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Climate change increases resource-constrained international immobility

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Abstract

Migration is a widely used adaptation strategy to climate change impacts. Yet resource constraints caused by such impacts may limit the ability to migrate, thereby leading to immobility. Here, we provide a quantitative, global analysis of reduced international mobility due to resource deprivation caused by climate change. We incorporate both migration dynamics and within-region income distributions in an Integrated Assessment Model. We show that climate change induces decreases in emigration of lowest income levels by over 10% in 2100 for medium development and climate scenarios compared to no climate change, and by up to 35% for more pessimistic scenarios including catastrophic damages. This effect would leave resource-constrained populations extremely vulnerable to both subsequent climate change impacts and increased poverty.

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Central America has recently seen a highly publicized increase in emigrants from its rural areas towards, among other destinations, the United States [1]. On another continent, Syria witnessed a large surge in migration to nearby countries and further destinations, including Europe, in 2015 [2]. Both events have been used – however controversially – as illustrations of the role that climate change impacts such as increased droughts or flooding could, and already might, play in amplifying international migration flows [3, 4, 5, 6].

Just as instances of migration do not always result from a long-held intention to move, immobility can happen as a choice or as the less voluntary consequence of a given context [7, 8, 9]. While immobility can be a choice, resource constraints can unequivocally limit one’s ability to migrate: as migration – and, in particular, international migration – requires resources, whether economic, social or health-related, those who move are those who can afford to do so [10, 11, 12, 13, 14]. The migration literature has developed a resulting theory of mobility based on an aspirations-capabilities framework [10, 7, 15]. This literature has labeled people in a situation of involuntary immobility due to resources constraints as “trapped populations”. We note that the term “trapped populations” implies a total lack of agency on the would-be migrant’s part. As our data does not allow us to directly capture individuals’ aspirations to migrate, here we rather use the more appropriate term resource-constrained immobility.

The role of environmental change in (im)mobility is multi-faceted and complex. Migration decisions are rarely due to environmental stress alone. Climate change may influence migration both directly and indirectly through various channels [16], both enhancing and reducing migration flows [17]. Migration is expected to be increasingly used as an adaptation strategy to climate change [18, 19, 20, 21]. Yet climate change is likely to lead to resource depletion in some of the most deprived areas, thereby trapping individuals who cannot afford to move [22, 23, 24, 25, 16, 19, 26].

Recent efforts have been deployed by the authors and others to study effects of future climate change on migration using a variety of models [27, 28, 29, 30, 31], yet without highlighting resource-constrained immobility. Conversely, a recent and upcoming strand of literature has been focusing on considerations of inequality and poverty in assessments of climate change

damages [32, 33, 34, 35], albeit without specifying migration dynamics. Hence to the best of our knowledge, there is no available estimate of the number of people who might be affected by the impact of climate change on resource-constrained international immobility, now or in the future. Such people are likely to represent as much a concern to the international community as those who do migrate in the context of environmental change [16, 36].

Here we provide a quantitative, global analysis of international immobility due to resource deprivation caused by climate change. We define said immobility as an international move of resource-constrained populations that would have taken place in a world without climate change but does not in a world with climate change. Note that this definition of immobility does not relate to internal migration. While most of climate-related migration is expected to take place within countries [18], many severe political controversies taking place around migration both generally and in the context of climate change tend to focus on cross-border migration [27, 37, 38].

In order to quantify this effect of climate change on resource-constrained immobility, we proceed in two steps. First, we develop a model of international migration and remittances including income distributions, so as to capture how individuals with different incomes are more or less constrained in their mobility decisions. Second, we embed our migration model in an Integrated Assessment Model (IAM, a global climate-economy model), in order to capture the effects of climate change on resource deprivation and subsequent immobility. The benefit of using this two-step approach is twofold: first, to endogenize the evolution of multiple migration drivers in a climate change context; and second, to include explicit, time-varying inequality in an IAM, which is paramount to understand how future climate change might affect resources for the poorest populations. Using this approach, we then conduct projection exercises of resource-constrained immobility following five different scenarios of future development and climate change over the 21st century, which illustrate a range of possible evolutions for underlying drivers of migration. We observe a substantial effect of climate change on resource-constrained immobility in all these varied futures, which ensures the robustness of our central finding on the key role of immobility in the climate-migration nexus.

A gravity model of migration at the income quintile level

We design a model of international migration and remittances dynamics, following a gravity structure [39, 40, 41] (see Methods). This model aims at representing all sources of international migration – not only climate-related migration. The specificity of our gravity model is that we design it at the income quintile level. The reason for this is that resource deprivation depends on the income level of the population considered. We express bilateral migrant flows as a function of population sizes at origin and destination; quintile-specific per capita income at origin; and ratio of average per capita income at destination over quintile-specific income at origin. By doing so, we capture three key aspects of migration dynamics: the income at origin illustrates the resource constraint to be overcome in order to migrate, while the income ratio highlights both the pull factor from richer areas and the fact that areas with higher average income levels tend to attract more international migrants, regardless of their domestic income distributions. In our model, migration flows also depend on characteristics of remittances typically sent by migrants between two given locations, illustrating the role of existing migration networks in the persistence of migration flows. Note that one of these characteristics, the share of income that migrants send as remittance, is modelled endogenously as a function of average per capita income levels at origin and destination (see Methods). Finally, we include a set of bilateral characteristics of the origin/destination pair depicting the geographic and cultural proximity between origin and destination (distance, common official language).

To estimate this model, bilateral migrant flows are derived from 2010-2015 stock data (World Bank) using [42] as collected in [43]. To get to income quintiles, we use population projections from the now standard Shared Socioeconomic Pathways (SSP) scenarios, which provide in- and out-migration flows at the country level by education levels for 2015-2100 (see Methods). The SSP projections, however, do not provide *bilateral* migration flows, which are necessary to explicitly project both migration and remittances over time – hence our use of a gravity model. Note that migration flows in the SSP projections are independent of climate change impacts, which we include as described below. We estimate our gravity equation by OLS regression; each quintile at origin has its own set of coefficients. Data on population,

average income levels and remittance flows are available from the World Bank. We use Gini coefficients – a commonly used measure of inequality considering the population-weighted distribution of income within a given country – from the SSP for 2010-2015 for income distributions. The resulting estimation (see top panel of Table 1) implies that migration flows between two countries increase with origin population size, with income per capita differences between origin and destination, and with the existence of a common language, and decrease with distance between countries, as suggested in other studies using similar models (e.g. [39]). As the most important feature of our model and mirroring SSP data on migrants’ education profiles, migration flows also tend to increase with origin quintile per capita income, highlighting the fact that migration is costly, and hinting at the importance of the resource constraint to be overcome in order to migrate (see Methods and Supplementary Information Section D for robustness checks). Thus, our model captures two counterbalancing effects of income on migration: on the one hand, an increase in income reduces the resource constraint and allows for more migration, but on the other hand the pull factor towards richer locations is reduced. Our findings are the results of these two counterbalancing effects.

We then endogenously distribute this number of migrants over each income quintile at destination. We estimate this distribution by OLS regression, separately for each income quintile at destination. The resulting estimation (see bottom panel of Table 1) suggests that migrants arriving in countries that are much richer than their home country arrive in lowest income levels at destination, while migrants arriving in highest income quintiles at destination already come from countries where they enjoyed higher income levels than the average income at destination. We further assume that migrants can change income quintile when they move but not once arrived at destination (see Methods for further details).

Including climate change impacts on resource deprivation

In a second step, we incorporate climate change effects on resource deprivation and subsequent immobility. Resource deprivation caused by climate change impacts, and potentially responsible for immobility, can be quantified through climate change damages, typically computed with IAM. For most models, migration is absent from the IAM itself and considered only implicitly, as part of required input population growth scenarios [27]. Yet in a previous

project [27] we proposed a model of international migration and remittances dynamics and included it in the FUND IAM [44]. In this paper, we add a layer to our migration-in-IAM exercise, including within-region income distributions as well [34]. By doing so, we can directly tackle this question of resource-constrained immobility.

Following the approach developed by [34], each region is split into population quintiles. The damage distribution over income quintiles depends on the income distribution through the income elasticity of damages. The regressive character of damages, i.e. the extent to which they affect the poor disproportionately, is qualitatively likely but quantitatively still unsettled – see Supplementary Information Section E for a literature review. Thus, we provide results with three variants corresponding to damages being proportional, independent, and inversely proportional to income; see Supplementary Information Section F.1 for a discussion of our choice of values for the income elasticity of damages. Mitigation costs for reducing greenhouse gas emissions are distributed across income groups following an income elasticity of mitigation, which we keep at 1 for this project. Income distributions before damages are driven by exogenous inequality growth scenarios, and are modified by migration and remittance dynamics. Importantly, migration and climate change impacts interact only indirectly through the income channel: migration changes population distribution and generates income transfers between regions, which modifies each region’s emissions profile and damages [27]. Conversely, climate change generates region- and quintile-specific damages, hence modifies absolute and relative income levels – two drivers of our migration dynamics model. Thus in our model, migration and remittances, damages, and emissions mitigation costs are specific to each income level considered (see further details in Methods). Finally, we use the SSP projections coupled to relevant climate scenarios among the Representative Concentration Pathways (RCP) as input scenarios for our projection exercise of resource-constrained immobility (see Methods).

Migrants income profiles, net migration and remittance flows

Income profiles of yearly migrant flows over time can be explored with our model. Results for a medium climate and development scenario (SSP2 coupled to RCP4.5), when damages are assumed to be inversely proportional to income, are displayed in Fig. 1. By and large, most

migrants tend to come from richer income levels at origin (top panel). Conversely, migrants tend to end up in lower income quintiles when the destination is a developed region, and in higher income quintiles when the destination is a developing region (bottom panel). Both results hold over time, across regions, across SSP narratives, and across income elasticities of damages. When considering cumulative number of migrants, the income profiles of foreign-born people tend to be unbalanced at the beginning of the century with a majority of low income migrants in developed countries and a majority of high income migrants in least developed regions; yet income profiles even out over time (see Supplementary Fig. B.1).

Damages as income shocks on poorest populations

The magnitude of damage impacts on income for poorest populations necessarily depends on the extent to which damages from climate change fall disproportionately on the poor. When such damages are assumed to be particularly regressive and for a medium climate and development scenario (SSP2-RCP4.5), we find that by the end of the century, the poorest populations of six regions suffer damages that reach at least 5% of their income: Central and Eastern Europe, Former Soviet Union, North Africa, South America, Sub-Saharan Africa and the United States (Fig. 2, left panel). For direr development and climate scenarios, many more regions cross this threshold (right panel): for SSP3-RCP7.0, the lowest quintiles of 11 of the 16 regions suffer damages that are over 5% of their income; for two of those regions – North Africa and Former Soviet Union – damages reach above 100% of their income. When damages are assumed to be less regressive, specifically independent of income, damage impacts on income for the poorest populations are still substantial in two regions for the medium scenario, and in 11 regions for the pessimistic scenario, reaching up to 48% in North Africa. Conversely, damages always stay under 5% of income for the richest quintile under both scenarios and for all elasticities of damages (see Supplementary Figs. B.6 and B.7). Thus damages from climate change represent a substantial shock on available resources, in particular for the poorest populations.

Damages not compensated by remittances in the future

Migration could conceivably alleviate this important shock on income, both for migrants and for home communities who would receive remittances. We test this hypothesis by computing the difference between remittances received and climate change damages as a share of income for the poorest populations. Results for all climate and development scenarios, when damages are assumed to be inversely proportional to income, are displayed in Fig. 3. Early in the century, remittances still largely compensate for damages in all regions. Yet starting mid-century, once climate change impacts reach larger scales, we find that resources lost through damages are not compensated anymore by gains from remittances in 10 of the 16 regions for the medium scenario (SSP2-RCP4.5), and in 11 for the more pessimistic scenario (SSP3-RCP7.0). When damages are assumed to be independent of income, this is still the case in 7 regions for the medium scenario, and in 11 regions for the pessimistic scenario (see Supplementary Fig. B.8). Since resource constraints on migration limit subsequent remittances received, and since remittances are not enough to compensate for damages from climate change, it is therefore especially important to understand how many people will be left without the necessary resources to emigrate internationally.

Climate change effect on immobility for lowest income levels

To quantify the effect of climate change on resource-constrained immobility, we run our model without the climate change effect – that is, without climate change damages affecting the economy – and compare the number of emigrants for each income quintile to the run with climate change effects. We identify climate change-related resource-constrained immobility as a decrease in the number of emigrants from the lowest income quintiles compared to without climate change effects. We find evidence of such immobility starting mid-century for SSP2-RCP4.5 in three regions: Sub-Saharan Africa, North Africa, and the Former Soviet Union, with decreases in emigration from the lowest quintiles of up to 2%, 10% and 10% respectively by the end of the century when damages are inversely proportional to income (see top left panel of Fig. 4 and Extended Data Fig. E.1). This corresponds to 40,000, 40,000, and 25,000 less emigrants over the last decade of the century (see Supplementary Fig.

B.9). Those regions present the highest level of damages as percentage of GDP, which can be interpreted as a measure of exposure and vulnerability to climate change impacts [27]. More pessimistic development and climate scenarios do not witness resource-constrained immobility in more regions, however the decrease in poorest emigration becomes much more significant for those three regions: -9%, -28% and -14% respectively for SSP3 coupled to RCP7.0 (see top right panel of Fig. 4 and Extended Data Fig. E.2). Similar results, although with smaller magnitude, stand for damages assumed to be proportional to (Extended Data Fig. E.3) and independent of income (Extended Data Fig. E.4).

Our results naturally depend on damages specification. We discuss the role of damages calibration specifically in the Supplementary Information Section B.10. Furthermore, in order to assess our results for more pessimistic damages specifications, we run our model adding catastrophic damages: following Weitzman [45], we add to the aggregated damages a term dependent on increase in global mean temperature to the power 7, and calibrate it such that global GDP loss from damages equals 50% for an increase in temperature of 6°C. These catastrophic damages are then affected to income quintiles as the original damages. For the moderate SSP2-RCP4.5 scenario, we find a marked increase in the magnitude of the effect of climate change on immobility, with evidence of resource-constrained immobility now displayed in 14 of the 16 regions and a decrease in the number of migrants from lowest quintiles of up to 21% (see top bottom panel of Fig. 4 and Supplementary Fig. B.13). Here as well, the effect of climate change on immobility increases with more pessimistic development and climate scenarios, up until reaching a 33% decrease in emigrants from North Africa's lowest quintile by the end of the century for SSP3-RCP7.0 when damages are assumed to be inversely proportional to income (see bottom right panel of Fig. 4 and Supplementary Fig. B.14). This result is not self-evident: in the catastrophic case, increased damages reduce resources, but also increase the pull to move towards richer regions, as poorer regions are more affected by damages. This finding suggests that the resource constraint dominates the pull towards richer regions.

Conversely for other regions, migration of poorest populations appears to be more prevalent with climate change. This is in particular the case of China, which displays higher levels of

emigration from lowest quintiles by up to 20% – or 120,000 more emigrants – by 2100 for SSP2-RCP4.5 when damages are inversely proportional to income. The reason for this is as follows. In our model, income affects migration in two directions: a decrease in income decreases resources, but increases the pull factor towards richer locations. In turn, income can be affected both by damages, which reduce income more in origin regions, and by remittances, which increase income more in origin regions. Remittances are proportional to cumulative migrants over time, not to yearly migrant flows, as migrants don’t send remittances only once, but over the course of their lifetime. Therefore, in regions for which climate change is still beneficial up until late in the century – which is the case of China in FUND, more migration takes place with climate change than without up until late because people have more resources to migrate due to positive climate change effects. Thus by 2100, there is a larger number of people sending back remittances with climate change than without, which increases resources.

Therefore this finding suggests, first, that the resources that are available or not to migrate dominate the pull to move towards richer regions; and second, that in most places resources decrease with climate change for the poorest populations, which induces significant increases in immobility and vulnerability. We note that increased international immobility does not preclude internal mobility, whether voluntary or not. Heterogeneous exposure and vulnerability to climate change impacts within each country is also expected to affect more local migration decisions [18, 46], again in either direction depending on the social, economic, and demographic context [47].

Migration, immobility and the social cost of carbon

Our modeling framework, just like any cost-benefit IAM, allows us to compute the marginal effect of emissions on social welfare — also called the Social Cost of Carbon (SCC), an indicator of high relevance for climate change mitigation policy [48]. We find that the effect of including migration and remittances in the IAM strongly depends on the income elasticity of damages (see Supplementary Table B.1). When damages are proportional to income, there is little effect of including migration on the SCC in all climate and development scenarios. Yet the more regressive damages are, the more the SCC increases with migration. This result

does not mean that migration can be assimilated to a climate change damage, but rather that the inclusion of migration dynamics in the IAM highlights an additional inequality in terms of access to migration as an adaptation strategy to climate change. Namely, this strategy is less readily available to populations with the least resources.

Conclusions

In summary, we design a gravity model of migration and remittances dynamics at the income quintile level, which we include in an IAM to analyze climate change effects on resource-constrained (im)mobility. We find that climate change increases international immobility of the poorest populations in at least a few world regions across all possible futures considered. In particular, climate change leads to decreases in emigration of the lowest income levels by over 10% in 2100 for medium development and climate scenarios as compared to no climate change, and by up to 35% for more pessimistic scenarios including catastrophic damages. Therefore, our results suggest that far from being a rare circumstance, resource-constrained immobility is likely to play a substantial role in the climate-migration nexus. While this study focuses on international immobility, a natural avenue for future research would involve projecting climate change effects on internal immobility as well.

Moreover, this analysis confirms the potentially devastating effect of climate change impacts on the poorest populations, as well as the limits of migration as an adaptation solution for the migrant and those who stay in the origin region. When damages are assumed to be regressive, resulting income shocks on the poorest populations can be substantial in most world regions, and are not compensated by economic benefits provided by migration in the form of remittances. Hence, populations who do and will find themselves unable to leave as an adaptive response to climate changes are and will be in a state of extreme vulnerability, both to subsequent impacts from climate change, and more generally to risks derived from increased poverty. Such acute vulnerability should be of immediate and substantial policy concern.

Relevant international institutions for this issue of climate-driven immobility include the UN Sustainable Development Goals, the UN Global Compact for Migration – a non-binding

agreement signed in 2018, and the Warsaw International Mechanism for Loss and Damage within the UN Framework Convention on Climate Change. Currently, none of these institutions explicitly addresses this issue of resource-constrained immobility; their sole focus is on migration and displacement. It is to be hoped that these and other institutions will develop policy responses that address this issue in the future.

