Supplementary Material: More people too poor to move: Divergent effects of climate change on global migration patterns

1 Methods

1.1 Data

Historical population data, for bilateral migrant stocks [1] and total national residents [2], come from the UN Department of Economic and Social Affairs and are available for the historical period of our analysis on a five-year temporal scale. Historical annual country-level GDPc comes from the Penn World Tables (PWT), version 8.1 [3], expanded for including missing countries using the PWT 9.0 [4]. Data on bilateral migration flows comes from a recently updated global matrix of estimates of bilateral migration flows. Here flows were derived from reported bilateral migrant stocks using a pseudo-Bayesian method including also return migraton flows [5, 6]. This panel data covers the historical period of interest from 1990 to 2020, using a five-year interval, as the population data and as the estimates produced by our model. Because of missing data our model includes only 182 of the 202 countries that are in this global dataset. Missing countries include Serbia and Montenegro which are considered as one single country before 2010; and Sudan and South Sudan, where the same issue applies. A full list of missing countries in our model is reported below. The factual (observed) temperature data for the period 1901-2019 is taken from the WFDE5 global reanalysis [7] from 1979 onwards, and an adjusted version of the GSWP3 reanalysis [8] before 1979, where discontinuities at the transition are minimized [9]. The corresponding counterfactual temperature data was created by removing from this dataset the long-term trend at each grid cell, using quantile mapping, while preserving short-term variability [10]. For this study, we calculate for each country the annual mean, area-weighted average temperature, both factual and counterfactual. When data was not available for a country, the temperature of the nearest country has been used.

For the countries where the temperature data was missing the temperature of the nearest country was used. The following list reports these countries (3digits ISO code) in the format country with missing data : country used as substitute:

'ATG':'TTO','BHR': 'SAU', 'BRB': 'TTO', 'GRD':'TTO', 'HKG': 'CHN', 'LCA': 'TTO', 'MAC':'CHN', 'MLT': 'TUN', 'SGP': 'MYS', 'SYC':'TZA','TLS':'IDN', 'TON': 'FJI' .

List of ountries that are included in the observed migration dataset but not in our model simulation: ABW, CHI, CUW, ESH, GLP, GUF, GUM, MNE, MTQ, MYT, NCL, PRK, PYF, REU, SCG, SDN, SRB, SSD, SUD, VIR.

List of countries and years for which GDPc values were missing and have been extrapolated from the past: SOM(years 2010,2015), ERI(year 2015)

1.2 Parameter estimation.

The values of the parameters used for the climate change effect on the GDPc, in equations 5 and 13, are taken directly from [11] and reported in Table 1 of the main manuscript. For estimating the parameters of the migration model, we proceed in three steps, following and expanding the methods in [12]. (i) First, using the total relative emigration flows at the country level, we estimate the parameters of the function $F(G_i)$ in equation 1a. To this end we exclude return migration and refugee migration flows from the observed migration data(see [12] for more details). Indeed, the "migration hump" is not a good representation for the refugee flows, neither is it included in the return flow equation 1b. The remaining observed flows are then aggregated to obtain total relative emigration values. The result from a Nonlinear Least Squares (NLS) method gives a fit that well represents the distribution of observed data and matches very well the result of a nonparametric fit to the same data (Fig. S1). Next, expanding on [12] we attempt to disentangle and capture the effect of different unobserved variables. We split the scaling factors a_j and b_i in two components: $a_j = a \cdot \tilde{a}_j$ and $b_i = b \cdot \tilde{b}_i$. a and b are scaling factors covering unobserved variables which are specific to the type of migration, e.g. return, transit or emigration from country of birth, and independent on the country of origin or destination. $\tilde{a}_j$ and $\tilde{b}_i$ are country-specific scaling factors which would capture unobserved variables such as immigration policies. Due to high collinearity between country-specific scaling factors, $\tilde{a}_j$ and $\tilde{b}_i$, and the global scaling factors, a and b, we estimate first a and b. (ii) In this second step we use the full dataset of observed bilateral migration flows, without excluding refugee or return flows, to estimate, through NLS, the remaining global parameters in equations 1a and 1b, i.e. a, b, α_p and α_g. The estimates of $\widehat{G}$, and $\tilde{G}$ obtained in (i) are used to evaluate $F(G_i)$. The country-specific scaling factors, $\tilde{a}_j$ and $\tilde{b}_i$, are not included in this step of the estimation. (iii) In the last step we estimate, by linear Least Squares, the country-specific scaling factors. We use the equations 1a and 1b, where the global parameters are set to the values estimated in (i) and (ii), and estimate the scaling factors on the mean observed bilateral migration flows for the period of study.

