recent decades. In further robustness checks (Table S7), we include all of the additional variables considered in this section to our main models. None of our main findings displayed in Table 1 is sensitive to the inclusion of further controls in our meta-regressions.

G. Predicting Environmental Migration

We use the estimates from our meta-regressions to graphically identify hotspots of environmental migration worldwide. For this, a country-level data set with 221 countries is constructed which contains information about country-level exposure to environmental change between 1960 and 2000, as well as the economic and sociopolitical characteristics used to construct the compositional shares for the main models in Table 1 (Model 5): income status, agricultural dependence, and conflict. In our meta-regressions, we show that, depending on the country context, migration responses to environmental change can be very different. In this part of our analysis, we combine our estimates for differential migration responses with the actually observed environmental change in countries in the past decades.

In a first step, based on a simplified version of our main model (Table S15), we fit for each country in the dataset the expected migration response to a one standard deviation variation in its environmental conditions. Recall that our model shows differences in this migration response for studies with different sample compositions. For example, a model with only low-income countries in its sample is predicted to have a 0.097 standard deviation lower migration response compared to a sample with no low-income countries. For our country predictions, we use this information assuming that the migration response is uniform across low-income countries. For a single low-income country we would hence expect a migration response that is lower by 0.097 as compared to the baseline environmental migration response, which is the intercept/constant in our models (representing a sample with no low, middle, agricultural dependent, conflict countries). We proceed similarly for countries belonging to the lower-middle-income country category, upper-middle-income category, agricultural dependent countries and countries that have experienced a long-term conflict.

Table S15 – Weighted mixed effects meta-regressions: Simplified model for predictions

	Outcome Standardized environmental effect
	Model 1
Baseline migration response	
Intercept/constant	0.010 (0.015)
Sample composition effects	
% low-income-countries in sample	-0.097*** (0.011)
% lower-middle-income-countries in sample	0.016*** (0.005)
% upper-middle-income-countries in sample	0.046*** (0.007)
% agriculturally dependent countries in sample	0.130*** (0.013)
% conflict countries in sample	-0.022*** (0.007)
# of case observations (k)	1,803
# of studies (n)	30
Akaike Information Criterion	-4,524.969
Bayesian Information Criterion	-4,448.008

Notes: Meta-regression coefficients with cluster robust standard errors in parentheses. Clustering of standard errors on study level (n=30). The dependent variable is the weighted standardized coefficient derived from the original models (k=1803). All models control for the baseline controls: whether the estimate was derived from an interaction term, whether the original study controls for spatial fixed effects and time fixed effects, and the sum of all control variables included in the original specification. P-values: * 0.1 ** 0.05 *** 0.01

For our country-level predictions, we replace all compositional share variable ranging from 0 to 1 with binary coded variables (0/1) indicating whether a specific country in our country data set belongs to a certain category or not (low-income, lower/upper-middle income/agriculturally dependent, conflict). Based on the estimates from the meta-regression models in Table S15, we then predict migration responses for different countries using the following formula:

$$mig.response_c = 0.01 - 0.097L_c + 0.016LM_c + 0.046UM_c + 0.13AGR_c - 0.022CON_c \qquad \text{(S10)}$$

where $mig.response_c$ is the predicted unique migration response of country c, which is calculated based on the country's characteristics. L_c, LM_c, UM_c, AGR_c, and CON_c are binary variables indicating whether a country belongs to a certain category (1) or not (0). The resulting estimated migration response can be interpreted as expected change in migration in standard deviations for a one standard deviation change in the country's environmental conditions.

In a second step, we combine the estimated differential migration response with information on actually observed environmental hazards. For this, we construct a unique measure, which reflects the exposure to environmental change in each of the 221 countries for the period 1960-2000. The measure is based on three commonly used indicators to capture environmental change and hazards: anomalies in precipitation (absolute values, expressed as standardized deviations from the long-term mean) anomalies in temperature (absolute values, expressed as standardized deviations from the long-term mean), and the share of the population affected by rapid-onset disasters. The first two indicators are based on data from the *Climatic Research Unit* (CRU) *at the University of East Anglia (*time series TS3.26) [25], the third one is based on EM-DAT data[26].

In order to mirror the approach used for the standardization of the model coefficients and to make the three environmental indicators comparable, we standardize them using the standard deviation of the world distribution of each of the three environmental indicators. This allows us to obtain relative measures reflecting the exposure to environmental hazards in relation to the world distribution. The information for the three environmental indicators is summed up in a unique environmental measure capturing the country's aggregate exposure to environmental hazards in the past decades (See Figure S4).