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Competing Interests Statement: Authors declare no competing interests.

| Bilateral migrant flows for a given origin income quintile | | | | | |
|--|----------------------|----------------------|----------------------|----------------------|----------------------|
| | qorig1 | qorig2 | qorig3 | qorig4 | qorig5 |
| Origin population | 0.824*** (0.061) | 0.809*** (0.070) | 0.792*** (0.059) | 0.807*** (0.058) | 0.805*** (0.057) |
| Destination population | 0.719*** (0.062) | 0.717*** (0.062) | 0.719*** (0.062) | 0.718*** (0.062) | 0.720*** (0.062) |
| Origin quintile per capita income | 1.808*** (0.134) | 1.760*** (0.144) | 1.865*** (0.143) | 1.834*** (0.145) | 1.808*** (0.151) |
| Ratio of per capita incomes | 1.166*** (0.106) | 1.174*** (0.106) | 1.170*** (0.106) | 1.166*** (0.106) | 1.153*** (0.106) |
| Distance between locations | -1.100*** (0.097) | -1.081*** (0.102) | -1.099*** (0.097) | -1.086*** (0.094) | -1.120*** (0.091) |
| Residuals from share of income sent as remittances | -0.002 (0.008) | -0.002 (0.009) | -0.001 (0.009) | -0.000 (0.008) | 0.001 (0.007) |
| Cost of sending remittances | -22.604 (24.028) | -25.734 (24.304) | -24.555 (24.678) | -24.232 (24.050) | -24.610 (23.755) |
| Common official language | 1.433*** (0.251) | 1.490*** (0.245) | 1.422*** (0.247) | 1.436*** (0.253) | 1.320*** (0.254) |
| N | 24,100 | 24,100 | 24,100 | 24,100 | 24,100 |
| R^2 | 0.554 | 0.540 | 0.549 | 0.545 | 0.543 |
| Share of migrants to a given quintile at destination | | | | | |
| | qdest1 | qdest2 | qdest3 | qdest4 | qdest5 |
| Ratio of per capita incomes | 0.142*** (0.019) | 0.073*** (0.017) | 0.027 (0.019) | 0.023 (0.016) | -0.149*** (0.018) |
| N | 24,100 | 24,100 | 24,100 | 24,100 | 24,100 |
| R^2 | 0.251 | 0.100 | 0.006 | 0.012 | 0.281 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1: Estimation of the migration model. (Top panel) Results from OLS regression on country-level bilateral migration flows, separately for each origin income quintile. (Bottom panel) Results from OLS regression on share of migrants arriving in a given income quintile at destination, separately for each destination income quintile. Standard errors clustered at the origin and destination levels in parentheses.

Figure 1: Migration per income quintile. Top panel: outmigration for each income quintile at origin. Bottom panel: in-migration for each income quintile at destination. Results per year for SSP2 (middle-of-the-road) coupled to RCP4.5 for each of the 16 regions in FUND, for within-region damages inversely proportional to income, for the period 2015-2100. Color code indicates income quintiles, with lowest quintiles in blue shades and highest quintiles in yellow shades.

Figure 2: Damages from climate change as share of income for the poorest income quintile. Results in the 16 FUND regions for 2100 for within-region damages inversely proportional to income. Left panel: SSP2 (middle-of-the-road) coupled to RCP4.5. Right panel: SSP3 (regional rivalry) coupled to RCP7.0.

Figure 3: Difference between remittances received and climate change damages as a share of income for the poorest income quintile. Results per year for each of the 16 regions in FUND, for within-region damages inversely proportional to income, for the period 2015-2100. Color code indicates scenarios of future development and climate change.

Figure 4: Relative effect of climate change (CC) on number of emigrants from lowest income quintile. Results in the 16 FUND regions for 2100 for within-region damages inversely proportional to income. Left panel: SSP2 coupled to RCP4.5. Right panel: SSP3 coupled to RCP7.0. Top panel: results with baseline damages calibration. Bottom panel: results with catastrophic damages.

References

- [1] *2018 Yearbook of Immigration Statistics*. Tech. rep. Washington, D.C.: United States Department of Homeland Security, Office of Immigration Statistics, 2019.
- [2] Frontex. *Risk Analysis for 2016*. Tech. rep. Frontex, 2016. DOI: 10.2819/416783.
- [3] Abrahm Lustgarten. “The Great Climate Migration”. In: *New York Times Magazine* (2020). URL: <https://www.nytimes.com/interactive/2020/07/23/magazine/climate-migration.html>.
- [4] Colin P. Kelley et al. “Climate change in the Fertile Crescent and implications of the recent Syrian drought”. In: *Proceedings of the National Academy of Sciences* 112.11 (2015), pp. 3241–3246. DOI: <https://doi.org/10.1073/pnas.1421533112>.
- [5] Ingrid Boas et al. “Climate migration myths”. In: *Nature Climate Change* 9.12 (2019), pp. 901–903.
- [6] Jan Selby et al. “Climate change and the Syrian civil war revisited”. In: *Political Geography* 60 (2017), pp. 232–244.

- [7] K. Schewel. “Understanding immobility: Moving beyond the mobility bias in migration studies”. In: *International Migration Review* 54.2 (2020), pp. 328–355.
- [8] Caroline Zickgraf. “Immobility”. In: *Routledge Handbook of Environmental Displacement and Migration*. Ed. by Robert McLeman and François Gemenne. Routledge, 2018.
- [9] Helen Adams. “Why populations persist: mobility, place attachment and climate change”. In: *Population and Environment* 37 (2016). DOI: <https://doi.org/10.1007/s11111-015-0246-3>.
- [10] Jorgen Carling. “Migration in the age of involuntary immobility: Theoretical reflections and Cape Verdean experiences”. In: *Journal of Ethnic and Migration Studies* 28 (1 2002). DOI: <https://doi.org/10.1080/13691830120103912>.
- [11] Timothy J. Hatton and Jeffrey G. Williamson. *The age of mass migration: Causes and economic impact*. Oxford University Press on Demand, 1998.
- [12] Gharad Bryan, Shyamal Chowdhury, and Ahmed Mushfiq Mobarak. “Underinvestment in a Profitable Technology: The Case of Seasonal Migration in Bangladesh”. In: *Econometrica* 82.5 (2014), pp. 1671–1748.
- [13] Cally Ardington, Anne Case, and Victoria Hosegood. “Labor Supply Responses to Large Social Transfers: Longitudinal Evidence from South Africa”. In: *American Economic Journal: Applied Economics* 1.1 (2009), pp. 22–48.
- [14] Hein De Haas et al. “International Migration: Trends, Determinants, and Policy Effects”. In: *Population and Development Review* 45 (4 2019), pp. 885–922.
- [15] H de Haas. “A theory of migration: the aspirations-capabilities framework”. In: *Comparative Migration Studies* 9.8 (2021). DOI: <https://doi.org/10.1186/s40878-020-00210-4>.
- [16] *Foresight: Migration and Global Environmental Change*. The Government Office for Science, London, 2011.
- [17] Roman Hoffmann et al. “A meta-analysis of country-level studies on environmental change and migration”. In: *Nature Climate Change* 10.10 (2020), pp. 904–912. DOI: <https://doi.org/10.1038/s41558-020-0898-6>.

- [18] Kanta Kumari Rigaud et al. *Groundswell: Preparing for Internal Climate Migration*. The World Bank, Washington, DC, 2018, 2021.
- [19] Richard Black et al. “Migration as adaptation”. In: *Nature* 478 (2011), pp. 447–449. DOI: <https://doi.org/10.1038/478477a>.
- [20] Robert McLeman. “International migration and climate adaptation in an era of hardening borders”. In: *Nature Climate Change* 9 (2019), pp. 911–918. DOI: <https://doi.org/10.1038/s41558-019-0634-2>.
- [21] Els Bekaert, Ilse Ruysen, and Sara Salomone. “Domestic and international migration intentions in response to environmental stress: A global cross-country analysis”. In: *Journal of Demographic Economics* (2021), pp. 1–54.
- [22] Cristina Cattaneo and Giovanni Peri. “The migration response to increasing temperatures”. In: *Journal of Development Economics* 122 (2016), pp. 127–146. DOI: <https://doi.org/10.1016/j.jdeveco.2016.05.004>.
- [23] Giovanni Peri and Akira Sasahara. “The Impact of Global Warming on Rural-Urban Migrations: Evidence from Global Big Data”. In: *National Bureau of Economic Research* 25728 (2019). URL: <http://www.nber.org/papers/w25728>.
- [24] Raphael J. Nawrotzki and Jack DeWaard. “Putting trapped populations into place: climate change and inter-district migration flows in Zambia”. In: *Regional Environmental Change* 18 (2018). DOI: <https://doi.org/10.1007/s10113-017-1224-3>.
- [25] Martina Grecequet et al. “Climate Vulnerability and Human Migration in Global Perspective”. In: *Sustainability* 9 (720 2017). DOI: <http://dx.doi.org/10.3390/su9050720>.
- [26] W. Neil Adger et al. “Focus on environmental risks and migration: causes and consequences”. In: *Environmental Research Letters* 10.6 (2015). DOI: <http://dx.doi.org/10.1088/1748-9326/10/6/060201>.
- [27] Hélène Benveniste, Michael Oppenheimer, and Marc Fleurbaey. “Effect of Border Policy on Exposure and Vulnerability to Climate Change”. In: *Proceedings of the National Academy of Sciences* 117.43 (2020), pp. 26692–26702. DOI: <https://doi.org/10.1073/pnas.2007597117>.

- [28] Klaus Desmet and Esteban Rossi-Hansberg. “On the spatial economic impact of global warming”. In: *Journal of Urban Economics* 88 (2015), pp. 16–37. DOI: <http://dx.doi.org/10.1016/j.jue.2015.04.004>.
- [29] Michal Burzynski et al. “Climate change, Inequality and Migration”. In: *Working Paper* (2018). URL: https://novafrica.org/wp-content/uploads/2018/08/Fr%C3%A9d%C3%A9ricDocquier_Climate-change-Inequality-and-Migration.pdf.
- [30] José Luis Cruz Alvarez and Esteban Rossi-Hansberg. “The Economic Geography of Global Warming”. In: *National Bureau of Economic Research* w28466 (2021).
- [31] Michał Burzyński, Frédéric Docquier, and Hendrik Scheewel. “The geography of climate migration”. In: *Journal of Demographic Economics* (2021), pp. 1–37.
- [32] Stéphane Hallegatte and Julie Rozenberg. “Climate change through a poverty lens”. In: *Nature Climate Change* 7 (2017), pp. 250–256. DOI: <https://doi.org/10.1038/nclimate3253>.
- [33] Narasimha D. Rao et al. “Improving poverty and inequality modelling in climate research”. In: *Nature Climate Change* 7 (2017), pp. 857–862. DOI: <https://doi.org/10.1038/s41558-017-0004-x>.
- [34] Francis Dennig et al. “Inequality, climate impacts on the future poor, and carbon prices”. In: *Proceedings of the National Academy of Sciences* 112.52 (2015), pp. 15827–15832. DOI: <https://dx.doi.org/10.1073/pnas.1513967112>.
- [35] Mark B. Budolfson et al. “The comparative importance for optimal climate policy of discounting, inequalities and catastrophes”. In: *Climatic Change* 145 (2017), pp. 481–494. DOI: <https://doi.org/10.1007/s10584-017-2094-x>.
- [36] Allan M. Findlay. “Migrant destinations in an era of environmental change”. In: *Global Environmental Change* 21.1 (2011). DOI: <https://doi.org/10.1016/j.gloenvcha.2011.09.004>.
- [37] Guy J. Abel et al. “Climate, conflict and forced migration”. In: *Global Environmental Change* 54 (2019), pp. 239–249. DOI: <https://doi.org/10.1016/j.gloenvcha.2018.12.003>.

- [38] Cristina Cattaneo et al. “Human Migration in the Era of Climate Change”. In: *Review of Environmental Economics and Policy* 13.2 (2019). DOI: <http://dx.doi.org/10.1093/reep/rez008>.
- [39] Joel E. Cohen et al. “International migration beyond gravity: A statistical model for use in population projections”. In: *Proceedings of the National Academy of Sciences* 105.40 (2008), pp. 15269–15274. DOI: <https://doi.org/10.1073/pnas.0808185105>.
- [40] Keuntae Kim and Joel E. Cohen. “Determinants of International Migration Flows to and from Industrialized Countries: A Panel Data Approach Beyond Gravity”. In: *International Migration Review* 44.4 (2010), pp. 899–932. DOI: <https://doi.org/10.1111/j.1747-7379.2010.00830.x>.
- [41] Marina Mastrorillo et al. “The influence of climate variability on internal migration flows in South Africa”. In: *Global Environmental Change* 39 (2016). DOI: <http://dx.doi.org/10.1016/j.gloenvcha.2016.04.014>.
- [42] Jonathan J. Azose and Adrian E. Raftery. “Estimation of emigration, return migration, and transit migration between all pairs of countries”. In: *Proceedings of the National Academy of Sciences* 116.1 (2019), pp. 116–122. DOI: <https://doi.org/10.1073/pnas.1722334116>.
- [43] Guy J. Abel and Joel E. Cohen. “Bilateral international migration flow estimates for 200 countries”. In: *Scientific Data* 6.82 (2019). DOI: <http://dx.doi.org/10.1038/s41597-019-0089-3>.
- [44] David Anthoff and Richard J. Tol. “The uncertainty about the social cost of carbon: A decomposition analysis using FUND”. In: *Climatic Change* 117.3 (2013), 515–530. DOI: <https://doi.org/10.1007/s10584-013-0706-7>.
- [45] Martin L. Weitzman. “GHG targets as insurance against catastrophic climate damages”. In: *Journal of Public Economic Theory* 14.2 (2012), pp. 221–244. DOI: <https://doi.org/10.1111/j.1467-9779.2011.01539.x>.
- [46] Chi Xu et al. “Future of the human climate niche”. In: *Proceedings of the National Academy of Sciences* 117.21 (2020), pp. 11350–11355.

- [47] Barbora Sedova and Matthias Kalkuhl. “Who are the climate migrants and where do they go? Evidence from rural India”. In: *World Development* 129 (2020), p. 104848. DOI: <https://doi.org/10.1016/j.worlddev.2019.104848>.
- [48] National Academies of Sciences, Engineering, and Medicine. *Valuing Climate Damages: Updating Estimation of the Social Cost of Carbon Dioxide*. 2017. DOI: <http://dx.doi.org/10.17226/24651>.

Materials and Methods

Migration and Remittance Flows: a Gravity Model. In a first step, we model migration dynamics by downscaling the gravity model detailed in [27] to the income quintile level. In particular, we express bilateral migrant flows as a function of three variables: 1) population sizes pop at origin and destination; 2) per capita income ypc of the quintile at origin; and 3) ratio of average per capita income at destination over quintile-specific income at origin. By doing so, we capture three key aspects of migration dynamics: the resource constraint to be overcome in order to migrate, the pull factor from richer areas and the fact that the migrant knows her economic situation before departure but does not know how well she will fare once at destination. We also include a set of bilateral characteristics of the origin/destination pair indicating: geodesic distances between regions’ centers of population, the cost of sending remittances, ϕ , and whether the two regions share a common official language, ψ . The fourth characteristic we include is the residual ϵ from the share of migrant’s income at destination sent as remittance (as defined in equation 5). Since the remittance share also depends on income at origin and destination, adding the full share would create collinearity. Yet the residual, reflecting missing variables influencing remittances, may still play a role. Our resulting gravity model encapsulated in equation 1 computes in essence the number of migrants leaving a given income quintile q of a given origin o and entering an average quintile of a given destination d .

$$\begin{aligned}
move_{od,q}(t) &= \beta_{0,q} \times pop_{o,q}(t)^{\beta_{1,q}} \times pop_{d,q}(t)^{\beta_{2,q}} \times ypc_{o,q}(t)^{\beta_{4,q}} \times (ypc_d(t)/ypc_{o,q}(t))^{\beta_{5,q}} \\
&\times dist_{od}^{\beta_{7,q}} \times exp(\beta_{8,q}exp(\epsilon_{od})) \times exp(\beta_{9,q}\phi_{od}) \times exp(\beta_{10,q}\psi_{od})
\end{aligned} \tag{1}$$

481 We then separately distribute this number of migrants over each destination quintile. We
 482 treat this redistribution endogenously, by modelling the share of migrants going to a given
 483 destination quintile *destshare* as a function of the ratio of average per capita income at
 484 destination over quintile-specific income level at origin. By doing so, we capture the relative
 485 development levels of origin and destination from the migrant's perspective. We then rescale
 486 this share so that the sum of all shares is equal to 1 (see equation 2).

$$\begin{aligned}
destshare_{od,qr}^*(t) &= \gamma_{0,r} \times (ypc_d(t)/ypc_{o,q}(t))^{\gamma_{1,r}} \\
destshare_{od,qr}(t) &= destshare_{od,qr}^*(t) / \sum_r destshare_{od,qr}^*(t)
\end{aligned} \tag{2}$$

487 The number of migrants leaving a given income quintile of a given origin and entering a given
 488 quintile of a given destination is thus described by equation 3. The total number of migrants
 489 leaving a given quintile of a given country at time t is given by $leave_{o,q}(t) = \sum_{d,r} move_{od,qr}(t)$,
 490 while the number of immigrants into a given destination quintile is given by $enter_{d,r}(t) =$
 491 $\sum_{o,q} move_{od,qr}(t)$.

$$move_{od,qr}(t) = move_{od,q}(t) \times \sum_r 1 \times destshare_{od,qr}(t) \tag{3}$$

492 To model how many migrants send remittances, we compute a state variable, *stock*, that
 493 keeps count of how many migrants from one quintile of one region are present in a quintile of
 494 another region at a given time (see equation 4). This bilateral “stock” of migrants is initiated
 495 as described in Section Calibration of other migration parameters, accumulates over time
 496 with new arrivals *move*, and decreases over time once migrants pass away [27]. This duration
 497 is computed as life expectancy at birth, λ , in the destination region minus median age of
 498 migrants at time of migration, μ . We derive remittance flows by assuming that only first-

generation migrants send money back to their origin region in the form of remittances, for the duration of their life [27]. This assumption coarsely illustrates the few empirical findings of the migration literature focusing on second-generation remittances, suggesting that second-generation migrants are significantly less likely to send remittances than their parents, and send smaller amounts [49].

$$stock_{od,qr}(t) = stock_{od,qr}(t-1) + move_{od,qr}(t) - \mathbf{1}_{t > \lambda_d - \mu_{qr}}[enter_{d,r}(t - \lambda_d(t) + \mu_{qr}(t))] \quad (4)$$