One of the major sources of uncertainty in our model comes from the estimated "migration hump" function. Indeed, depending on the values of the parameters the function will assume a different peak. We include this sensitivity analysis by considering the outcome of the model when using, one per time, the extreme values of each of the parameters of the hump function, while keeping all the others at their central estimated value. We then use each of these sets of parameters to evaluate the migration flows for the factual and the two counterfactual cases. For each of the three cases the results obtained using the new parameters produce a measure of uncertainty for our model's output.

2 Extended discussion

We turn now to an extended discussion of the main limitations of our analysis, in terms of the assumptions included in our international migration model. While motivated by plausible theory, these assumptions (see Discussion in the main paper) have mainly been empirically verified in cross-sectional or panel datasets, and much less in time-series analyses [e.g. 13, 14]. That means that it can be empirically shown that they explain well spatial patterns of international migration, i.e. the variation between countries or between bilateral links; but less agreement there is on whether they can explain also the temporal variation of the flows. Indeed, it can be shown that commonly used models of international migration do not explain the temporal variations in global bilateral migration flow data [15].

The assumption of our study as well as of other recent work on modeling migration [e.g. 16], is thus that the observed cross-sectional relationships reflect universal mechanisms that remain effective in different time periods or different climatic conditions; while the short-term variations observed in the available time-series or panel data are caused by different mechanisms, whose effects mask those of the former on short time scales. For example, we assume that the "migration hump" pattern found in emigration data still applies when individual countries' GDPc changes over time or – as assumed in our modeling exercise – between different climate states. The fact that emigration rates from individual countries have not, in general, traced the "migration hump" in recent decades according to the available data, is assumed to be due to other factors being much more influential in the short run; e.g. economic or political crises, changes in employment rates or immigration policies, or public attention and news coverage.

It is also important to keep in mind that turning these assumptions into equations neglects much of the complexity of real-world migration patterns and leaves aside many other important mechanisms and heterogeneities. The migration model, for instance, does not account for differences in within-country income distributions, nor for changes in the shape of these distributions; i.e. changes in within-country inequality. The parameterization of the relation between emigration and GDPc in equation 2 of the main paper does reflect the fact that emigration changes only gradually as a country gets richer, because at any given level of average income, some people in that country may still be too poor to afford migration, while other people may have very high incomes and little reason to emigrate. However, the shape of the income distribution clearly differs between countries, and might have changed in the past due to various factors, including climate change impacts and mitigation [17–19]. Accounting for these differences and changes will be an important step to refine our estimates in future works.

Another shortcoming is that the model still omits important factors shaping global migration, today. An example are immigration policies, which influence migration flows especially to many high-income destination countries, and which also change over time [20, 21]. A crude first attempt to include immigration policies in our estimates can be found in the country-specific scaling factors. Refugee flows – whether due to conflicts or disasters – are also not represented in our model, though in reality they contribute large parts of the migrant stocks in many countries, and thereby also influence non-refugee migration. That being said, it is worth noting that the model does account explicitly for return and transit migration flows, which are important components of global migration but not commonly considered in migration estimates.

Our counterfactual analysis assumes that the present-day population distribution, and the shape and position of the "migration hump" function, are invariant to the effects of recent climate change. There is uncertainty about the location of the peak of the function [22], and given that climate change has also affected total global economic growth, and that the hump function is measured in terms of absolute GDPc, its peak may have been located at a somewhat higher value without climate change. However, a small shift in the location or shape of the function would not affect our qualitative results much since it would not change most countries' position on either side of the peak. In other words, our results hold true as long as a long-term rise in incomes is associated with more emigration in very poor countries, and with less emigration in upper-middle to high-income countries.