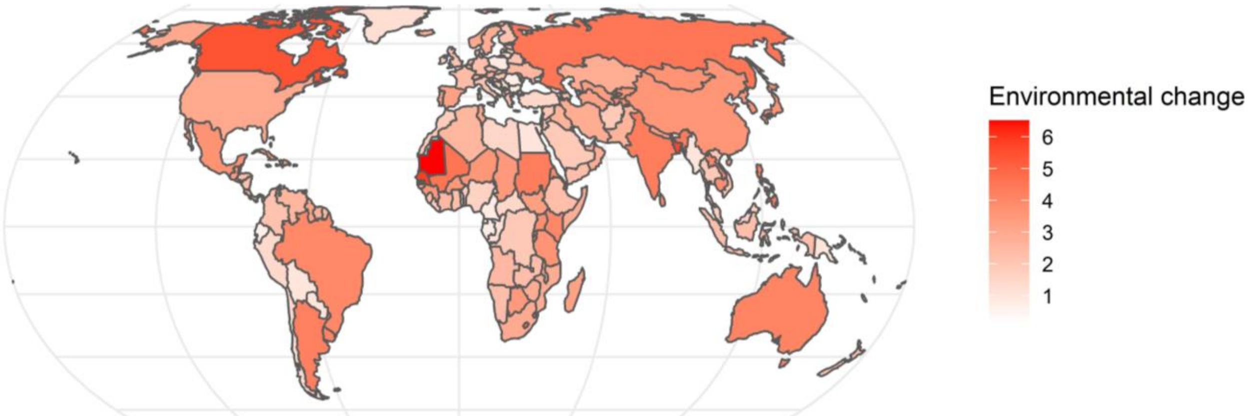

Figure S4 – Observed exposure to environmental change and hazards worldwide, 1960-2000. The aggregated exposure measure is based on three standardized indicators: rainfall anomalies, temperature anomalies, and the share of the population affected by disasters in relation to the world distribution

Multiplying the observed environmental hazard variable (step 2) with the estimated migration response (step 1), we predict the level of environmental migration for each country in our sample. This allows us to identify countries or regions in which environmental change may have led to a stronger migration response. Please note that the derived estimates are only predictions which serve as illustration of our model results. They do not reflect actually observed environmentally-induced migration outcomes and do not represent projections of future migration.

H. Testing for Publication Bias

Publication biases are a major concern in meta-analytical studies. These can arise due to a preference of the research community for significant results, for example, leading to a lower probability of publication for studies with null results. We account for publication biases in our analysis in different ways. First, in the screening and selection phase, we rigorously searched the grey literature to make sure that we include all relevant findings in the field, thus eliminating editorial selection biases. Five of the included studies (16.6%) are unpublished work. In addition, the main models in our analysis control for study-specific intercepts to rule out any systematic differences between published and unpublished work.