In terms of amount of money sent as remittances, we assume that migrants send a corridor-specific share of their income to their origin region, ρ , for a corridor-specific cost, ϕ . While we take ϕ as exogenous, we model ρ as a function of average per capita income levels ypc of origin and destination regions, and of the corridor-specific cost. Our resulting model describing the share of a migrant's income sent as remittance is featured in equation 5. Corridor-specific residuals, ϵ , are then used in our gravity model featured in equation 1. Note that remittances might also increase with climate change damages at origin, given their use as a form of insurance for households. To test the robustness of our results on immobility to the inclusion of this insurance mechanism, we additionally conduct a sensitivity analysis when remittances catch up with damages (see Supplementary Fig. B.11). Our central finding on immobility holds as quantitative results are minimally affected.

$$\rho_{od}(t) = \alpha_0 * ypc_o(t)^{\alpha_1} * ypc_d(t)^{\alpha_2} * exp(\alpha_3 \phi_{od}) * exp(\epsilon_{od}) \quad (5)$$

Furthermore, migrants' income at destination is modeled as the per capita income of their destination quintile. We use two simplifying assumptions. First, we assume that migrants can change income quintile when they move but, once at destination, stay in the same income quintile over time. This is a reasonable assumption for migrants who arrive at older ages. For younger migrants, the literature appears divided as to whether they fare better or worse than native populations. Some argue that migrants are more likely to move up the income

ladder once at destination [50, 51], while others counter that migrants' income growth, in fact, differs little from native populations [52, 53, 54], and that the ladder climbing rather takes place for children of immigrants [55]. Second, we assume that immigration does not modify destination income per capita levels [56]. Total net flows rem into a given region are computed as the difference between remittances received from all emigrants' destinations d and remittances sent by all immigrants to their origin p , again notwithstanding corridor-specific costs of sending remittances ϕ (equation 6).

$$\begin{aligned}
rem_{o,q}(t) = & \sum_d stock_{od,qr}(t) \times ypc_{d,r}(t) \times \rho_{od}(t) \times (1 - \phi_{od}) \\
& - \sum_p stock_{po,sq}(t) \times ypc_{o,q}(t) \times \rho_{po}(t) \times (1 - \phi_{po})
\end{aligned} \tag{6}$$

Finally, we consider a corridor-specific risk of dying while attempting to migrate, δ . We assume that only migrants coming from the three bottom income quintiles are at risk of dying, as more vulnerable migrants are likely to be the ones using more dangerous routes. In order to compare such migrants deaths to other damages from climate change, we use the value of statistical life (VSL) [57]. For a discussion of ethical issues surrounding the use of VSL, see [58, 59]. Here, we use time- and region-specific VSL endogenously computed by the IAM (equation 7). We use the larger of origin and destination VSL, as a migrant heading for a higher income would have a greater willingness to pay for safety than if she stayed in her country. Indeed the purpose of the VSL is to monetize deaths costs by taking people's willingness to pay to reduce the risk of death. This follows the valuation method used by [60]. The value selected here represents the upper bound of plausible values for a migrant's VSL.

$$\begin{aligned}
deadmig_{o,q}(t) = & \mathbf{1}_{q \leq 3} \sum_d \delta_{od} \times move_{od,qr}(t) \\
deadmigcost_{o,q}(t) = & \mathbf{1}_{q \leq 3} \sum_d \delta_{od} \times move_{od,qr}(t) \times \max(VSL_d(t), VSL_o(t))
\end{aligned} \tag{7}$$

We estimate our migration model using past data, then use it for our projection exercise.

Bilateral Migrant Flows per Income Quintile. Data on the independent variables of our migration model are quite straightforward to obtain and are chiefly obtained from the World Bank. However, data on the dependent variable is more difficult to obtain. Our model requires data on bilateral migration flows per income level, yet to our knowledge there is no dataset available on migrants' income profiles both before and after migration at the global scale. Instead, we proceed as follows. Bilateral migrant flows data at the country level are derived from 1990-2015 stock data (World Bank, 5-year periods) using two sources for the derivation: [42] as collected in [43], and [61] for robustness checks. We thus use secondary data on bilateral migration flows. These datasets have the benefit of exhaustivity, crucial for our purpose. Note that existing primary datasets on international bilateral flows, often based on OECD data [62], omit many migration corridors, in particular for South-South migration [27].

We then calculate income levels of migrants, using quintiles as description of income distributions. To that end, we use population projections from the Shared Socioeconomic Pathways (SSP), which provide in- and out-migration flows at the country level by education levels for the period 2015-2100. The initial distribution of education levels among migrants is based on census (IPUMS) and survey data as well as the available literature [63, 64]. The SSP projections consider six education levels: no education (e1), some primary (e2), primary completed (e3), lower secondary completed (e4), upper secondary completed (e5), post-secondary completed (e6). Because education levels among migrants vary a lot over the period 2015-2030 (see Supplementary Fig. A.1), we cannot assume constant levels for all of 1990-2015. Thus we restrict migrant flows data to the 2010-2015 period, assuming that migrants' education level is the same as the mean of SSP scenarios for 2015-2020.

We convert education levels into income levels by assuming that education level is perfectly correlated with income level, e.g. people in the lowest education level are also in the lowest income quintile. In practice, people sometimes hold jobs for which they are either over- or under-qualified. For instance, in OECD countries 51% of highly qualified persons held jobs that corresponded to their education level in 2006, 36% were under-qualified and 13% were overqualified [65]. We further assume that migrants' income profile per education level is the

571 same as the general population at destination. Note that this is a simplifying assumption.
572 For instance, highly qualified migrants to OECD countries hold high-skilled jobs less often
573 than highly-qualified natives (55% compared to 70% in 2006). This is often not because they
574 are more likely to occupy less skilled jobs than highly qualified natives (20% compared to
575 16%), but rather because they are unemployed or not in the labour force (26% compared
576 to 14%) [65]. Thus this assumption biases remittances toward higher values and inequality
577 toward smaller values.

578 For information purposes, we analyze out- and in-migration as a function of a migrant's
579 income level (see Supplementary Fig. A.2). We find that migrants tend to come from
580 income levels above the poorest, which hints at the resource constraint to be overcome in
581 order to migrate in the case of developing countries. Conversely, we find that the majority of
582 migrants to developed countries end up in lower income levels at destination, while migrants
583 to developing countries end up in higher income levels at destination.

584 Finally, we apply this income distribution of in- and out-migrants to bilateral migrant flows
585 by assuming that the distribution of migrants over each pair of quintiles for a given origin
586 and destination is the product of the distribution of emigrants' incomes at origin with the
587 distribution of immigrants' incomes at destination (equation 8).

$$mig_{od,qr}(t) = mig_{od}(t) \times \frac{outmig_{o,q}(t)}{outmig_o(t)} \times \frac{inmig_{d,r}(t)}{inmig_d(t)} \quad (8)$$

588 **Gravity Estimation.** Using the dataset described right above for the dependent variable,
589 we estimate our gravity equation using OLS regression (equation 9). We perform the estima-
590 tion over moves between countries; each quintile at origin has its own set of coefficients. Data
591 on population, average income levels and remittance flows are available from the World Bank.
592 We use Gini coefficients from the SSP projections [66] for the 2010-2015 period to determine
593 within-country income distributions, assuming that the underlying income distribution can
594 be fitted by a lognormal distribution.

$$\begin{aligned}
\ln(move_{od,q}) = & \ln(\beta_{0,q}) + \beta_{1,q}\ln(pop_{o,q}) + \beta_{2,q}\ln(pop_{d,q}) + \beta_{4,q}\ln(ypc_{o,q}) \\
& + \beta_{5,q}\ln(ypc_d/ypc_{o,q}) + \beta_{7,q}\ln(dist_{od}) + \beta_{8,q}\exp(\epsilon_{od}) \\
& + \beta_{9,q}\phi_{od} + \beta_{10,q}\psi_{od} + \varepsilon_{odqr}
\end{aligned} \tag{9}$$

The resulting estimation is presented in the top panel of Table 1. Results imply that migration flows between two countries increase with origin population size, with income per capita differences between origin and destination, and with the existence of a common language, and decrease with distance between countries, as suggested in other studies using similar models (e.g. [39]). Crucially, migration flows also tend to increase with origin quintile per capita income, hinting at the importance of the resource constraint to be overcome in order to migrate. The effect of income level in the origin quintile on migration follows a slight but discernible inverse U-shaped relationship across quintiles, suggesting that people with income levels comparable to their country's average income are most responsive to the resource constraint to migration being relaxed. We note that this relationship is distinct from the widely documented and similarly shaped relationship between a country's level of development and its emigration propensity [67]. Indeed, here we estimate the effect of income pulls and constraints on migration for individuals grouped by level of income in their respective countries. As a result, observations used to estimate income effects in each quintile include observations from countries with various development levels. Finally, the effects of bilateral characteristics (distance, remittances shares and costs, common official language) are as we would expect. Unsurprisingly, remittance costs reduce migration – yet the effect is not significant. The variable measuring remittances as share of income has an interesting effect on migration: although not significant, this effect goes from slightly negative to slightly positive with increasing relative income at origin. This suggests that the fact that people tend to move to areas where strong remittance traditions with their home countries exist, i.e. the effect of migration networks on the persistence of migration flows, plays in particular for the richest emigrants.

Note that including origin and destination fixed effects in our estimation would imply that we are considering effects inferred from the deviations of migration flows from origin- and

destination-specific long-run equilibria, which can be thought of as summarizing short- to medium-run elasticities. Conversely, effects on changes in the long-run equilibria are factored into the parameter estimates of the model without these country fixed effects. For that reason, we consider the model with only year fixed effects to be the more appropriate for the projection exercise. In addition, projecting country fixed effects would lead to flow differences across countries remaining constant in the long run, hiding potential long-term effects of our socioeconomic covariates [27]. For information, we discuss estimations with country fixed effects in the Supplementary Information Section D.7.

We provide a first robustness check by estimating parameters using migration data from [61] (Supplementary Table D.1), and find that our projections are virtually not affected by the data source. As a second robustness check, we test for reverse causality of migration on income at origin, in particular through remittances, by using income minus remittances received as an independent variable (Supplementary Table D.2); we find that the coefficients are not affected. We provide a third set of robustness checks by testing for the presence of non-monotonicity in the role of income at origin on the migration decision, by including a quadratic and a cubic specifications (Supplementary Tables D.3 and D.4); we do not find any significant non-monotonic effect of origin income. As a fourth set of robustness checks, we use the ratio of average incomes levels $\ln(ypc_d/ypc_o)$ (Supplementary Table D.5) and the ratio of quintile-specific income levels $\ln(ypc_{d,r}/ypc_{o,q})$ (Supplementary Table D.6) in place of the income ratio used in our main specification. We find that both specifications display slightly weaker effects of income on migration. Fifth, we estimate our gravity equation including measures of inequality at origin and destination, or their ratio, as potential drivers of migration (Supplementary Tables D.7 and D.8). While we do not find any significant effect of inequality, the signs and relative magnitudes of coefficients suggest that people tend to move to more equal locations, and that it is especially true for those among the poorest populations who move, consistently with the Roy-Borjas model of migrants self-selection [68]. Finally, we estimate our gravity equation including a dummy for shared border between two countries (Supplementary Table D.9), and find a somewhat significant and positive effect of common borders on migration, yet with little effect on the overall goodness-of-fit of our estimation.

This migration model, once estimated, is then used for our projection exercise. As migration flows, GDP, and remittances are also co-determined by other characteristics of countries' economies not explicitly represented in our model (e.g. availability of physical and human capital), concerns about omitted variables might arise. Here, as done in [18, 27], we assume that the effects of such characteristics on migration flows follow the same path as their effects on income per capita and population sizes, the two explicit drivers of our gravity model. Such effects are explicitly modeled at the country level in the scenarios used as input to our projection exercises (see Section Input Scenarios). Indeed, population projections are driven by fertility, mortality, migration rates, and level of educational attainment [63], while income per capita projections are driven by physical capital, labour, human capital, energy demand and natural resources extraction, and total factor productivity [69].

We then distribute migrants across income quintiles at destination. We estimate this endogenous distribution by OLS regression separately for each destination quintile (equation 10).

$$\ln(destshare_{od,q}^*) = \ln(\gamma_{0,r}) + \ln(\gamma_{1,r}) \times \ln(ypc_d/ypc_{o,q}) \quad (10)$$

The resulting estimation is presented in the bottom panel of Table 1. Results suggest that migrants arriving in countries that are much richer than their home country end up in lowest income levels at destination (positive coefficients in Columns 1 and 2), while migrants ending up in highest income quintiles at destination already come from countries where they are doing well compared to where they go (negative coefficient in Column 5). Coefficients for middle quintiles (Columns 3 and 4) are weakly positive and not significant. While this estimation displays a weak goodness-of-fit – in particular for the middle income quintiles – we argue that it still provides an improved specification over exogenous repartition in destination quintiles, as it allows to capture effects of converging levels of economic development over time on migrants' income levels at destination.

We provide a robustness check by estimating coefficients using income terciles at destination (see Supplementary Table D.10). We find rather similar coefficients for all quantiles, with

an increased significance of the coefficient on income per capita ratio as well as a better goodness-of-fit ($R^2=0.154$) for the middle tercile. This result suggests that we appropriately distribute migrants onto middle income quintiles at destination.

We then use the estimated coefficients of Table 1 in our migration model at the regional level. Remittance parameters ρ and ϕ are transposed from country to region level as described below. Distances between regions are calculated as Haversine distances between centers of population of regions, computed as arithmetic means of coordinates of a region’s countries’ capitals weighted by 2010 country-level population [27]. The presence of a common official language between two regions becomes a coefficient between 0 and 1, weighting all dummies for country pairs of the two regions with migration flows between the regions in the period 2010-2015 from [42].

Finally, in order to realistically reflect each migration corridor’s specificity, we incorporate pair- and quintile-specific residuals from equation 9 in our migration model (see equation 11 and Supplementary Fig. A.3).

$$move_{od,qr}^* = move_{od,qr} + \varepsilon_{odqr} \quad (11)$$

Remittance Share Estimation. For the estimation of our remittance share equation, we exactly follow [27]. Because our remittance data does not distinguish remittances per migrant’s income or education level, we treat this estimation using average income levels, without taking into account income distributions within countries. To calculate the share of income sent as remittance, we use World Bank data on bilateral remittances estimates, bilateral estimates of migrant stocks, and per capita GDP data for 2017, the last year for which all three data types are available. Data on independent variables is available from the World Bank. The resulting estimation is presented in Supplementary Table A.1. Results suggest that the proportion of migrant’s income sent as remittance increases with the gap in per capita income between origin and destination, and decreases with destination per capita income. Note that the World Bank defines remittances as current transfers by migrants and assumes for its remittances estimates that the transfer of such funds takes place from the

migrant to her home community. This is also what we assume in our model.

We then use the estimated coefficients in our remittance model at the regional level. Remittance parameter ϕ is transposed from country to region level as described below. Residuals ϵ , used both in our remittance and our gravity models (equations 1 and 5), are aggregated at the region level as described in the Supplementary Information (Section F.4).

Calibration of other migration parameters. Other remittance parameters are calibrated as follows. First, duration of migrants' stay in the destination region is computed as the difference between life expectancy λ in the destination region, and age of migrants at time of migration μ , both calibrated using SSP projections available at the country level. We derive age of migrants per income quintile from age of migrants per education levels – available in the SSP projections – using the same method as for migrant flows (see above); because this age distribution varies little over time and across SSP, we use country- and quintile-specific values for the middle scenario SSP2 for the year 2020. As a coarse approximation, we assume that life expectancy is equal across income quintiles. We assume constant parameters after 2100; here we only show results for 2015-2100, so this assumption does not affect our results. For both parameters, we transpose from country to region level by weighting countries within each region by 2015 population size, using data from the Wittgenstein Centre. As our migration dynamics model only starts in 2015, we also include an initial stock of migrants for that year. For that purpose, we use data on bilateral migrant stocks from the World Bank for 2017, the closest available year [27]. We assume that the income distribution of this initial stock of migrants can be approximated by the income distribution of people migrating during the period 2015-2020; that distribution is derived from education profiles of migrants as described above. Furthermore, we build the age distribution of the initial migrant stock as the average of two distributions: the age distribution of migrants at time of migration in the period 2015-2020, and the age distribution of overall destination population in the same period, both sourced from the SSP population projections.

Second, we estimate the share of migrant's income ρ sent as remittances as described above. We also assume that the cost ϕ of sending remittances is constant over time, across income quintiles and across SSP narrative, but specific to the origin/destination pair. We calibrate

this parameter using data from the World Bank’s database Remittance Prices Worldwide for the year 2017. We transpose it from country to region level by weighting migration corridors within each region by remittances flows. Remittance cost values range from 2% to 17% of the amount sent as remittance, depending on the corridor.

Finally, the risk of dying while attempting to migrate δ is also assumed constant over time and across SSP narrative, but specific to the origin/destination pair and applied only to the three bottom quintiles. We calculate this risk as the ratio of missing migrants to the migrant flows on that journey [27]. We calibrate this parameter using data on missing migrants for the period 2014-2018 from the International Organization for Migration, as well as data on migration flows between regions in the period 2010-2015 from [42].

Including Migration and Income Distributions in an IAM. In a second step, we include our migration and remittances dynamics model with income distributions in an existing IAM, in order to incorporate the effect of climate change on resource deprivation and resulting immobility. For most models, migration is absent from the IAM itself and considered only implicitly, as part of required input population growth scenarios [27]. The only IAM that includes it somewhat more explicitly in its damage function is the Climate Framework for Uncertainty, Negotiation and Distribution (FUND), only for displacement caused by sea-level rise [44]. For our second step, as in [27], we choose FUND, as it presents useful features for this project: some regional disaggregation (16 regions, two of them representing one country each: United States and Canada; Supplementary Table C.1), and a sectoral quantification of damages (12 impact sectors). In FUND, damage functions are thus impact-specific. For a detailed description of each impact module, see <https://fundjl.readthedocs.io/en/latest/science.html>.