With respect to the population distribution, our analysis neglects path dependencies in the migration system induced by the effect of diasporas. At any time since 1901, the difference between actual and counterfactual temperature would have induced deviations in countries' GDPc, implying potential deviations in migration patterns; and thus, migrant stocks would have evolved to be increasingly different from the actual ones. Nevertheless, given that climate change has accelerated over time, the larger portion of the GDPc impacts have occurred rather recently, and thus the accumulated deviations in migrant stocks may be small. Moreover, the diaspora effect constitutes a positive feedback, so our estimate of the difference between factual and counterfactual scenario is best seen as a conservative estimate, perhaps a lower bound, on the difference that would be expected if dynamic adjustments over time were taken into account.

3 Estimates

In the following table we report the rounded estimates of the country-specific scaling factors.

Table S1: Estimates of the country-specific scaling factors as described in the section 1.2. The values are rounded off to three decimals digit. The countries are grouped by region. These regions correspond to the those used throughout the paper.

Country	$\tilde{a}_j$	$\tilde{b}_i$	Country	$\tilde{a}_j$	$\tilde{b}_i$
Region: Africa					
Angola	0.000	1.315	Lesotho	4.268	0.000
Burundi	0.000	3.053	Morocco	0.000	7.456
Benin	2.008	0.679	Madagascar	1.287	4.836
Burkina Faso	0.264	2.171	Mali	0.295	2.599
Botswana	2.621	0.759	Mozambique	0.682	0.642
Central African Republic	1.745	17.820	Mauritania	1.096	0.871
Ivory Coast	1.884	1.619	Mauritius	1.207	0.770
Cameroon	2.424	1.251	Malawi	0.222	4.512
DR Congo	0.531	3.877	Namibia	0.848	0.872
Congo	2.578	1.079	Niger	4.301	2.136
Comoros	0.000	2.133	Nigeria	1.934	1.055
Cape Verde	0.626	3.365	Rwanda	0.808	5.498
Djibouti	2.907	0.942	Senegal	1.266	1.455
Algeria	0.804	0.746	Sierra Leone	1.173	6.518
Egypt	1.458	0.844	Somalia	0.000	9.477
Eritrea	1.674	5.035	Sao Tome & Principe	0.000	3.402
Ethiopia	5.023	0.893	Swaziland	0.527	0.263
Gabon	1.738	3.184	Seychelles	0.932	0.966
Ghana	2.641	0.423	Chad	0.495	0.000
Guinea	2.363	5.052	Togo	2.781	1.597
Gambia	1.916	0.989	Tunisia	1.304	0.000
Guinea-Bissau	0.555	1.642	Tanzania	3.577	3.128
Equatorial Guinea	14.238	0.000	Uganda	1.319	1.706
Kenya	3.170	0.896	South Africa	4.014	0.624
Liberia	0.000	2.758	Zambia	0.480	4.239
Libya	0.688	0.902	Zimbabwe	0.956	2.725
Region: East Asia					
China	0.756	1.061	South Korea	1.384	1.228
Hong Kong	0.616	1.160	Macao	0.651	1.084
Japan	0.882	1.076	Mongolia	1.821	8.111