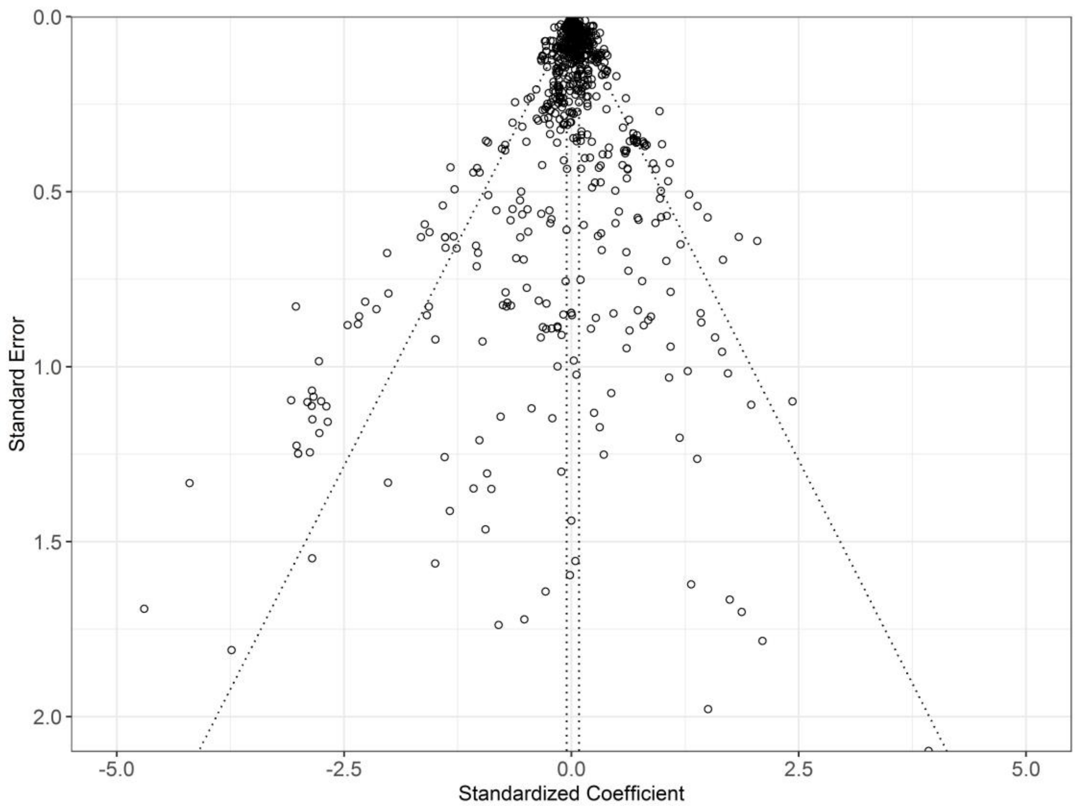

Figure S5 – Funnel Plot. Relationship between standardized coefficients and their corresponding standard errors. Extreme outliers with standardized coefficients > 10 (k=2) were removed

Figure S5 shows a funnel plot, which displays the standardized effect estimates on the x-axis against their standard errors as measure of uncertainty on the y-axis [27]. In the absence of publication biases, we expect studies with higher precision to be located closer to the actual true effect, and studies with lower precision to be located further away. The increasing spread of lower precision studies on both sides of the average should create a funnel-shaped distribution. The depicted distribution follows the described pattern, suggesting that publication bias is not likely to be driving the findings of our analysis.

In Table S16, we explicitly model differences between published and unpublished work. We consider both differences in the standardized coefficients (models 1 and 3) and in the absolute size of the coefficients (models 2, and 4). Models 3 and 4 additionally include the baseline controls. We do not find evidence for publication effect in any of our models. Differences between the effect estimates derived from published and unpublished work are minor and insignificant further suggesting that publication bias is not likely to be driving the findings of our analysis.

Table S16 – Weighted mixed effects meta-regression models: Testing for publication effects

	Outcome			
	Stan. coeff	Absolute stan. coeff	Stan. coeff	Absolute stan. coeff
	Model 1	Model 2	Model 3	Model 4
Published in journal	0.005 (0.013)	0.002 (0.022)	0.006 (0.013)	0.004 (0.022)
Constant	0.006 (0.012)	0.038* (0.020)	0.009 (0.018)	0.055** (0.027)
Baseline controls included	No	No	Yes	Yes
# of case observations (k)	1,803	1,803	1,803	1,803
# of studies (n)	30	30	30	30
Akaike Information Criterion	-4,528.442	-4,967.249	-4,486.573	-4,946.426
Bayesian Information Criterion	-4,506.453	-4,945.260	-4,431.601	-4,891.454

Notes Meta-regression coefficients with cluster robust standard errors in parentheses. Clustering of standard errors on study level (n=30). The dependent variable is the weighted standardized coefficients derived from the original study models (Models 1 and 3) and the absolute standardized coefficient (Models 2 and 4). Models 3 and 4 also control for the baseline controls: whether the estimate was derived from an interaction term, whether the original study controls for spatial fixed effects and time fixed effects, and the sum of all control variables included in the original specification. P-values: * 0.1 ** 0.05 *** 0.01

I. Detailed Documentation of Procedures

Based on the selection criteria described in section A of the supplementary materials, we identify 30 studies to be included in the meta-analysis. For each of these studies, the coefficients are standardized based on the formulas presented in section B. We use the coefficients of all environmental variables reported in the studies, including robustness checks and alternative specifications, as long as the data employed are at the country level, all the information necessary for standardizing the coefficients is available, and the coefficients can be interpreted as a linear effect of an environmental variable on migration.

While some of the studies provide all the information necessary to perform the standardization, for example in detailed summary statistics tables or by providing access to the data, the majority of the studies either do not report such information or the available information is incomplete. For example, in some cases the reported summary statistics do not account for certain data transformations (such as log transformations) or the focus on specific sub-samples of countries.

In the case of missing or incomplete summary statistics, we contacted the authors and requested the original data used in the analysis. If the data were not provided, we retrieved data from the original sources or, in few cases, from alternative sources, and calculated the standard deviations (SD) of the respective variables. Below we provide details on the standardization procedure for each of the studies included in our meta-analysis.