FUND also displays a version that includes within-region income distributions, based on the work of [34] who implemented a similar representation of income distributions in RICE, the regional version of the Nordhaus IAM DICE – which they aptly call NICE. This declination of [34]’s work into FUND, as well as into PAGE, was performed by Frank Errickson. We are grateful for his work. The implementation of income distributions in FUND goes as follows. First, each of its 16 regions is split into population quintiles. Second, the damage

760 distribution over income quintiles depends on the income distribution through the income
 761 elasticity of damages ξ (equation 12). Elasticity values of 1, 0, and -1 correspond to damages
 762 being proportional, independent, and inversely proportional to income. Since the regressive
 763 character of damages is still unsettled, we provide results with all three variants; we discuss
 764 our choice of values for the income elasticity of damages in light of what can be inferred
 765 from the literature in Supplementary Information Section F.1. Third, mitigation cost is
 766 distributed across income groups following the income elasticity of mitigation ω (equation
 767 13). Here, elasticity values of 0, 1, and 2 correspond to mitigation costs being independent,
 768 proportional to income, and progressively redistributed. In this study, we focus on the
 769 distributional effects of climate impacts rather than on effects of mitigation policies. Hence,
 770 while we vary ξ , we keep ω constant at 1. Fourth, as an important difference with [34,
 771 35], in our FUND implementation income distributions before damages are not constant
 772 over time but rather driven by exogenous inequality growth scenarios (see Section Input
 773 Scenarios).

$$damshare_{r,q}(t) = k_{\xi}(GDP_{r,q}/GDP_r)^{\xi}, \quad \xi \in \{1, 0, -1\} \quad (12)$$

774

$$mitigcostshare_{r,q}(t) = k'_{\omega}(GDP_{r,q}/GDP_r)^{\omega}, \quad \omega \in \{1, 0, -1\} \quad (13)$$

775 We use this version of FUND and complement it by introducing our quintile-specific mi-
 776 gration and remittance dynamics model. To this end, we use a modular approach, i.e. we
 777 use the version of FUND implemented with Mimi. Mimi is a Julia package that provides a
 778 component model for integrated assessment models. It is being developed by a team led by
 779 UC Berkeley's David Anthoff, in connection with Resources for the Future's Social Cost of
 780 Carbon Initiative. This IAM being constructed as an ensemble of components, we create a
 781 migration component and plug it into FUND (see Extended Data Fig. E.5). Importantly,
 782 migration and climate change impacts interact only indirectly through the income channel:
 783 migration changes population distribution and generates income transfers between regions,
 784 which modifies each region's emissions profile and damages. Conversely, climate change

generates region- and quintile-specific damages, hence modifies relative income levels – a driver of our migration dynamics model. Note that in the FUND IAM, damages do not just modify income, they also induce harms which are monetized and included in income. Thus our migration model also captures some effects of non-income impacts of climate change – although we estimate it with data that do not incorporate these non-income impacts, which incurs a bias in the estimation. Still, this income effect is a crucial channel through which climate change affects international migration decisions, as income levels and differences across countries are key drivers of international movements, and as climate change affects income levels differently in different countries. Other channels could also be at play; see Supplementary Information Section F.2 for a discussion of the effect of changing perceptions of future climate change on mobility decisions. Finally, while FUND requires an exogenous input scenario of GDP growth, part of the climate change damages in one period reduces the production of the next period instead of only reducing the consumption of the present period. Hence, in our model income is determined by region-specific endogenous growth, climate change damages, and remittances.

Input Scenarios. The final step of our modeling exercise involves using the proper input scenarios. Indeed, FUND requires input scenarios of population, economic, energy and carbon intensity growth. Our version with income distributions also requires input scenarios of income inequality growth. While default scenarios in FUND are based on the SRES scenarios developed for the IPCC Special Report on Emissions Scenarios published in 2000, here we use the more recently developed SSP framework. SSP scenarios involve quantified projections of, among other indicators, population, GDP, Gini coefficients, final energy consumption, greenhouse gas emissions, and carbon prices along five narratives of future world development for the 21st century. However, SSP narratives include built-in assumptions on international migration [70], explicit only in population projections [63] (see Extended Data Fig. E.6). Thus using the original SSP quantifications as input to our migration dynamics model coupled to FUND would lead us to count migration twice: once in the input scenarios and once in the migration model itself [27]. In order to avoid double counting of migration, we use versions of those scenarios without migration, which some of us developed in a pre-

vious project [71]. The corresponding approach is described in detail in the Supplementary Information Section F.3. Additionally, for the energy consumption and emissions projections, we select relevant combinations of SSP with the RCP (see Supplementary Figs. A.4 and A.5). Finally, as FUND runs for the period 1950-3000 in yearly time steps, we extend the SSP projections as described in Supplementary Table C.2.

Data Availability: The data generated and analyzed for this study has been deposited on Figshare: <https://doi.org/10.6084/m9.figshare.19698901.v1> [72].

Code Availability : All data were edited and analyzed in Julia. The complete codes used to generate and visualize the results reported in this study has been deposited on Figshare: <https://doi.org/10.6084/m9.figshare.19698901.v1> [72].

References

- [49] Tineke Fokkema, Eralba Cela, and Elena Ambrosetti. “Giving from the Heart or from the Ego? Motives behind Remittances of the Second Generation in Europe”. In: *International Migration Review* 47.3 (2013), pp. 539–572. DOI: <https://doi.org/10.1111/imre.12032>.
- [50] Yann Algan et al. “The Economic Situation of First and Second-Generation Immigrants in France, Germany and the United Kingdom”. In: *The Economic Journal* 120.542 (2010), F4—F30. DOI: <https://doi.org/10.1111/j.1468-0297.2009.02338.x>.
- [51] George J. Borjas and Lawrence F. Katz. “The Evolution of the Mexican-Born Workforce in the United States”. In: *Mexican immigration to the United States*. Ed. by George J. Borjas. University of Chicago Press, 2007, pp. 13–56.
- [52] Ran Abramitzky, Leah Platt Boustan, and Katherine Eriksson. “A Nation of Immigrants: Assimilation and Economic Outcomes in the Age of Mass Migration”. In:

Journal of Political Economy 122.3 (2014), pp. 467–506. DOI: <http://dx.doi.org/10.1086/675805>.

[53] Ran Abramitzky and Leah Platt Boustan. “Immigration in American Economic History”. In: *Journal of Economic Literature* 55.4 (2017), pp. 1311–1345. DOI: <http://dx.doi.org/10.1257/jel.20151189>.

[54] Darren Lubotsky. “Chutes or Ladders? A Longitudinal Analysis of Immigrant Earnings”. In: *Journal of Political Economy* 115.5 (2007). DOI: <https://doi.org/10.1086/522871>.

[55] Ran Abramitzky et al. “Intergenerational mobility of immigrants in the United States over two centuries”. In: *American Economic Review* 111.2 (2021), pp. 580–608. DOI: <https://doi.org/10.1257/aer.20191586>.

[56] Francesc Ortega and Giovanni Peri. “The Causes and Effects of International Migrations: Evidence from OECD Countries 1980-2005”. In: *National Bureau of Economic Research* 14833 (2009). URL: <http://www.nber.org/papers/w14833>.

[57] M W Jones-Lee. “Paternalistic Altruism and the Value of Statistical Life”. In: *The Economic Journal* 102.410 (1992), pp. 80–90. DOI: <https://doi.org/10.2307/2234853>.

[58] C R Sunstein. “Lives, life-years, and willingness to pay”. In: *Columbia Law Review* 104 (2004), p. 205. DOI: <https://doi.org/10.2307/2234853>.

[59] Olof Johansson-Stenman and Peter Martinsson. “Are some lives more valuable? An ethical preferences approach”. In: *Journal of Health Economics* 27.3 (2008), pp. 739–752. DOI: <https://doi.org/10.1016/j.jhealeco.2007.10.001>.

[60] William D Nordhaus and Joseph Boyer. *Warming the world: economic models of global warming*. MIT press, 2000.

[61] Guy J. Abel. “Estimates of Global Bilateral Migration Flows by Gender between 1960 and 2015”. In: *International Migration Review* 52.3 (2018), pp. 809–852. DOI: <http://dx.doi.org/10.1111/imre.12327>.

[62] Ruohong Cai, Shuaizhang Feng, and Michael Oppenheimer. “Climate variability and international migration: The importance of the agricultural linkage”. In: *Journal of Environmental Economics and Management* 79 (2016), pp. 135–151. DOI: <http://dx.doi.org/10.1016/j.jeem.2016.06.005>.

- [63] Samir KC and Wolfgang Lutz. “The human core of the shared socioeconomic pathways: Population scenarios by age, sex and level of education for all countries to 2100”. In: *Global Environmental Change* 42 (2017), pp. 181–192. DOI: <http://dx.doi.org/10.1016/j.gloenvcha.2014.06.004>.
- [64] Samir KC et al. *Summary of data, assumptions and methods for new Wittgenstein Centre for Demography and Global Human Capital (WIC) population projections by age, sex and level of education for 195 countries to 2100*. IIASA Interim Report IR-13-018. Laxenburg Austria: IIASA, 2013.
- [65] Jonathan Chaloff and Georges Lemaître. *Managing Highly-Skilled Labour Migration: A Comparative Analysis of Migration Policies and Challenges in OECD Countries*. Social, Employment and Migration Working Papers 79. OECD, 2009. DOI: <https://doi.org/10.1787/1815199X>.
- [66] Narasimha D. Rao et al. “Income inequality projections for the Shared Socioeconomic Pathways (SSPs)”. In: *Futures* 105 (2019), pp. 27–39. DOI: <http://dx.doi.org/10.1016/j.futures.2018.07.001>.
- [67] Thu Hien Dao et al. “Migration and development: Dissecting the anatomy of the mobility transition”. In: *Journal of Development Economics* 132 (2018), pp. 88–101. DOI: <https://doi.org/10.1016/j.jdeveco.2017.12.003>.
- [68] George J. Borjas. “Self-selection and the earnings of immigrants”. In: *The American Economic Review* 77.4 (1987), pp. 531–553.
- [69] Rob Dellink et al. “Long-term economic growth projections in the Shared Socioeconomic Pathways”. In: *Global Environmental Change* 42 (2017), pp. 200–214. DOI: <http://dx.doi.org/10.1016/j.gloenvcha.2015.06.004>.
- [70] Brian C. O’Neill et al. “The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century”. In: *Global Environmental Change* 42 (2017), pp. 169–180. DOI: <http://dx.doi.org/10.1016/j.gloenvcha.2015.01.004>.
- [71] Hélène Benveniste et al. “Tracing International Migration in Projections of Income Levels and Inequality across the Shared Socioeconomic Pathways”. In: *Climatic Change* 166.39 (2021). DOI: 10.1007/s10584-021-03133-w.

900 [72] Hélène Benveniste, Michael Oppenheimer, and Marc Fleurbaey. *Climate change in-*
901 *creases resource-constrained international immobility*. Figshare software. Deposited 3
902 May 2022. URL: <https://doi.org/10.6084/m9.figshare.19698901.v1>.

Supplementary Information for Climate change increases resource-constrained international immobility

A Supplementary figures for Methods and Materials

A.1 Calculating migrants' income levels for the gravity estimation.

We calculate income levels of migrants, using quintiles as description of income distributions. To that end, we use population projections from the Shared Socioeconomic Pathways (SSP), which provide in- and out-migration flows at the country level by education levels for the period 2015-2100. The SSP projections consider six education levels: no education (e1), some primary (e2), primary completed (e3), lower secondary completed (e4), upper secondary completed (e5), post-secondary completed (e6). Education levels among migrants over time, as included in the SSP, are displayed in Fig. A.1.

In order to convert education levels into income levels, we proceed as follows. First, we start with the distribution of a location's population across the six education levels. Second, we distribute each education-specific population share across the relevant income quintile: for instance, if the share of people with the lowest education level is smaller than 20%, all these people are attributed to the bottom income quintile, but if it is higher, we attribute the share additional to 20% to the second lowest income quintile. Third, we assume that the migrants' income profile per education level is the same as the general population at destination. In practice, we multiply this distribution of education levels across income quintiles by the share of migrants per education levels to obtain the distribution of migrants per income quintile.

A.2 Migration as a function of income level for the estimation period.

Using the SSP projections of migration flows per education level as basis, we analyze out- and in-migration as a function of a migrant's income level. To this end, we use 2010 population

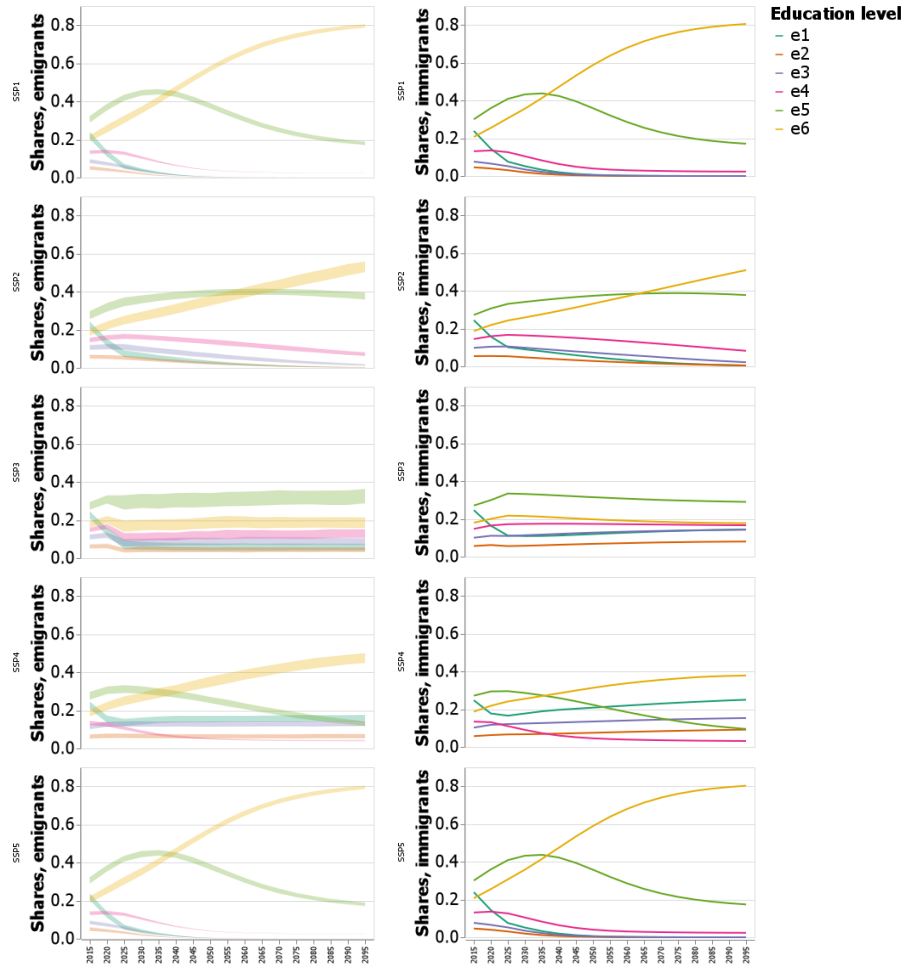


Figure A.1: Outmigration (left) and in-migration (right) as a function of education levels, for each of the five SSP narratives, for the period 2015-2100. Results displayed for the 95% confidence interval across countries. Color code indicates the six education levels.

data from the UN World Population Project 2019, 2010 GDP data from the World Bank’s World Development Indicators, and Gini coefficients from the SSP projections for the 2010-2015 period [66], which we transform into income quintiles by assuming that the underlying income distribution can be fitted by a lognormal distribution. Results are displayed in Fig. A.2. We find that migrants tend to come from income levels above the poorest, which hints at the resource constraint to be overcome in order to migrate in the case of developing countries. Conversely, we find that the majority of migrants to developed countries end up in lower income levels at destination, while migrants to developing countries end up in higher income levels at destination.

A.3 Residuals from gravity model estimation.

In order to realistically reflect each migration corridor’s specificity, we incorporate pair- and quintile-specific residuals from equation 9 in our migration model (see equation 11). Such residuals are plotted in Fig. A.3.

Positive numbers on the y-axis indicate an underestimation of actual migration flows by our gravity model, while negative numbers indicate an overestimation. We find that our model overestimates migration flows only between the US and Canada, and more often underestimates them for other corridors. Importantly, residuals keep the same sign across quintiles for all corridors, which suggests that our gravity model captures quintiles’ specificities well, and simply has to deal with migration corridors that are very different from one another.

A.4 Remittance share estimation.

For the estimation of our remittance share equation, we exactly follow [27]. Because our remittance data does not distinguish remittances per migrant’s income or education level, we treat this estimation using average income levels, without taking into account income distributions within countries. To calculate the share of income sent as remittance, we use World Bank data on bilateral remittances estimates. Note that the World Bank defines remittances as current transfers by migrants and assumes for its remittances estimates that the transfer of such funds takes place from the migrant to her home community. This is also what we assume in our model. We also use bilateral estimates of migrant stocks, and per capita GDP data for 2017, the last year for which all three data types are available. Data

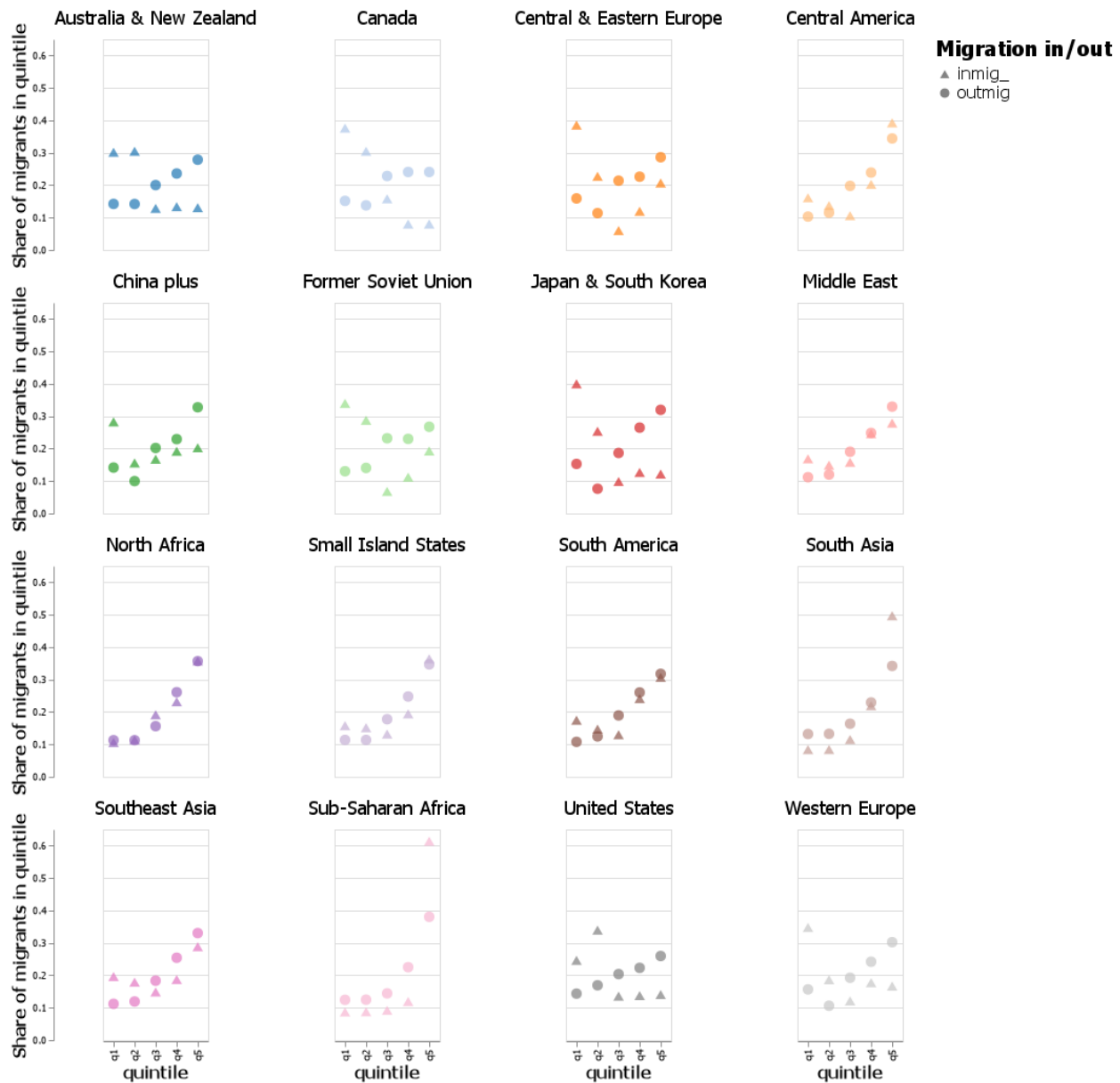


Figure A.2: Out- and in-migration as a function of income quintiles of migrants for the period 2010-2015. Results displayed separately for 16 world regions.