Region: Europe					
Albania	0.000	23.077	Hungary	1.172	0.829
Austria	1.157	1.137	Ireland	1.057	0.128
Belgium	0.780	1.066	Iceland	1.352	1.915
Bulgaria	2.191	0.000	Italy	1.327	1.053
Bosnia & Herzegovina	0.000	21.379	Luxembourg	1.037	1.167
Switzerland	1.156	1.352	Macedonia	1.174	0.000
Czech Republic	1.005	1.034	Malta	2.168	1.013
Germany	0.972	1.161	Netherlands	0.737	1.105
Denmark	1.030	1.106	Norway	1.203	0.967
Spain	1.141	1.190	Poland	0.482	1.080
Finland	1.071	0.000	Portugal	0.575	1.025
France	0.795	1.124	Romania	1.390	1.152
United Kingdom	1.233	0.947	Slovakia	0.988	1.463
Greece	0.000	1.023	Slovenia	0.850	0.899
Croatia	0.310	0.794	Sweden	1.011	1.164
Region: Fmr Soviet Union					
Armenia	0.768	1.839	Latvia	0.445	1.711
Azerbaijan	0.265	0.000	Moldova	0.645	1.094
Belarus	0.634	0.394	Russia	1.062	0.788
Estonia	0.461	1.408	Tajikistan	0.611	2.695
Georgia	0.000	14.845	Turkmenistan	0.526	1.837
Kazakhstan	0.593	1.668	Ukraine	0.710	0.453
Kyrgyzstan	0.661	2.190	Uzbekistan	0.741	0.830
Lithuania	0.432	2.576			
Region: Latin America					
Argentina	0.848	1.135	Haiti	0.000	44.716
Bahamas	1.643	1.011	Jamaica	0.000	0.000
Belize	1.188	0.825	Kiribati	0.000	18.332
Bolivia	0.393	0.414	Saint Lucia	1.291	0.000
Brazil	1.006	0.846	Mexico	0.000	0.000
Barbados	0.521	0.148	Nicaragua	0.000	8.118
Chile	3.144	1.132	Panama	1.268	0.999
Colombia	0.000	0.338	Peru	4.553	35.075
Costa Rica	1.432	0.965	Puerto Rico	0.000	2.422
Cuba	0.000	3.857	Paraguay	0.531	1.757
Dominican Republic	1.739	1.003	El Salvador	0.000	25.262
Ecuador	1.309	0.955	Suriname	0.000	0.106
Grenada	2.916	3.509	Trinidad & Tobago	0.173	0.000
Guatemala	0.000	1.153	Uruguay	0.512	2.788

Guyana	0.000	11.733	Saint Vincent & Grenadines	0.927	4.387
Honduras	0.000	0.609	Venezuela	1.078	4.798
Region: North America					
Canada	1.152	1.014	United States of America	1.062	1.034
Region: Oceania					
Antigua and Barbadua	1.399	1.081	Papua New Guinea	1.492	2.212
Australia	1.091	1.074	Solomon Islands	0.641	10.399
Fiji	0.000	7.908	Tonga	0.000	2.630
Micronesia	0.000	74.279	Vanuatu	0.667	2.860
New Zealand	1.111	1.272	Samoa	0.000	9.344
Region: South Asia					
Afghanistan	0.000	3.034	Sri Lanka	0.197	2.246
Bangladesh	2.180	2.826	Maldives	3.248	0.697
Bhutan	0.622	0.950	Nepal	0.974	4.400
India	1.408	0.866	Pakistan	1.156	1.659
Iran	0.896	1.484			
Region: Southeast Asia					
Brunei	0.554	1.178	Philippines	0.259	3.239
Indonesia	0.377	0.986	Singapore	1.057	1.015
Cambodia	2.346	0.024	Thailand	1.618	0.918
Laos	0.229	0.000	Timor-Leste	0.000	34.714
Myanmar	0.386	3.563	Vietnam	1.695	6.966
Malaysia	1.267	0.923			
Region: West Asia					
United Arab Emirates	0.864	1.083	Oman	1.405	1.076
Bahrain	1.096	1.011	Palestine	0.000	0.930
Cyprus	1.737	0.000	Qatar	0.893	1.049
Iraq	0.808	0.353	Saudi Arabia	0.912	1.117
Israel	0.855	1.286	Syria	1.044	3.884
Jordan	1.323	0.649	Turkey	2.654	0.682
Kuwait	0.866	1.154	Yemen	6.035	1.157
Lebanon	0.784	0.619			