Barrios, Bertinelli and Strobl 2006.

The study uses a log-log transformation of the input and outcome variables to model environmental effects on migration. The original sources were used to retrieve and transform the original variables necessary to perform the standardization of the coefficients. Environmental data: Rainfall data were retrieved from the *Tyndall Centre for Climate Change Research* (TYN CY 1.1) for the list of developing countries included in the study (see Appendix Table A). Following the method employed in the paper, the yearly data were normalized by the long-term mean annual rainfall (1900-1960) and five-year averages were generated for the period 1960-1990. The data were then converted to logs to calculate the standard deviations for the respective sample of countries. Migration data: The urbanization data were retrieved from the *UN World Urbanization Prospects 2018*. The urbanization rate data by country and five-year period were logged. The standard deviations are calculated separately for the full sample of countries and for the sample of Sub-Saharan African and Non Sub-Saharan African countries to account for the interaction term in Table 3, col. 3, between the climate variable and a dummy for SSA (see equations (S4) to (S8) in section B above). Results reported in Table 3, col. 6, are not included as separate cases due to the use of interactions with three variables.

Naude 2009, 2010

Standard deviations of the environmental and migration variables were retrieved from the summary statistics table (Table A1 in the Appendix).

Reuveny and Moore 2009

The original data were retrieved to reproduce the variables used in the study. The paper proposes three indicators of environmental conditions – arable land, crop land and disasters. We omit the first two indicators from our analysis because they measure agricultural activities rather than environmental or natural processes. We retrieve data on the number of affected people by disasters of natural origin (excluding earthquakes, insect infestation and volcanic eruptions, following the definition employed by the authors) from *GEO data portal* for the period 1980-2000. In order to avoid dropping zero values, when log-transforming the variables one is added to all observations, following the method employed by the authors. The migration indicator used in the study is the log of the number of migrants from the country of origin to the country of destination. We calculate the standard deviation of the migration variable based on OECD data for the sample of European countries covered in the analysis for the period 1990-2000. The study also includes some data points from the *Statistical Yearbooks* of the U.S. Citizenship and Immigration Services Office. Due to the inaccessibility of these data, these estimates were not included in our meta-analysis sample.

Alexeev, Good and Reuveny 2010

The study uses a log-log transformation of the input and outcome variables to model environmental effects on migration. The original sources were used to retrieve and transform the variables necessary to perform the standardization of the coefficients. Data on weather-related and non-weather-related disasters (total affected population, total number of people killed, area and total population size at national level) were retrieved from the *GEO Data Porta* for the period 1986-2004. We generated variables measuring the total number of affected people divided by country area and the total number of affected people divided by total population size. The standard deviations were calculated based on the log-transformed variables. The migration data employed in the study come from three different sources (*OECD*, *SOPEMIS* and *USINS*) and are therefore more difficult to reproduce. Instead, migration data from Cai et al. (2016) [28] are used, which provide comparable migration variables with an almost identical distribution (compared to the summary statistics reported in Table 1 of the paper). To avoid having to drop zero values when log-transforming the migration variable, one is added to all observations, following the method employed by the authors. For the standardization of interaction terms reported in Tables 2 and 3 we used data on GDP per capita available from Cai et al. (2016) and data on foreign aid flows retrieved from the *OECD* database (DAC2a). A covariance of zero across parameter estimates is assumed for the calculation of the standard error of the effect of interaction terms.

Bettin and Nicolli 2012

This paper uses a zero-inflated negative binomial model, whose parameters can be interpreted as semi-elasticities, i.e. percentage change in the migration variable due to a one-unit change in the environmental variable. We use the standard deviations of the log-transformed migration variable and of the level environmental variable to standardize the coefficients of interest. The original data were retrieved to perform the transformation. Yearly temperature and precipitation data were retrieved from *TYN CY 1.1* for all countries. Measures for temperature and precipitation anomalies are constructed based on 5-year mean values and relative to the long-term mean (1901-2000). Standard deviations of the temperature and precipitation anomaly variables are calculated for the respective sample of countries. Additionally, data on meteorological, hydrological and climatological disasters are retrieved from EM-DAT. Number of disasters by country and 5-year periods are calculated and standard deviations are obtained for the respective sample of countries. We retrieved data on bilateral migration stocks from the World Bank *Global Bilateral Migration Database* (GBMD) and constructed a measure of decadal migration flows per country-pair. To avoid dropping zero values, one was added to each observation before log-transforming the variable and calculating the standard deviations, following the method employed in the study.