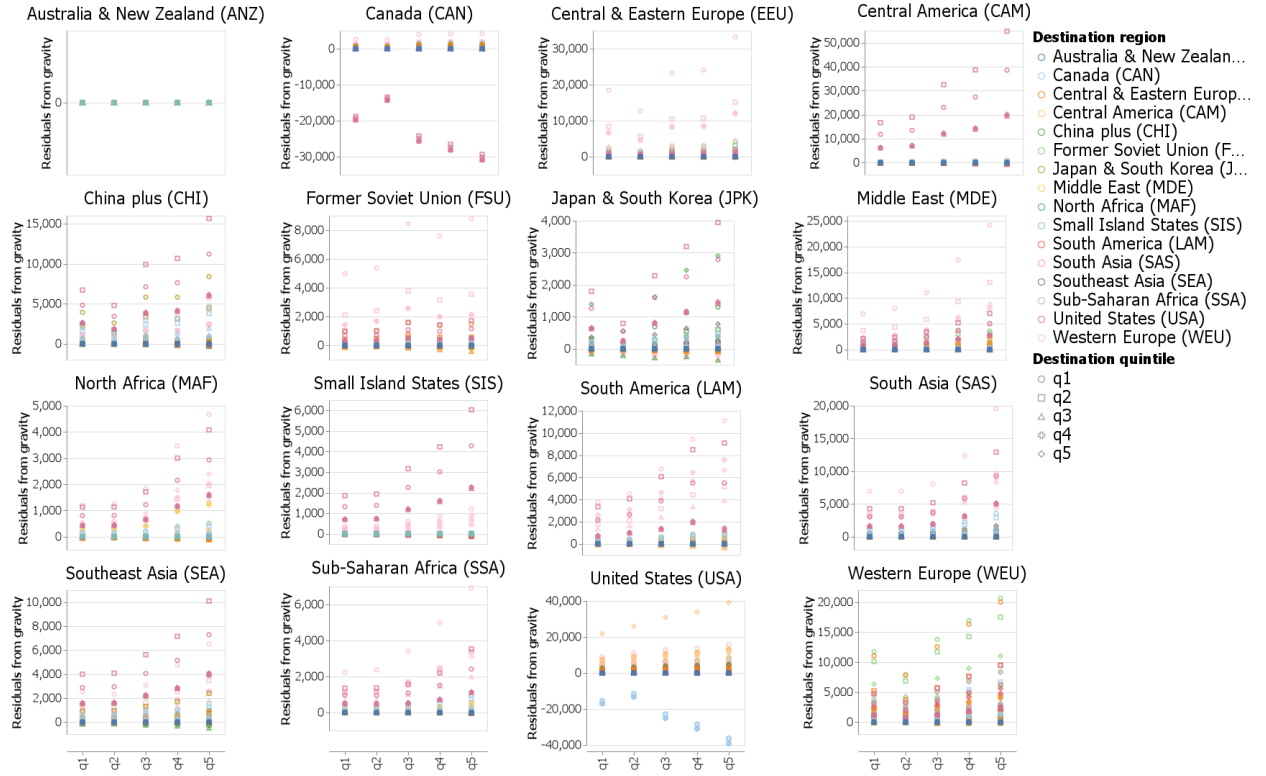


Figure A.3: Residuals of equation (9) estimating the number of people moving between quintiles of two regions following our gravity model. Each of the 16 panels illustrates an origin region. The color codes illustrate destination regions, while shapes signal destination income quintiles. Values for the 2010-2015 are represented.

| | Remittance share | | ln(remittance share) | |
|-------------------------------|------------------|---------|----------------------|-----------|
| Origin per capita income | -0.020** | | -0.242** | |
| | (0.006) | | (0.081) | |
| Destination per capita income | 0.001 | -0.019* | -0.361*** | -0.603*** |
| | (0.004) | (0.009) | (0.032) | (0.090) |
| Ratio of per capita incomes | | 0.020** | | 0.242** |
| | | (0.006) | | (0.081) |
| Cost of sending remittances | 1.284* | 1.284* | -5.783 | -5.783 |
| | (0.617) | (0.617) | (3.581) | (3.581) |
| N | 34,225 | 34,225 | 10,430 | 10,430 |
| R^2 | 0.005 | 0.005 | 0.133 | 0.133 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.1: Estimation of remittances sent as share of migrant’s income. Results from OLS regression of remittance shares (columns 1–2) and log remittance shares (columns 3–4). Dependent variables are regressed on income per capita at destination and cost of sending remittances (all columns), as well as income per capita at origin (columns 1 and 3) and ratios of destination to origin incomes (columns 2 and 4). Standard errors clustered at the origin and destination levels in parentheses.

on independent variables is available from the World Bank.

The resulting estimation is presented in Supplementary Table A.1. Results suggest that the proportion of migrant’s income sent as remittance increases with the gap in per capita income between origin and destination as represented by the income ratios (see columns 2 and 4), and decreases with destination per capita income. High remittances costs tend to take place in corridors sending high shares of remittances (columns 1 and 2), likely the most profitable corridors for intermediaries harvesting these costs. Yet, unsurprisingly, higher remittance costs reduce remittances shares (columns 3 and 4) though this effect is not significant. Finally, the specification in $\ln(\rho)$ provides a better fit, hence we use it for our remittance model.

A.5 Selected scenarios of future development and climate change.

For the energy consumption and emissions projections, we select relevant combinations of SSP with climate scenarios, the Representative Concentration Pathways, among the ones selected for the upcoming IPCC Assessment Report (see Fig. A.4): SSP1-RCP1.9, SSP2-RCP4.5, SSP3-RCP7.0, SSP4-RCP6.0, SSP5-RCP8.5.

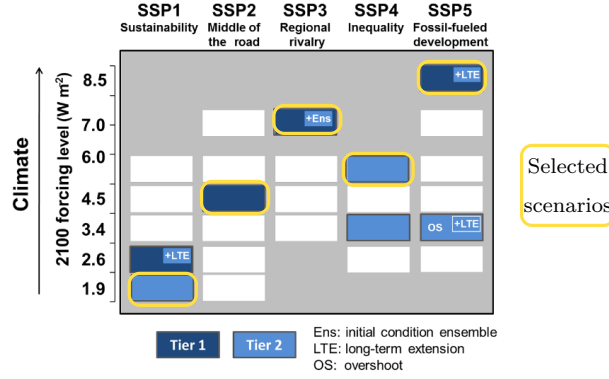


Figure A.4: Matrix of relevant combinations of development scenarios (SSP) and climate scenarios (RCP). Combinations shaded in blue are selected for the upcoming IPCC Assessment Report. Combinations also circled in yellow are the ones used in this study. Figure reprinted from [27] and [73], which is licensed under [https://creativecommons.org/licenses/by/3.0/CC BY 3.0](https://creativecommons.org/licenses/by/3.0/CC-BY-3.0). Source for CMIP6 data: [74].

A.6 Global carbon prices for selected scenarios.

To project consistent mitigation costs, we use carbon prices projections corresponding to the respective SSP-RCP combinations selected. These projections are computed using the process-based IAM described in [73]. They feature narrative-specific global carbon prices. We illustrate those carbon price projections in Fig. A.5.

B Supplementary figures for additional results

B.1 Cumulative immigrants per income quintile.

When considering cumulative number of migrants or migrant “stocks”, the income profiles of people living abroad tend to be unbalanced at the beginning of the century with a majority of low income migrants in developed countries and the opposite in least developed regions. However, income profiles even out over time in most regions, to a degree dependent on the SSP narrative considered (see Fig. B.1 for results with a medium climate and development scenario, SSP2-RCP4.5).

B.2 Net migration per income quintile.

Our model allows us to compute net migration numbers per income quintile in each region (see Fig. B.2). As expected, most developing regions are net origin regions for migrants

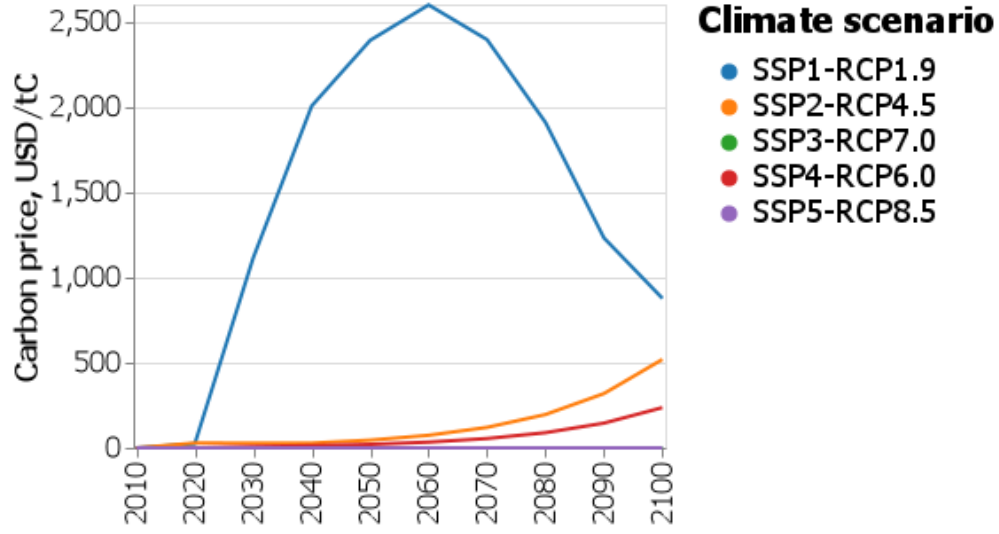


Figure A.5: Global carbon prices for all five SSP narratives coupled to respective RCP, used as input to FUND to ensure consistent mitigation costs. Source: IIASA SSP Database. Figure reprinted from [27].

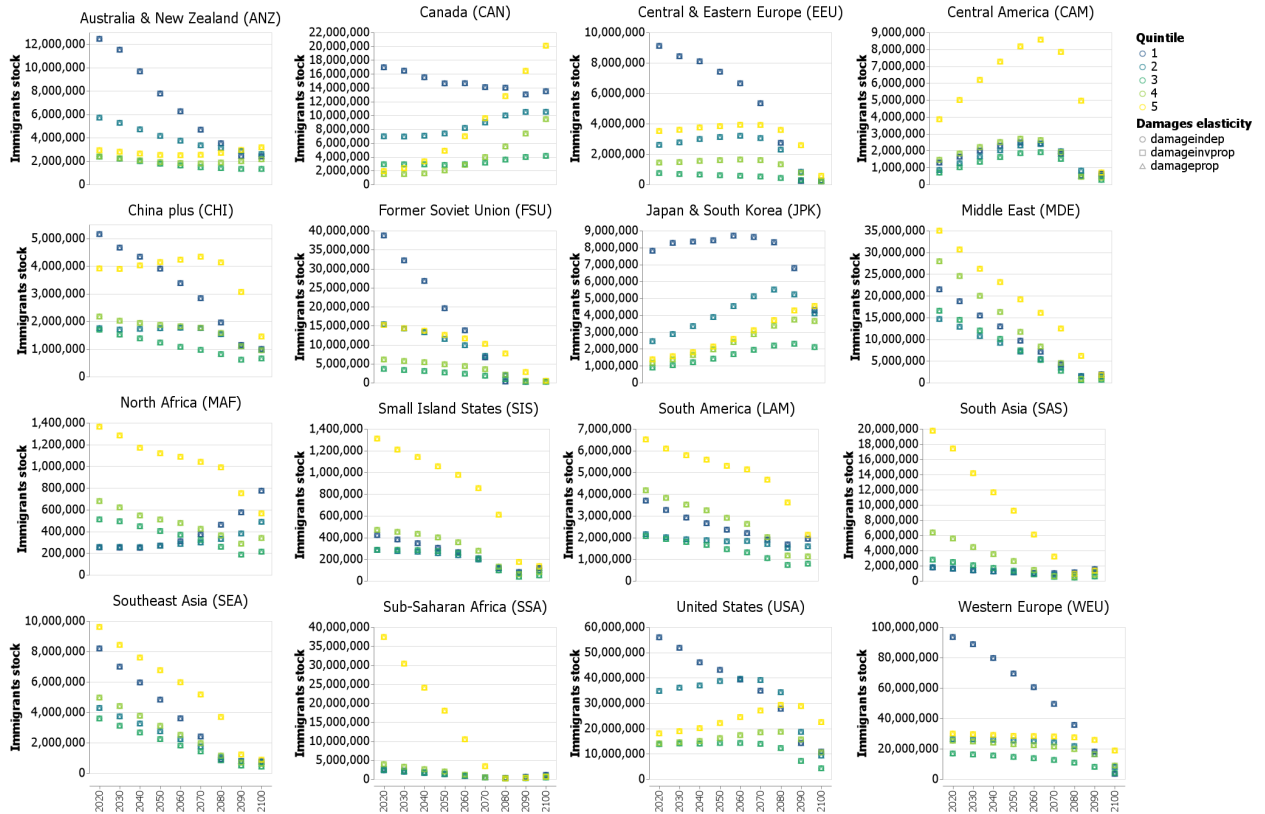


Figure B.1: Cumulative number of migrants living abroad per income quintile. Results for SSP2 (middle-of-the-road) coupled to RCP4.5 for each of the 16 regions in FUND, for the period 2015-2100. Color codes indicate income quintiles, while shapes indicate elasticity of damages.

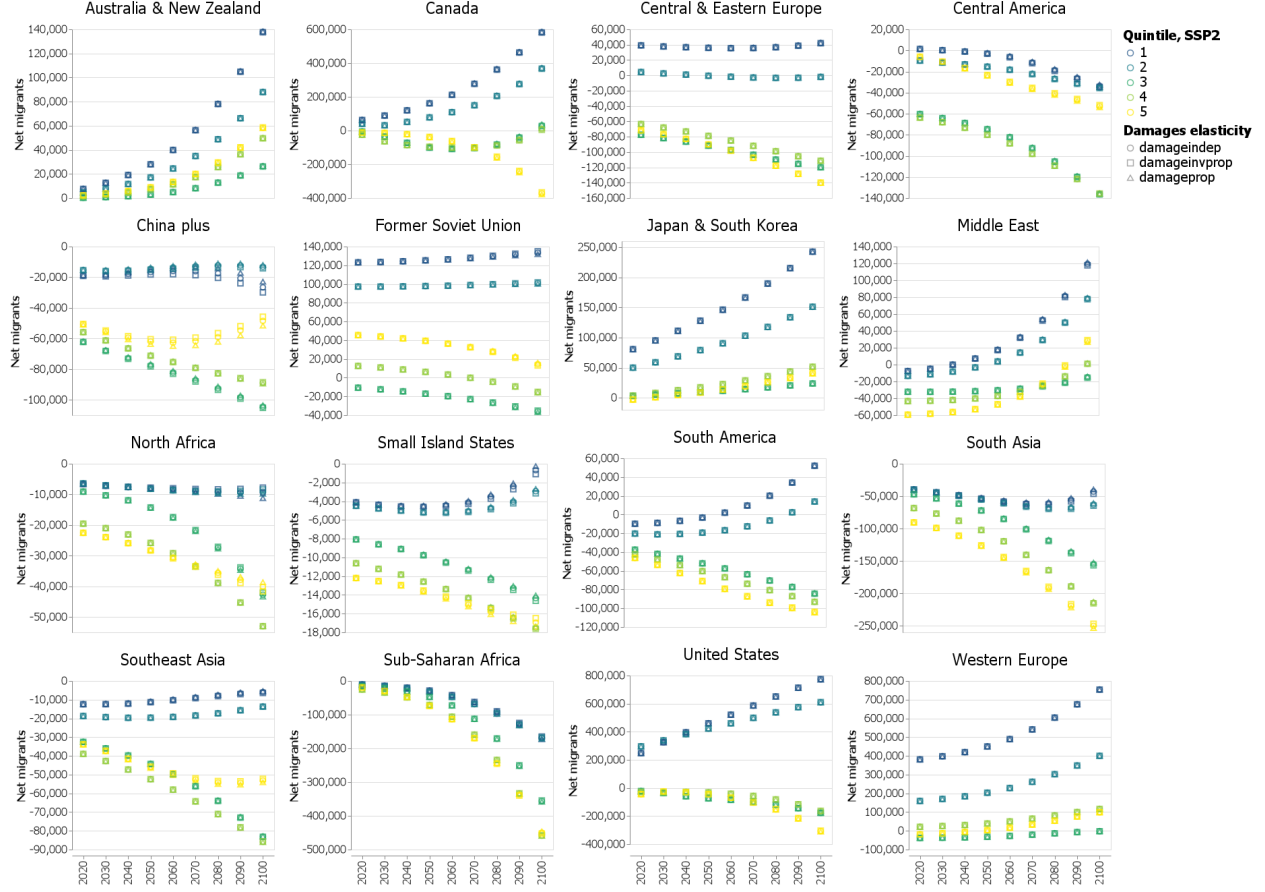


Figure B.2: Net migration per income quintile. Results for SSP2 (middle-of-the-road) coupled to RCP4.5 for each of the 16 regions in FUND, for the period 2015-2100. Color codes indicate income quintiles, while shapes indicate elasticity of damages.

for all income quintiles, and in particular for higher quintiles. This is, first, because higher income levels in developed regions act as a pull factor for migration; and second, because people in higher income quintiles have more resources to be able to migrate internationally. Conversely, most developed regions are net destination regions for lower income quintiles, and to a lesser extent are net origin regions for higher income quintiles. Note that migrant numbers are virtually not affected by the elasticity of damages ξ .