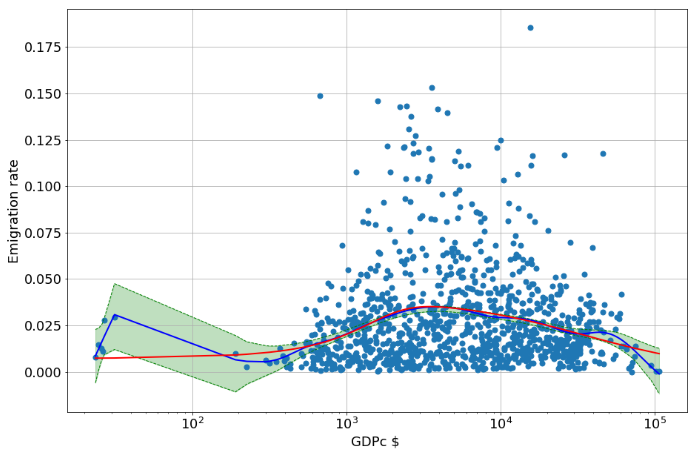
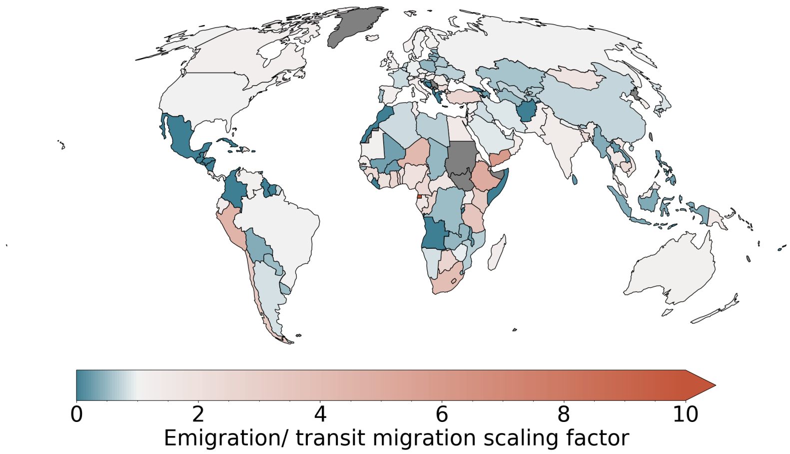
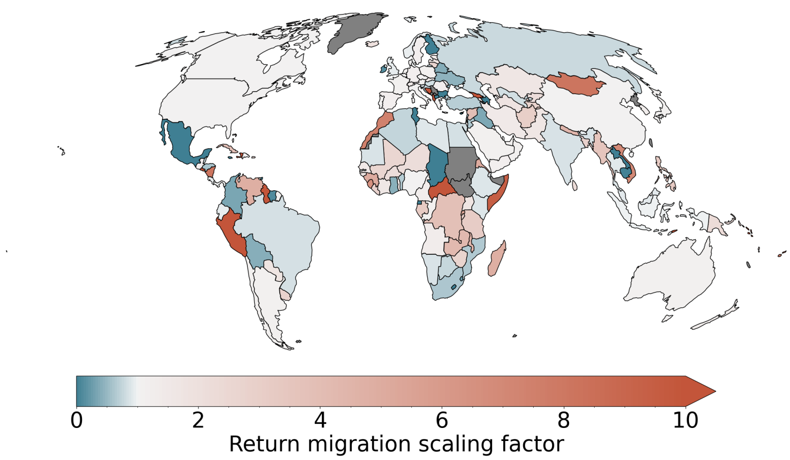


Figure S1: Migration hump function. Each point represents the total emigration rate and GDPc for a specific country in one specific year. All together they represent the set of points used for estimating the migration hump function via NLS (red curve) as described in the main paper. The blue curve is the result of a non-parametric, local-linear regression with a Gaussian kernel. The green area shows the confidence interval of 66% using a bootstrapping method on the nonparametric regression.