Brückner 2012

The summary statistics reported in Table 1 of the paper are used to standardize the climate coefficients. We only include results from Tables 2 and 3, which present the impact of different environmental variables on the urbanization rate as a main outcome. Selected models are estimated including quadratic terms. The non-linear functions are re-estimated and approximated with a linear functional form allowing us to derive coefficients from linear approximations which are comparable with the other cases (see section B for further details).

Gröschl 2012

Standard deviations of the environmental and migration variables were retrieved from the summary statistics table (Table 7 in the Appendix). The coefficient of the interaction terms in Tables 2, 4, 5 and 6 were standardized using the equations presented in Section B. For the standardization of coefficients in Table 3, we recalculated the corresponding standard deviations for the respective subgroups of countries.

Hanson and McIntosh 2012

We use the original data and codes provided by the authors to calculate standard deviations of the environmental and migration variables employed in the study. The coefficients of the interaction terms in Table 5 are the marginal effect of disasters at the mean of the interacted variables.

Marchiori, Maystadt and Schumacher 2012, 2017

We use the original data and codes provided by the authors to calculate the standard deviations of the environmental and migration variables employed in the studies. For our analysis, we include those models which consider international migration or urbanization as outcomes, including models estimated as the first stage of an instrumental variable estimation.

Drabo and Mbaye 2014

The summary statistics reported in Table 1 of the paper were used to standardize the climate coefficients. We did not include results from Tables 3, 4 and 5, which focus on migration of high, low and medium-educated people, respectively, because summary statistics are not reported for these groups separately. Similarly, we omit the results reported in Tables 8 and 10, which focus on high-educated migrants only. The results reported in Table 7 include interaction terms between the environmental variable and regional dummies. The standard deviations are calculated for the respective country sub-groups (e.g. SSA, EAP, ECA).

Ruyssen and Rayp 2014

Standard deviations of the environmental and migration variables were retrieved from the summary statistics table (Table A3 in the Appendix). We only include coefficients corresponding to direct effects of changes in environmental conditions in a country on migration from that country (Table 2) and omit the indirect effects on neighboring countries reported in Table 3.

Backhaus, Martinez-Zarzoso and Muris 2015.

We use the original data and codes provided by the authors to calculate standard deviations of the environmental and migration variables employed in the study. All environmental coefficients, including the ones calculated for the lagged temperature and precipitation variables (Table 3), are included in our meta-analysis. To standardize the coefficients of the interaction terms in Table 4, we follow the procedure outlined in equation (S9) above (see section B).

Beine and Parsons 2015.

This paper reports results of a Poisson Pseudo-Maximum Likelihood (PPML) estimator with log-transformed environmental regressors. The coefficients can be interpreted as elasticities, i.e. percent changes in the migration variable due to a one percent change in the environmental variable. Therefore, the standard deviations of the log-transformed variables is used for both the dependent migration variables and the independent environmental variables. The original data was retrieved from the sources mentioned in the paper to reproduce the variables used in the analysis. Data on the number of natural disasters (droughts, earthquakes, extreme temperature, floods, storms and volcanic eruption) are retrieved from EM-DAT for the period 1960-2000. We do not consider epidemics, insect infestations and miscellaneous occurrences because these go beyond our definition of environmental push factors. We generate variables for the number of disasters per country and decade for each type of disaster and log-transform the data. In order not to lose zero values, one is added to each observation. The standard deviations of the log-transformed data are calculated for the respective sample of countries. To capture long-run environmental factors, gridded data on monthly mean temperature and precipitation for the period 1901-2014 are obtained from the *Climatic Research Unit* (CRU) *at the University of East Anglia* (TS3.25 dataset) and cropped to country boundaries. First, annual mean values for temperature and precipitation are calculated for the sample of countries. Mean decadal values are then generated for each country for the period 1960-2000 and converted to decadal deviations and anomalies relative to the long-term average (1901-2000). Excess (positive values) and shortage (negative values) temperature and precipitation are considered separately. The data are then log-transformed and standard deviations are calculated for each climate measure for the respective sample of countries. We retrieve the original migration data used in the paper from the *World Bank GBMD* for the period 1960-2000. The migration stock variable is converted to flows by taking the difference in migration stocks between two consecutive censuses. Negative values are dropped from the sample. The flow data are merged with World Bank data on total population size to calculate decadal migration rates per country and decade (number of migrants from country *i* in country *j* as a ratio of natives from *i* who stayed in country *i*). The data are log-transformed with a value of one added to each observation in order not to lose zero values. Standard deviations are calculated for the respective sample of countries employed in the analysis. To standardize the coefficients of Tables 9 and 10, we adjust the migration measure for return migration before calculating the standard deviations. To standardize the environmental coefficients of Table 13, we retrieve data from the *UN World Urbanization Prospects* and generate a measure for the log of urbanization (share of the population living in urban areas).