B.3 Net remittances per income quintile.

We also compute net remittances transferred per income quintile in each region (see Fig. B.3). As expected, developing regions are net receivers of remittances for all income quintiles, whereas developed regions are net senders. Interestingly, highest income levels appear to benefit most in some developing regions (Central America, North Africa, South and Southeast Asia).

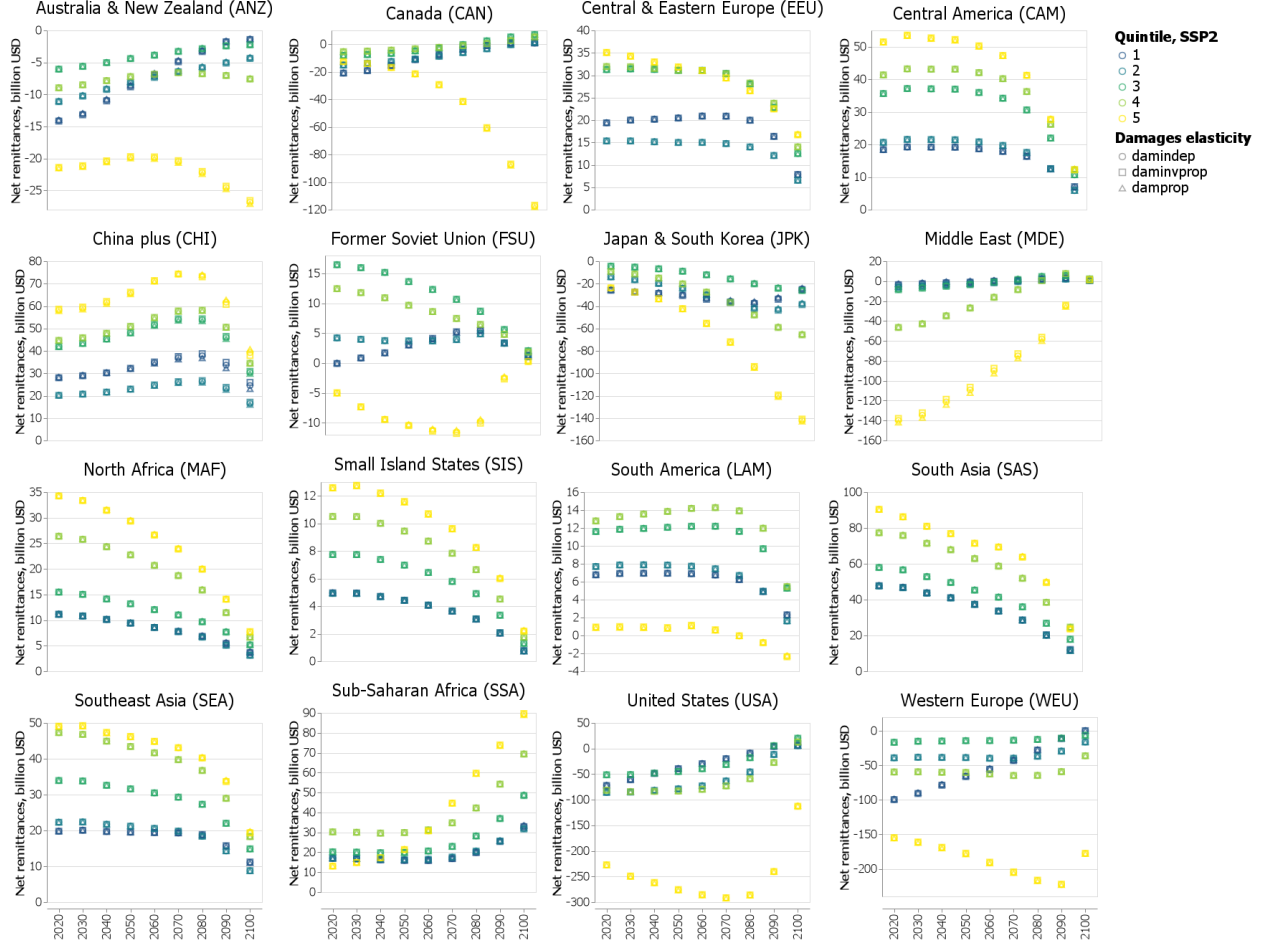


Figure B.3: Net remittances per income quintile. Results for SSP2 (middle-of-the-road) coupled to RCP4.5 for each of the 16 regions in FUND, for the period 2015-2100. Color codes indicate income quintiles, while shapes indicate elasticity of damages.

Asia) whereas in others (South America, Sub-Saharan Africa) the middle income quintiles are the ones benefiting from the highest amount of remittances. Conversely, in developed regions the highest income levels are the ones who send the most remittances, followed by the lowest income levels. Note that ξ does not affect net remittances either.

B.4 Within-region inequality.

In our model, within-region inequality, as measured by the Gini coefficient, is driven by exogenous inequality growth, migration and remittance dynamics, and damages distributions. We compare our results on within-region inequality to Gini projections obtained from the SSP [66] and from FUND without added migration (see Fig. B.4). We find that including migration in our model increases inequality in developed, often net destination, regions, but

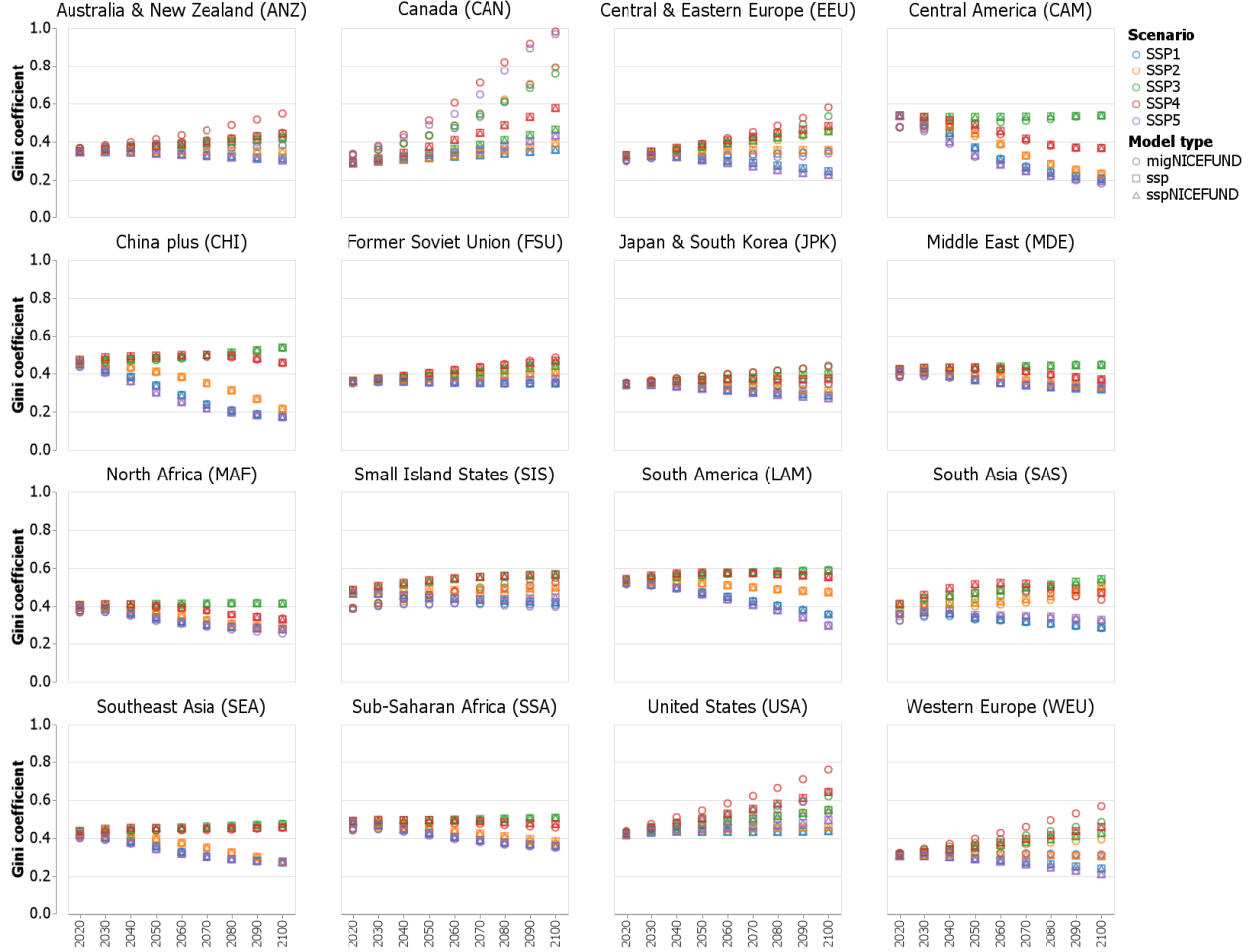


Figure B.4: Within-region Gini coefficients, for each of the five SSP narratives, for the period 2015-2100. Color code indicates SSP narratives. Shapes indicate results obtained with original SSP projections (squares), FUND with income distributions (triangles), and FUND with migration and income distributions (circles).

has little effect on inequality in developing, often net origin, regions, for all SSP narratives. Note that this result is true at the region level because interregional migration flows represent small shares of overall populations, but might not stand at the country level for some small countries.

Furthermore, the damage elasticity of income affects inequality in only a few regions, namely China/North Korea/Mongolia (called “China plus” in FUND), North Africa, and the Former Soviet Union (see Fig. B.5). Interestingly, China plus has higher inequality when damages are proportional to income as damages stay negative (beneficial climate impacts) over the century in FUND for that region, due to strongly beneficial CO2 fertilization effects. Con-

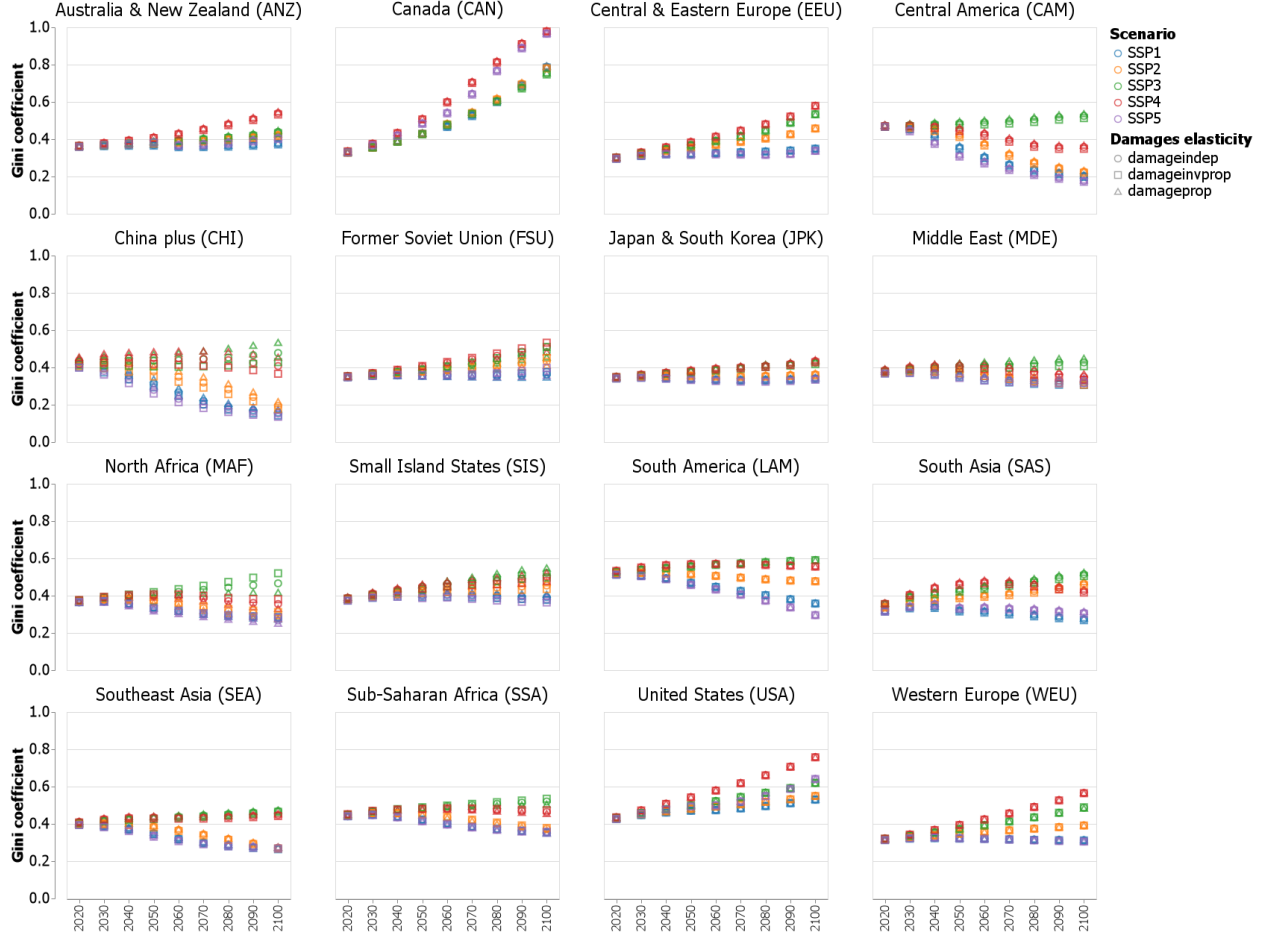


Figure B.5: Within-region Gini coefficients, for each of the five SSP narratives, for the period 2015-2100. Color code indicates SSP narratives. Shapes indicate the three variants for the income elasticity of damages: damages proportional to income ($\xi = 1$, triangles), independent of income ($\xi = 0$, circles), and inversely proportional to income ($\xi = -1$, squares).

versely, North Africa and the Former Soviet Union have higher inequality when damages are inversely proportional to income.

B.5 Damages as income shocks on poorest populations.

Our model allows us to analyze the magnitude of damages' shock on income for poorest populations, in particular when such damages are assumed to be particularly regressive ($\xi = -1$). Results quantifying this analysis for a medium climate and development scenario (SSP2 coupled to RCP4.5) are displayed in Fig. B.6. We find that by the end of the century, the poorest populations of six regions suffer damages that reach at least 5% of their income:

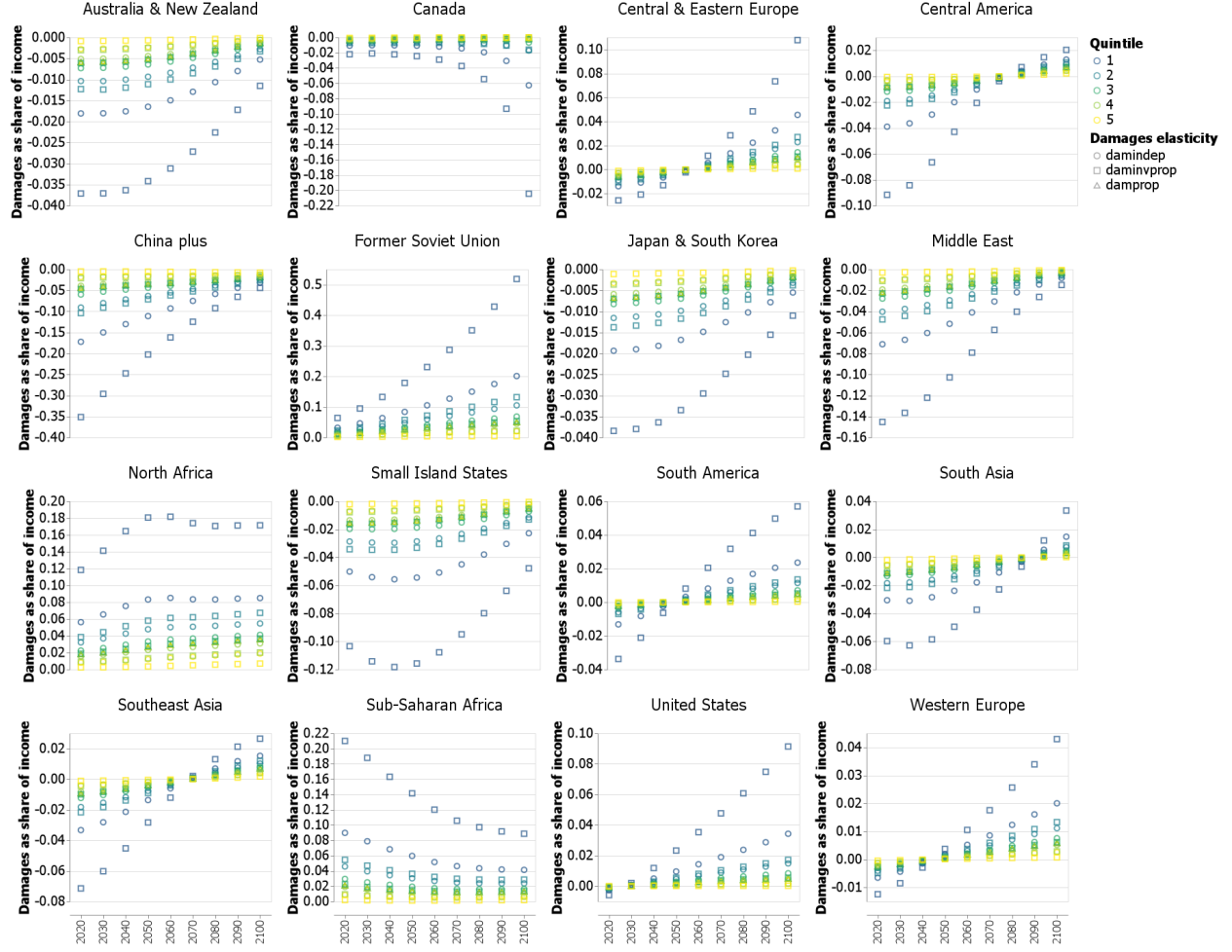


Figure B.6: Damages from climate change as share of quintile-specific income. Results for SSP2 (middle of the road) coupled to RCP4.5 for each of the 16 regions in FUND, for the period 2015-2100. Color code indicates income quintiles; shapes indicate the three variants for the income elasticity of damages: damages proportional to income (triangles), independent of income (circles), and inversely proportional to income (squares).

Central and Eastern Europe, the Former Soviet Union, North Africa, South America, Sub-Saharan Africa and the United States.