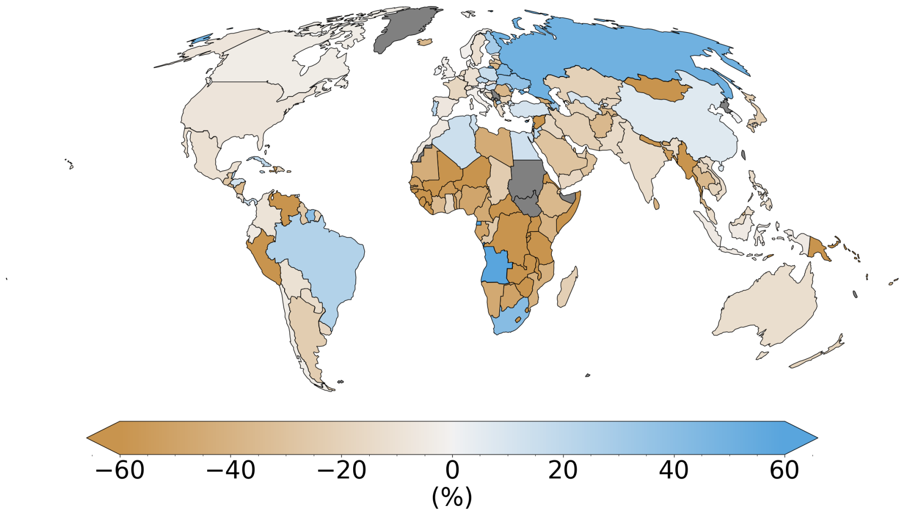


(a) Destination country-specific scaling factor.

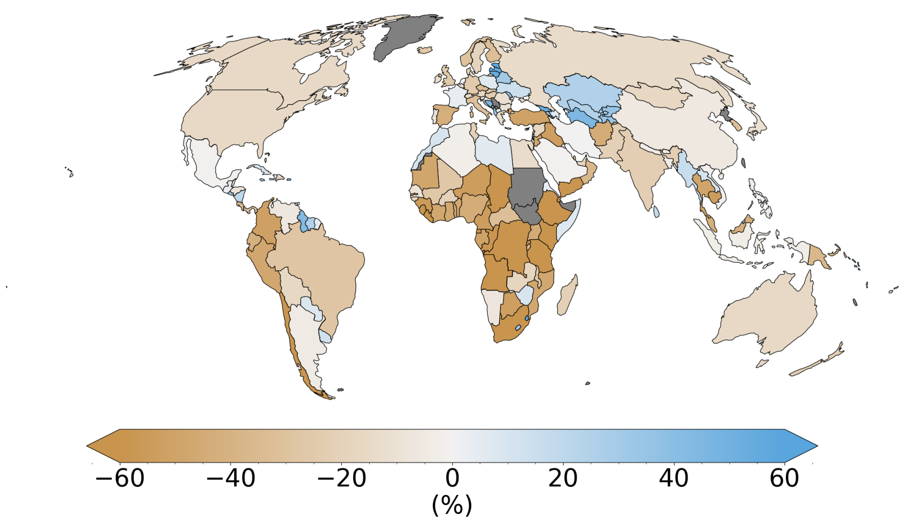


(b) Origin country-specific scaling factor

Figure S2: Country-specific scaling factors as estimated from the bilateral migration flows (see Methods). Panel (a) shows the values for the $\tilde{a}_j$ factors while panel (b) displays the estimated values for the return migration country-specific scaling factors $\tilde{b}_i$.



(a) Emigration



(b) Immigration

Figure S3: As in figure 2e and 2f of the main paper but for the model without country specific scaling factors.

References

1. United Nations, Department of Economic and Social Affairs, Population Division. International Migrant Stock 2020. *(United Nations database, POP/DB/MIG/Stock/Rev.2020* (2020).
2. United Nations Department of Economic and Social Affairs Population Division. *World Population Prospects 2019* tech. rep. (United Nations, Department of Economic and Social Affairs, Population Division, 2019). https://population.un.org/wpp/Download/Standard/Population/.
3. Feenstra, R. C., Inklaar, R. & Timmer, M. P. The Next Generation of the Penn World Table. *American Economic Review* **105,** 3150–3182. ISSN: 0002-8282. http://pubs.aeaweb.org/doi/10.1257/aer.20130954 (Oct. 2015).
4. Geiger, T. Continuous national gross domestic product (GDP) time series for 195 countries: past observations (1850–2005) harmonized with future projections according to the Shared Socio-economic Pathways (2006–2100). *Earth System Science Data* **10,** 847–856. ISSN: 1866-3516. https://www.earth-syst-sci-data.net/10/847/2018/ (Apr. 2018).
5. Abel, G. & Cohen, J. E. *Bilateral international migration flow estimates for 200 countries* 2019. https://doi.org/10.6084/m9.figshare.c.4470464.v5.
6. Azose, J. J. & Raftery, A. E. Estimation of emigration, return migration, and transit migration between all pairs of countries. *Proceedings of the National Academy of Sciences* **116,** 116–122. ISSN: 0027-8424. http://www.pnas.org/lookup/doi/10.1073/pnas.1722334116 (Jan. 2019).
7. Cucchi, M. *et al.* WFDE5: bias-adjusted ERA5 reanalysis data for impact studies. *Earth System Science Data* **12,** 2097–2120. https://essd.copernicus.org/articles/12/2097/2020/ (2020).
8. Dirmeyer, P. A. *et al.* GSWP-2: Multimodel Analysis and Implications for Our Perception of the Land Surface. *Bulletin of the American Meteorological Society* **87,** 1381–1398. https://journals.ametsoc.org/view/journals/bams/87/10/bams-87-10-1381.xml (2006).
9. Lange, S. Trend-preserving bias adjustment and statistical downscaling with ISIMIP3BASD (v1.0). *Geoscientific Model Development* **12,** 3055–3070. https://gmd.copernicus.org/articles/12/3055/2019/ (2019).
10. Mengel, M., Treu, S., Lange, S. & Frieler, K. ATTRICI v1.1 – counterfactual climate for impact attribution. **14,** 5269–5284. ISSN: 1991-9603.
11. Kalkuhl, M. & Wenz, L. The impact of climate conditions on economic production. Evidence from a global panel of regions. *Journal of Environmental Economics and Management* **103,** 102360 (2020).