Coniglio and Pesce 2015

This paper uses a PPML model. Its results can be interpreted as semi-elasticities, i.e. percentage change in the migration variable due to a unit change in the environmental variable. We use the standard deviation of the log-transformed migration data and of the level environmental data to standardize the coefficients of interest. Standard deviations for the environmental variables were retrieved from the summary statistics table in the Appendix. Bilateral migration data were retrieved from the OECD migration database. Yearly migration flows were calculated, the data were log-transformed after adding a value of one to each observation to avoid dropping zero values, and the standard deviations were calculated for the respective sample of countries. We calculated standard deviations also for subsamples defined by region of origin and region of destination from the original data as described above. Coefficients of the interaction terms in Table 2 and Table 4 were standardized using equation (S9) and coefficients of the interaction terms in Table 5a were standardized using equations (S4) to (S8) above (see section B). In the appendix the authors provide a robustness check using the International Migration Database of the UN Population Division as outcome variable. We calculate summary statistics from these data and use the same transformations to calculate migration flows.

Ghimire et al. 2015

Only the models which consider migration as the outcome variable (Tables 8 and 12) are included in our set of estimates. Standard deviations of the environmental and migration variables are directly retrieved from the summary statistics table (Table 1) in the paper.

Cai et al. 2016

We use the original data and codes provided by the authors to calculate standard deviations of the environmental and migration variables used in the study.

Cattaneo and Peri 2016

We use the original data and codes provided by the authors to calculate standard deviations of the environmental and migration variables employed in the study. Coefficients for country sub-samples were standardized using equations (S4) - (S8) (see section B).

Maurel and Tucchio 2016

Data were retrieved from the original sources. We retrieve data on yearly temperature and precipitation from the *TYN CY 1.1* dataset to calculate decadal averages by country. Based on these, we calculate standard deviations, coefficients of variation and anomalies relative to the country-specific long-term mean (1901-2000). The standard deviation of each climate variable is obtained for the sample of countries included in the analysis. Bilateral migration data are obtained from the *World Bank GBMD* dataset for the period 1960-2000. We convert the stock variable into flows by taking the difference between two consecutive decades. Negative values are dropped from the sample and one is added to each observation before converting it to logs to avoid losing zero values, following the method employed by the authors. We also retrieve decadal data from FAOSTAT for the period 1961-2001 to reproduce the urbanization variable (share of the population living in urban areas) and the share of urban workers in total population (difference between total workers and agricultural workers divided by total workers) by country and decade. The change in urbanization and in the share of urban workers is then calculated and converted to logs. Finally, the standard deviations are estimated for the sample of countries employed in the analysis. When standardizing the coefficients of Table 6, col.3, neighboring countries are not excluded from the sample (as in the models). Instead, we use the standard deviations for the full sample of countries for the standardization of the coefficients.

Beine and Parsons 2017

The data were retrieved from the original sources. The data and methods employed in this paper are identical to Beine and Parsons (2015) and the same standardization procedure is used. Two notable differences are that Beine and Parsons (2017) do not consider OECD countries of origin and that they analyse data for poor and middle-income countries separately. We make the necessary data adjustments and calculate the standard deviations for the environmental and migration variables for the respective samples of countries. In addition, the disasters variable is not disaggregated by type of disaster and an additional data source is used as a robustness check (*Ifo Game*) in Table 4. We retrieved the data from *Ifo Game* to reproduce the disasters variables and calculated the standard deviations for the respective sample of countries for the standardization of coefficients.

Cattaneo and Bosetti 2017

We only include models which consider migration as outcome variable (Table 1). The original data are retrieved to calculate standard deviations separately for the groups of low, middle and high-income countries needed for the standardization of the interaction terms in Table 1. Yearly temperature and precipitation data were retrieved from *TYN CY* 1.1 for all countries. Decadal averages were calculated for each country and standard deviations generated for the sample of low, middle, and high-income countries, respectively. Additionally, country-level data for floods, storms and droughts were retrieved from *EM-DAT*; Measures for number of disasters per decade were constructed for each type of disaster and standard deviations were calculated for the three country groups separately. Migration data: Data on bilateral migration stocks were retrieved from the *World Bank GBMD*. The data were converted to decadal migration flows per 1000 population and standard deviations were calculated for the respective sample of countries.