The number of regions above this threshold grows considerably when looking at direr development and climate scenarios (see Fig. B.7): for SSP3 coupled to RCP7.0, the lowest quintiles of 11 of the 16 regions suffer damages that are higher than 5% of their income; for two of those regions – North Africa and the Former Soviet Union – damages represent above 100% of their income.

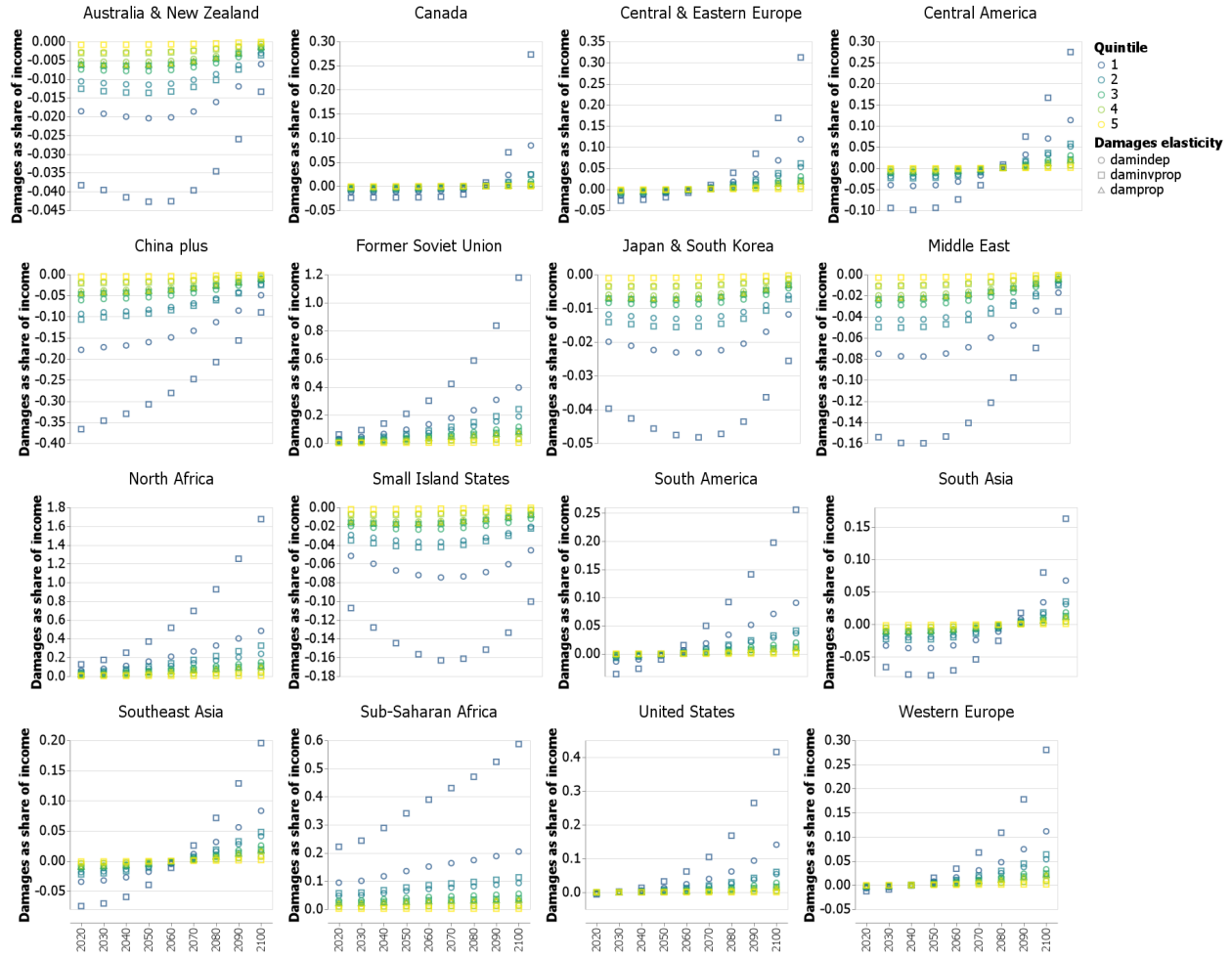


Figure B.7: Damages from climate change as share of quintile-specific income. Results for SSP3 (regional rivalry) coupled to RCP7.0 for each of the 16 regions in FUND, for the period 2015-2100. Color code indicates income quintiles; shapes indicate the three variants for the income elasticity of damages: damages proportional to income ($\xi = 1$, triangles), independent of income ($\xi = 0$, circles), and inversely proportional to income ($\xi = -1$, squares).

B.6 Remittances are not enough to compensate for resources lost to damages.

Migration could conceivably alleviate this important shock on income, both for migrants and for home communities who would receive remittances. We test this hypothesis by computing the difference between remittances received and climate change damages as a share of income for the poorest populations. Results for all climate and development scenarios, when damages are assumed to be independent of income, are displayed in Fig. B.8. As in the more regressive case, early in the century, remittances still largely compensate for damages in all regions. Yet starting mid-century, once climate change impacts reach larger scales, we find that resources lost through damages are not compensated anymore by gains from remittances in 7 of the 16 regions for the medium scenario (SSP2-RCP4.5), and in 11 for the more pessimistic scenario (SSP3-RCP7.0).

B.7 Change in numbers of migrants from climate change per income quintile.

The absolute effect of climate change on resource-constrained immobility, in numbers of migrants per decade, is shown in Fig. B.9. The effect of climate change on emigrants from the lowest income quintiles (blue shades) reaches 40,000 less emigrants in Sub-Saharan Africa and North Africa, and 25,000 less emigrants in the Former Soviet Union by the end of the century when damages are inversely proportional to income. Conversely for other regions, migration appears to be more prevalent with climate change, perhaps playing the role of adaptation mechanism: we find an increase of 10,000 emigrants from lowest quintiles in the Small Island States, 40,000 in the Middle East and up to 80,000 in South Asia by 2100 for SSP2-RCP4.5 when damages are inversely proportional to income.

B.8 Using original SSP projections as input scenarios.

In order to test the sensitivity of our results to input scenarios, we also conduct projections using the original SSP quantifications, hence not modified for migration (see section Additional details on Methods for a discussion of consistency in migration accounting with both sets of scenarios). We show the effect of climate change on resource-constrained immobility for SSP2 coupled to RCP4.5 in Fig. B.10. Our central finding on immobility holds as

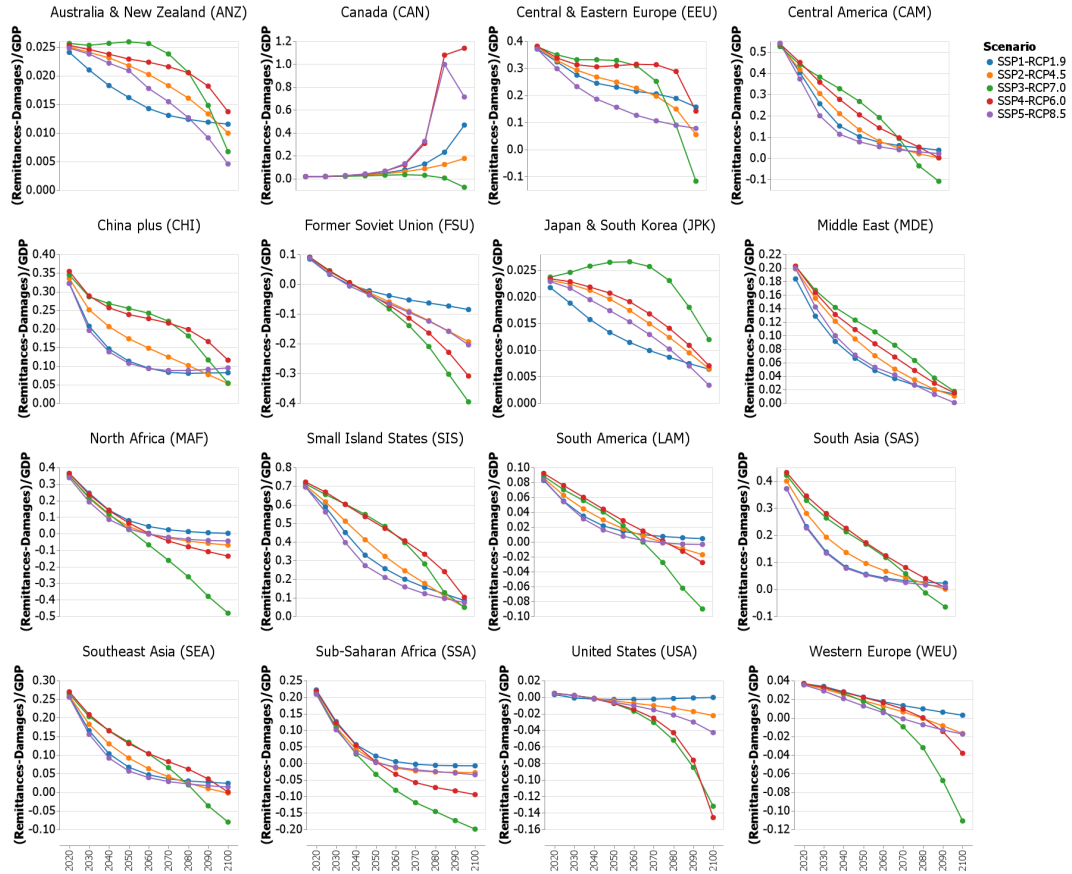


Figure B.8: Difference between remittances received and climate change damages as a share of income for the poorest income quintile. Results per year for each of the 16 regions in FUND, for within-region damages independent of income, for the period 2015-2100. Color code indicates scenarios of future development and climate change.

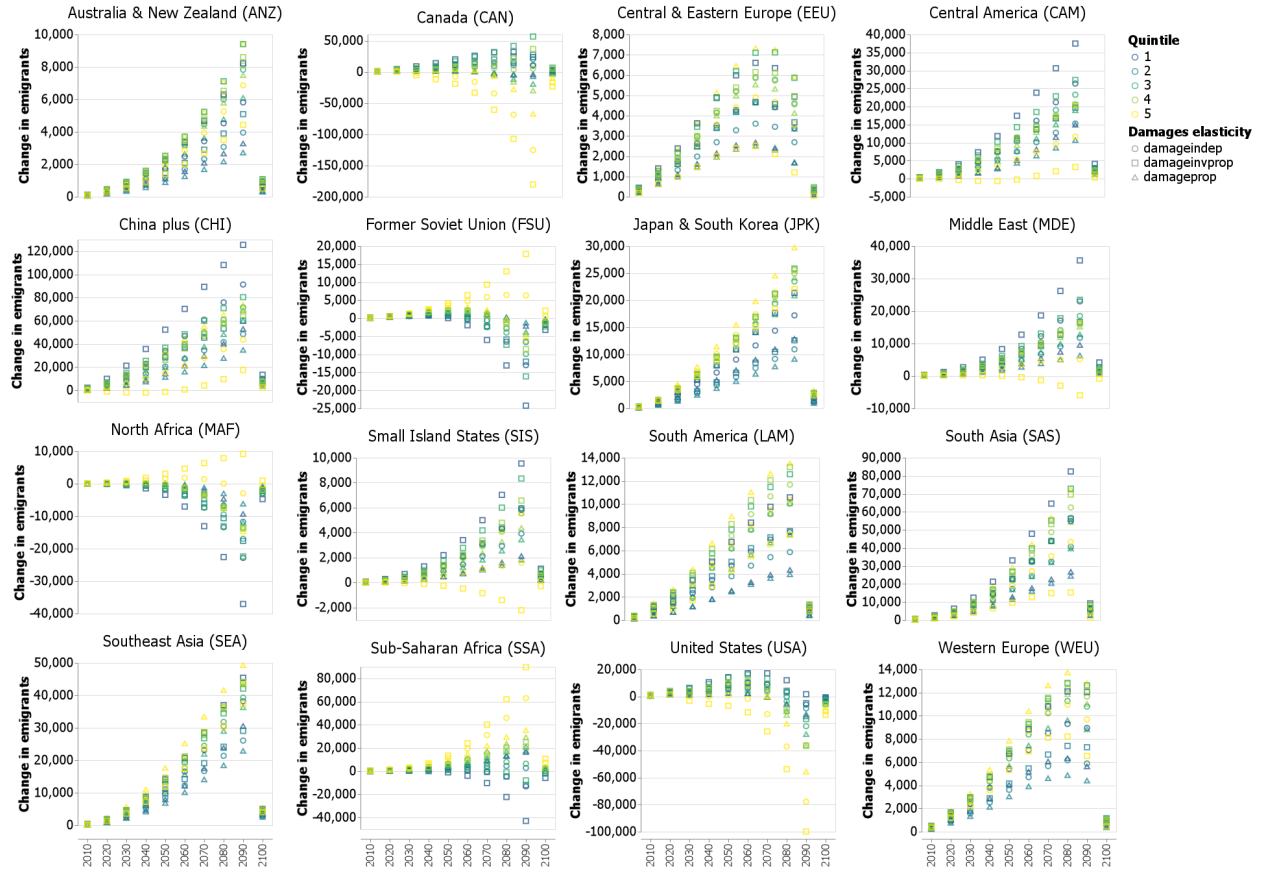


Figure B.9: Absolute effect of climate change on quintile-specific number of emigrants, per decade. Results for SSP2 (middle-of-the-road) coupled to RCP4.5 for each of the 16 regions in FUND, for the period 2015-2100. Color code indicates income quintiles; shapes indicate the three variants for the income elasticity of damages: damages proportional to income ($\xi = 1$, triangles), independent of income ($\xi = 0$, circles), and inversely proportional to income ($\xi = -1$, squares).

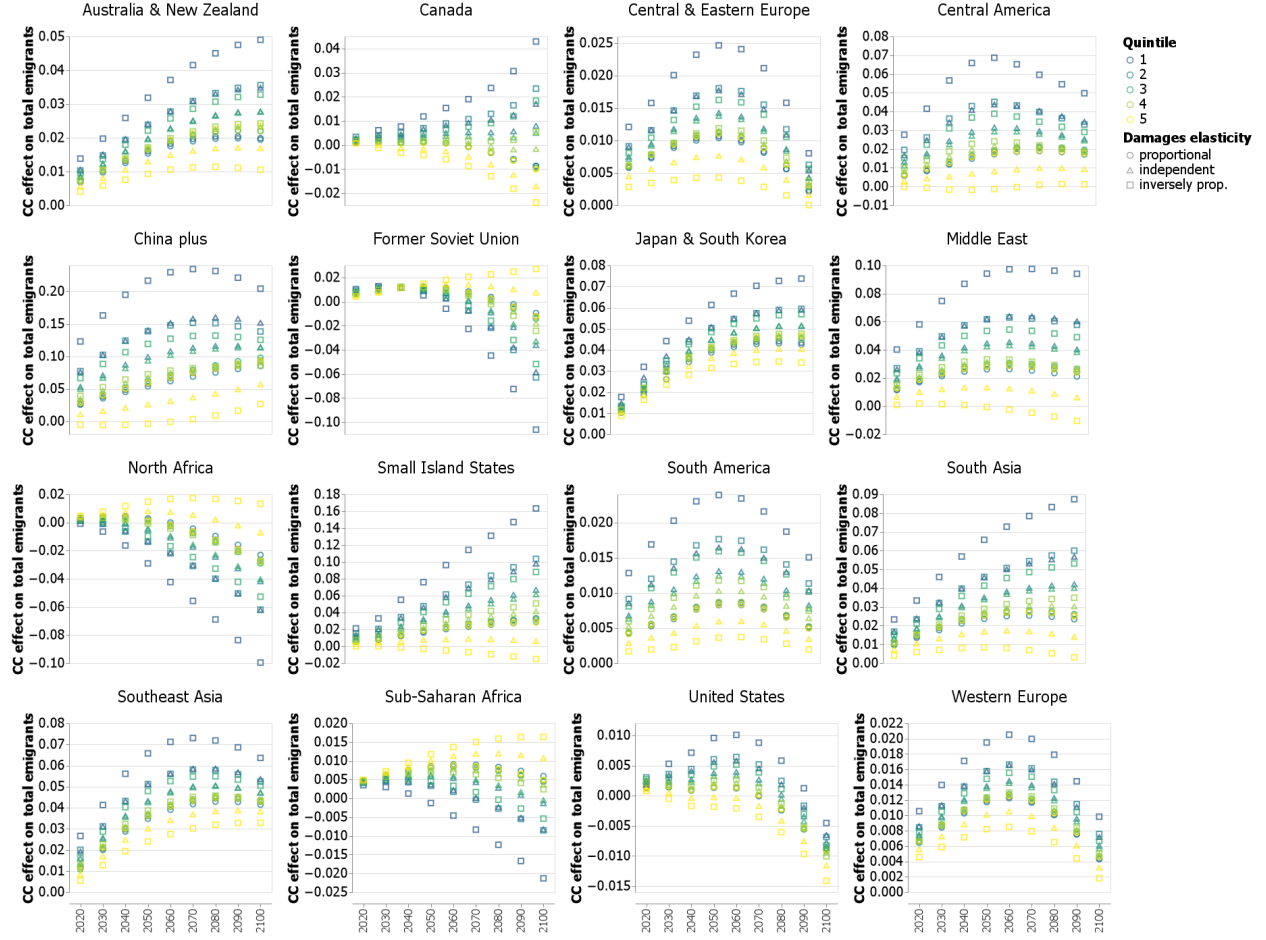


Figure B.10: Relative effect of climate change on quintile-specific number of emigrants, with original SSP quantifications as input scenarios. Results for SSP2 (middle of the road) coupled to RCP4.5 for each of the 16 regions in FUND, for the period 2015-2100. Color code indicates income quintiles; shapes indicate the three variants for the income elasticity of damages: damages proportional to income ($\xi = 1$, triangles), independent of income ($\xi = 0$, circles), and inversely proportional to income ($\xi = -1$, squares).

quantitative results are minimally affected.