12. Rikani, A. & Schewe, J. Global bilateral migration projections accounting for diasporas, transit and return flows, and poverty constraints. *Demographic Research* (2021).

13. Benček, D. & Schneiderheinze, C. More Development, Less Emigration to OECD Countries – Identifying Inconsistencies Between Cross-sectional and Time-series Estimates of the Migration Hump, 1–24 (2019).

14. Clemens, M. A. The Emigration Life Cycle: How Development Shapes Emigration from Poor Countries. *Working Paper 540.* ISSN: 1556-5068 (2020).

15. Beyer, R., Schewe, J. & Lotze-Campen, H. Gravity models do not explain, and cannot predict, international migration dynamics. *Nature Communications Humanities and Social Sciences* **9.** ISSN: 2662-9992 (2022).

16. Buettner, T. & Muenz, R. Migration Projections: The Economic Case, v, 1–31. `https://www.knomad.org/publication/migration-projections-economic-case` (2020).

17. Rao, N. D., Sauer, P., Gidden, M. & Riahi, K. Income inequality projections for the Shared Socioeconomic Pathways (SSPs). *Futures* **105,** 27–39. ISSN: 00163287. `https://linkinghub.elsevier.com/retrieve/pii/S001632871730349X` (Jan. 2019).

18. Hallegatte, S. & Rozenberg, J. Climate change through a poverty lens. *Nature Climate Change* **7,** 250–256. ISSN: 1758-678X. `http://www.nature.com/articles/nclimate3253` (Apr. 2017).

19. Markkanen, S. & Anger-Kraavi, A. Social impacts of climate change mitigation policies and their implications for inequality. *Climate Policy* **19,** 827–844. ISSN: 1469-3062. `https://www.tandfonline.com/doi/full/10.1080/14693062.2019.1596873` (Aug. 2019).

20. Helbling, M. & Leblang, D. Controlling immigration? How regulations affect migration flows. *European Journal of Political Research* **58,** 248–269. ISSN: 0304-4130. `http://doi.wiley.com/10.1111/1475-6765.12279%20https://onlinelibrary.wiley.com/doi/abs/10.1111/1475-6765.12279` (Feb. 2019).

21. Ortega, F. & Peri, G. The effect of income and immigration policies on international migration. *Migration Studies* **1,** 47–74. ISSN: 2049-5846. arXiv: `arXiv:1011.1669v3`. `https://academic.oup.com/migration/article-lookup/doi/10.1093/migration/mns004` (2013).

22. Clemens, M. A. & Postel, H. M. Deterring Emigration with Foreign Aid: An Overview of Evidence from Low-Income Countries. *Population and Development Review* **44,** 667–693. ISSN: 00987921. `https://onlinelibrary.wiley.com/doi/10.1111/padr.12184` (Dec. 2018).