Damette and Gittard 2017

The authors use the same data as Marchiori et al. (2012), which are extended by including a measure for remittances (Table 1 and 2). The original data and codes provided by Marchiori et al.

are used to calculate the standard deviations of the environmental and migration variables. The models presented in Table 3 are not considered in our analysis, as they use agricultural income as main dependent variable.

Gröschl and Steinwachs 2017

This paper uses a PPML (Poisson pseudo maximum likelihood) model. The estimated coefficients can be interpreted as semi-elasticities, i.e. percentage change in the migration variable due to one-unit change in the environmental variable. We use the standard deviations of the log-transformed migration data and the level environmental data to standardize the coefficients of interest. The standard deviations of the environmental variables are retrieved from the summary statistics table (Table A1 in the Appendix). Data on bilateral migration stocks are retrieved from the *World Bank GBMD* and converted to decadal migration flows. Migration rates per country and decade are then calculated by dividing the migration flows by the country's total population size at the given period. One is added to each migration flow observation in order to avoid dropping zero values. The migration rate variable is log-transformed to calculate the standard deviations for the respective sample of countries.

Henderson, Storeygard and Deichmann 2017

We use the original data and codes provided by the authors to calculate standard deviations of the environmental and migration variables employed in the study. We only consider coefficients reported in Table 5 as all other estimates are not based on country-level data.

Mahajan and Yang 2017

Standard deviations of the environmental and migration variables were retrieved from the summary statistics table (Table 1). Results from Tables 3 and 6, which focus on specific age groups of migrants, are not included in our meta-analysis because summary statistics are not available for these age group separately. A covariance of zero is assumed to calculate the aggregated standard error of the parameter estimates for those cases that include an interaction term.

Missirian & Schlenker 2017

We use the authors' original data to calculate standard deviations of climate and migration variables. Selected models are estimated including quadratic terms. The non-linear functions are re-estimated and approximated with a linear functional form allowing us to derive linear coefficients, which are comparable with the other estimations (see section B for further details).

Spencer and Urquhart 2018

Standard deviations of the environmental variables are retrieved from the summary statistics table (Table 2 in the paper). Migration data from the *United States Immigration and Naturalization Service* and the *Office of Immigration Statistics* are used to calculate the standard deviations of the outcome variable. The data are collected from national statistical offices of destination countries and cover the period 1980-2010. We construct an indicator of emigration flow divided by origin country's population for the sample of countries covered in the analysis. The indicator is logged and standard deviations are calculated for the full sample, and for the period 1989-2000 and 1995-2005 for standardizing coefficients in Table 5.

Aburn and Wesselbaum 2019

Original data provided by the authors were used to calculate standard deviations of the environmental and migration variables. We consider only those results related to environmental conditions in the countries of origin. The manuscript contains coefficient estimated of interaction terms with continuous variables (Table 3, col. 17-19). For these, we re-calculated the effect of the environmental variable at the mean of the interaction variable, as described in formula S5 (see section B).

Peri and Sasahara 2019

This paper analyses data at the grid-cell level and aggregated data at the country level. To allow for a standardization of the coefficients, we focus on models using country level data only (Tables 3 and A7). The original gridded monthly temperature data were retrieved from the *CRU TS3.25* for the period 1960-2000. The gridded data were aggregated by country taking the average of all grid-cell values. The monthly data are converted to yearly averages by taking the mean of the monthly values. Standard deviations of the climate variable are calculated separately for the sample of poor, lower and upper-middle income countries. Standard deviations of the migration variables are retrieved from the summary statistics tables (Tables A1 and A2 in the Appendix).

References

1. Borenstein, M., Hedges, L. V., Higgins, J. P. T. & Rothstein, H. R. *Introduction to Meta-Analysis*. (John Wiley & Sons, 2009).
2. Piguet, E., Guélat, J. & Kaenzig, R. CLIMIG Bibliographic Database. https://www.unine.ch/geographie/Migration_and_Climate_Change (2019).
3. Afifi, T. & Warner, K. The impact of environmental degradation on migration flows across countries. UNU-EHS Working Paper 05/2008 (2008).
4. Ragazzi, P. Climate Change and Migration: A Gravity Model Approach. Working Paper, University of Ferrara, Department of Economics, 2012031 (2012).
5. Abel, G. J., Brottrager, M., Crespo Cuaresma, J. & Muttarak, R. Climate, conflict and forced migration. *Glob. Environ. Chang.* **52**, 239–249 (2019).
6. Hedges, L. V. & Olkin, I. *Statistical Methods for Meta-Analysis*. (Academic Press, 1985).
7. Borenstein, M., Hedges, L. V., Higgins, J. P. T. & Rothstein, H. R. A basic introduction to fixed-effect and random-effects models for meta-analysis. *Res. Synth. Methods* **1**, 97–111 (2010).
8. Hsiang, S. M., Burke, M. & Miguel, E. Quantifying the Influence of Climate on Human Conflict. *Science (80-.).* **341**, 1235367 (2013).
9. Marín-Martínez, F. & Sánchez-Meca, J. Weighting by Inverse Variance or by Sample Size in Random-Effects Meta-Analysis. *Educ. Psychol. Meas.* **58**, 211–220 (2010).
10. Beine, M. & Parsons, C. Climatic Factors as Determinants of International Migration. *Scand. J. Econ.* **117**, 723–767 (2015).
11. Wesselbaum, D. & Aburn, A. Gone with the Wind : International Migration. *Glob. Planet. Change* **178**, 96–109 (2019).
12. Marchiori, L., Maystadt, J. F. & Schumacher, I. The impact of weather anomalies on migration in sub-Saharan Africa. *J. Environ. Econ. Manage.* **63**, 355–374 (2012).
13. Marchiori, L., Maystadt, J. F. & Schumacher, I. Is environmentally-induced income variability a driver of migration? *Migr. Dev.* **6**, 33–59 (2017).
14. Brückner, M. Economic growth, size of the agricultural sector, and urbanization in Africa. *J. Urban Econ.* **71**, 26–36 (2012).
15. Missirian, A. & Schlenker, W. Asylum applications respond to temperature fluctuations. *Science (80-.).* **358**, 1610–1614 (2017).
16. Özden, Ç., Parsons, C. R., Schiff, M. & Walmsley, T. L. Where on earth is everybody? The evolution of global bilateral migration 1960-2000. *World Bank Econ. Rev.* **25**, 12–56 (2011).
17. Dell, M., Jones, B. F. & Olken, B. A. Temperature and income: Reconciling new cross-sectional and panel estimates. *Am. Econ. Rev.* **99**, 198–204 (2009).
18. Willmott, C. & Matsuura, K. Terrestrial air temperature and precipitation: Monthly and annual climatologies. *Centre for Climate Research, Department of Geography, University of Delaware* (2001).

19. Rienecker, M. M. *et al.* MERRA: NASA's modern-era retrospective analysis for research and applications. *J. Clim.* **24**, 3624–3648 (2011).

20. Pedersen, P. J., Pytlikova, M. & Smith, N. Selection and network effects-Migration flows into OECD countries 1990-2000. *Eur. Econ. Rev.* **52**, 1160–1186 (2008).

21. Adserà, A. & Pytliková, M. The Role of Language in Shaping International Migration. *Econ. J.* **125**, 49–81 (2015).

22. Dell, B. M., Jones, B. F. & Olken, B. A. Temperature Shocks and Economic Growth: Evidence from the Last Half Century. **4**, 66–95 (2012).

23. de Sherbinin, A. *et al.* Global Estimated Net Migration Grids by Decade: 1970-2000. NASA Socioeconomic Data and Applications Center (SEDAC), Palisades, NY (2015).

24. Auffhammer, M., Hsiangy, S. M., Schlenker, W. & Sobelz, A. Using weather data and climate model output in economic analyses of climate change. *Rev. Environ. Econ. Policy* (2013) doi:10.1093/reep/ret016.

25. Harris, I., Jones, P. D., Osborn, T. J. & Lister, D. H. Updated high-resolution grids of monthly climatic observations - the CRU TS3.10 Dataset. *Int. J. Climatol.* **34**, 623–642 (2014).

26. Centre for Research on the Epidemiology of Disasters. EM-DAT: The Emergency Events Database. www.emdat.be (2020).

27. Egger, M., Davey Smith, G., Schneider, M. & Minder, C. Bias in meta-analysis detected by a simple, graphical test. *BMJ* **13**, 629–634 (1997).

28. Cai, R., Feng, S., Oppenheimer, M. & Pytlikova, M. Climate variability and international migration: The importance of the agricultural linkage. *J. Environ. Econ. Manage.* **79**, 135–151 (2016).