B.9 Forcing remittances to catch up with damages

To test the robustness of our results on immobility to the relationship between remittances and damages, for instance through a remittance-as-insurance mechanism, we additionally conduct a sensitivity analysis when remittances catch up with damages, hence when remittances increase when damages at origin increase. In particular, for each region*quintile pair we distribute the difference between damages undergone and remittances received – when that difference is positive – proportionally to already modeled remittances. We show the

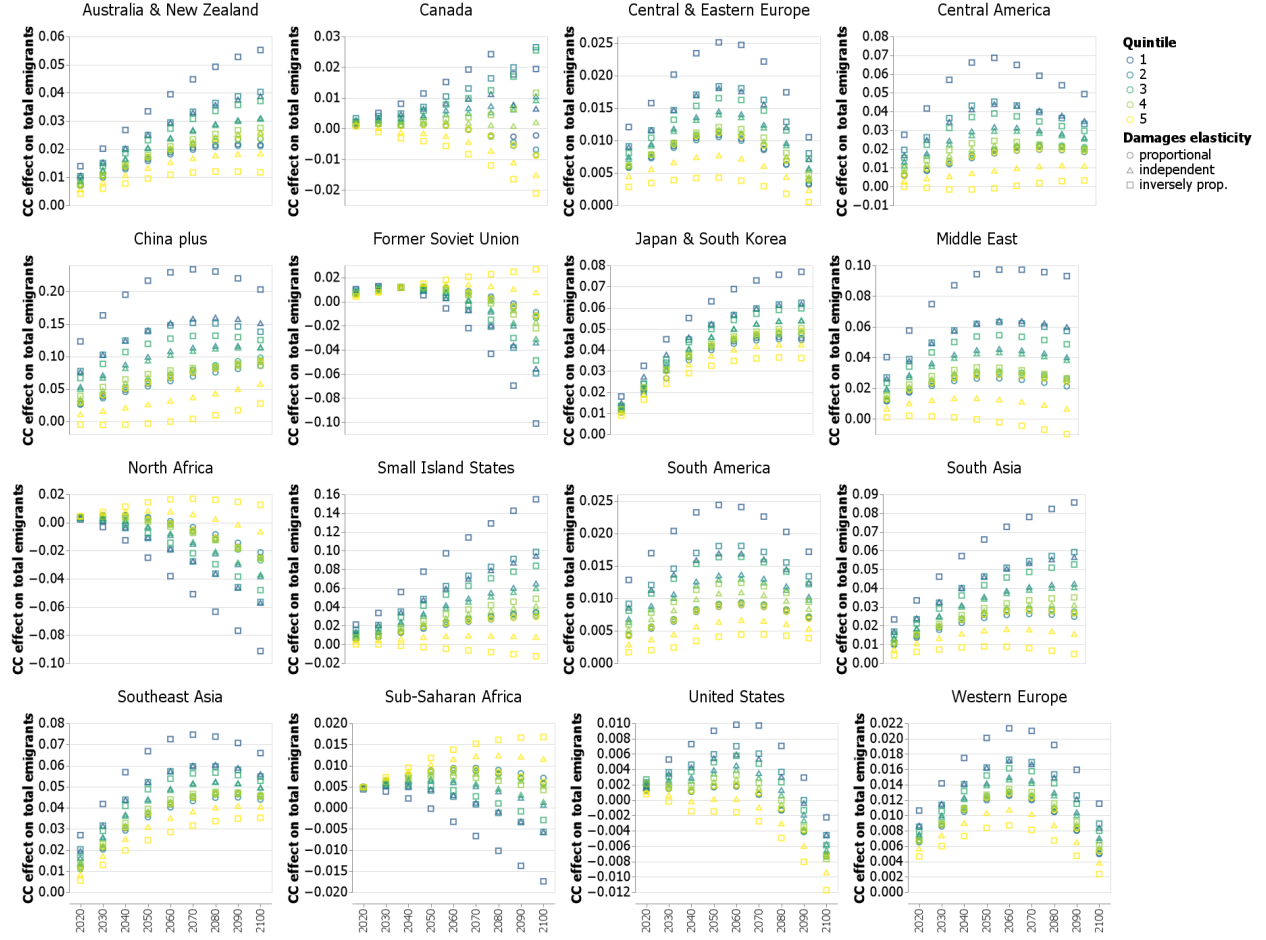


Figure B.11: Relative effect of climate change on quintile-specific number of emigrants, when remittances are modeled to catch up with damages. Results for SSP2 (middle of the road) coupled to RCP4.5 for each of the 16 regions in FUND, for the period 2015-2100. Color code indicates income quintiles; shapes indicate the three variants for the income elasticity of damages: damages proportional to income ($\xi = 1$, triangles), independent of income ($\xi = 0$, circles), and inversely proportional to income ($\xi = -1$, squares).

effect of climate change on resource-constrained immobility for SSP2 coupled to RCP4.5 in Fig. B.11. Our central finding on immobility holds as quantitative results are minimally affected.

B.10 Corrected FUND damages calibration.

Our results depend on damages calibration. FUND, whose current impact calibrations are based on various 1990s studies [75], presents well known, overly positive effects of climate change on agricultural yields in several regions, in particular China. We are aware of an ongoing project to update the FUND impact-specific damage functions based on more recent

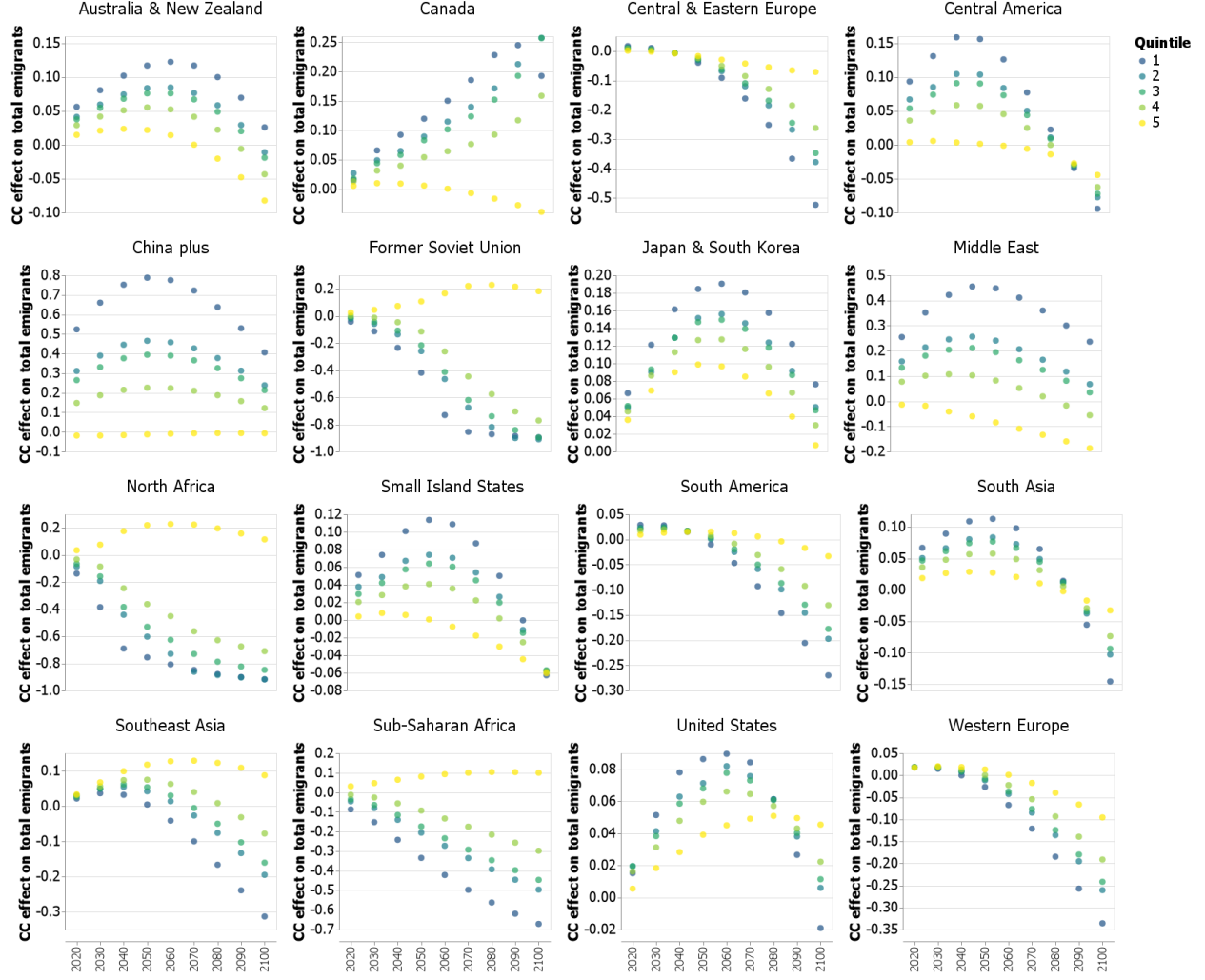


Figure B.12: Relative effect of climate change on quintile-specific number of emigrants, with modified FUND calibration. Results for SSP2 (middle of the road) coupled to RCP4.5 for each of the 16 regions in FUND, for within-region damages proportional to income, for the period 2015-2100. Color code indicates income quintiles.

empirical literature [76]. To ensure that our results hold for updated damage calibration, we perform runs modifying FUND damages calibration on aspects pointed by [48]: we divide the CO2 fertilization effect by 10, and multiply all other damages by 10. We show the effect of climate change on resource-constrained immobility for SSP2 coupled to RCP4.5, when damages are assumed to be inversely proportional to income in Fig. B.12. Our main finding on resource-constrained immobility holds and is quite reinforced: we observe a decrease in emigration of lowest income levels in 11 of the 16 regions, by up to 92%, 90%, and 67% for North Africa, the Former Soviet Union, and Sub-Saharan Africa respectively .

B.11 Adding catastrophic damages.

Finally, we quantify the effect of climate change on resource-constrained immobility in a modeling with catastrophic damages. For the moderate SSP2 scenario coupled to RCP4.5, we find a marked increase in the magnitude of the effect of climate change on immobility, with evidence of resource-constrained immobility now displayed in 14 of the 16 regions and a decrease in the number of migrants from lowest quintiles of up to 21% (see Fig. B.13). This effect increases with more pessimistic development and climate scenarios, up until reaching a 33% decrease in emigrants from North Africa’s lowest quintile by the end of the century for SSP3 (see Fig. B.14).

B.12 Computing the Social Cost of Carbon (SCC).

We compute the SCC using the FUND model with income distributions along the five SSP-RCP combinations and for the three values of income elasticity of damages used in our analysis. We compute SCC values for the year 2020 over the period 2020–2200 and use default FUND values for discounting parameters: elasticity of marginal utility of 1.45 and pure rate of time preference of 1.5%. We then compare these SCC numbers to ones when also including our migration and remittances model, using the same default parameters, scenarios, and elasticities of damages. We find that the effect of including migration strongly depends on the income elasticity of damages (see Table B.1). When damages are proportional to income, there is little effect of including migration on the SCC in all SSP-RCP scenarios. Yet the more regressive damages are, the more the SCC increases with the inclusion of migration in FUND. We note that this result does not signify that migration can be assimilated to a climate change damage, but rather that the inclusion of migration dynamics in the IAM highlights an additional inequality: in terms of access to migration as an adaptation strategy to climate change, strategy less readily available to populations with the least resources. Note that in limit cases of damages being particularly regressive, we must force incomes of the bottom quintiles to not become negative (whether adding the migration component or not). Therefore, bottom quintiles sometimes harbor negative growth rates, which can lead to negative SCC. Because of this, the SCC values appear very sensitive to limit cases assumptions. This is a version of Weitzman’s dismal theorem [77]: when marginal utility

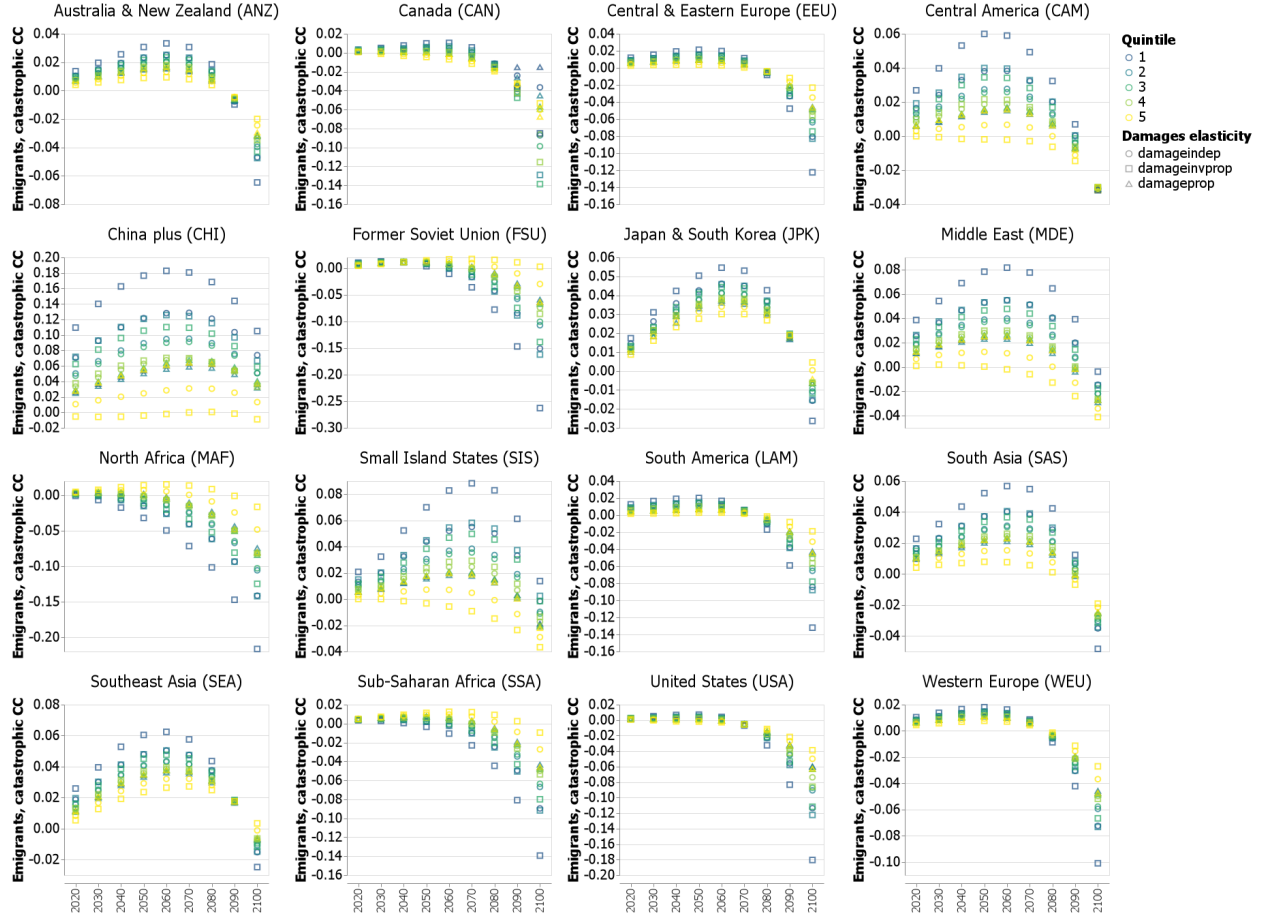


Figure B.13: Relative effect of catastrophic climate change on quintile-specific number of emigrants. Results for SSP2 (middle of the road) coupled to RCP4.5 for each of the 16 regions in FUND, for the period 2015-2100. Color code indicates income quintiles; shapes indicate the three variants for the income elasticity of damages: damages proportional to income (triangles), independent of income (circles), and inversely proportional to income (squares).

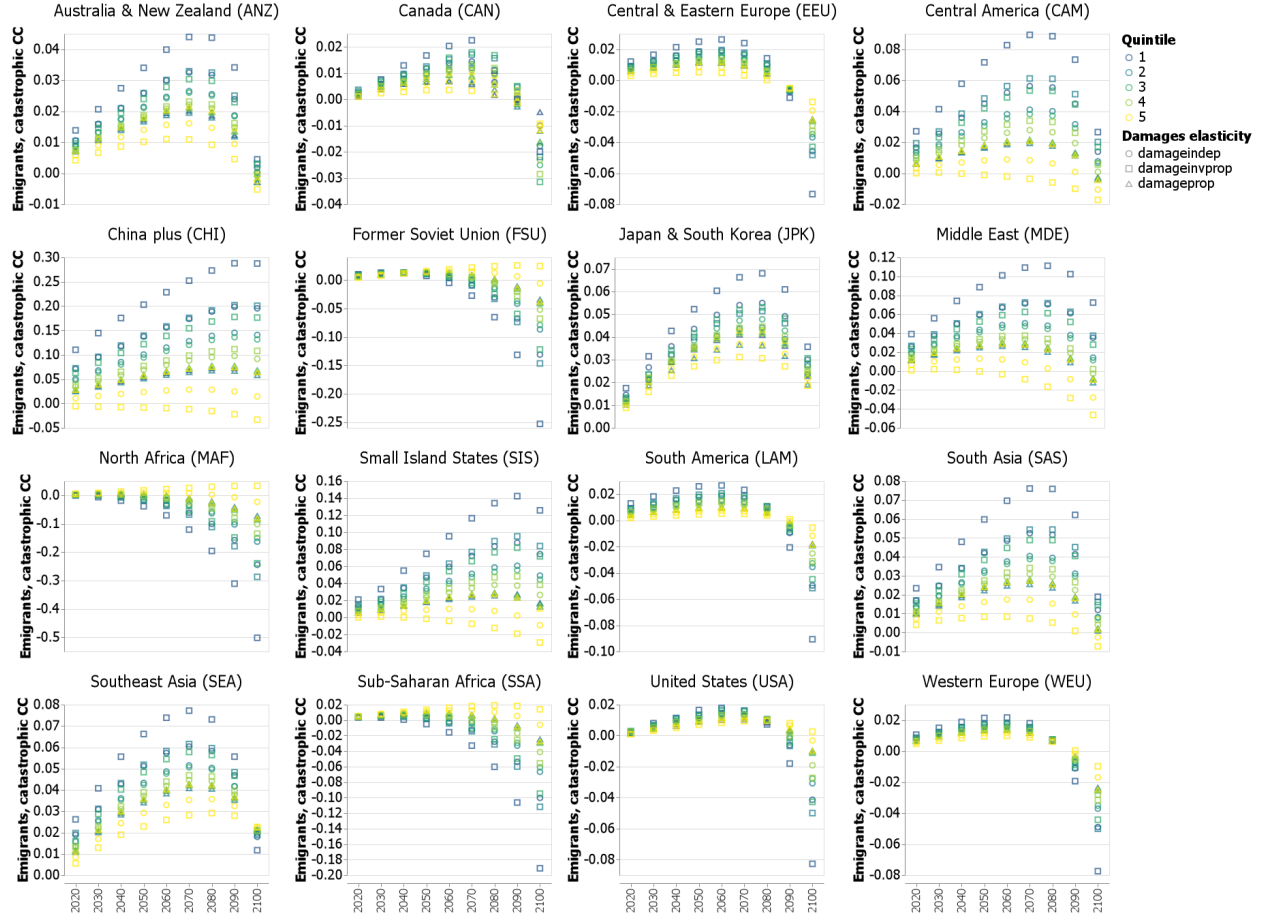


Figure B.14: Relative effect of catastrophic climate change on quintile-specific number of emigrants. Results for SSP3 (regional rivalry) coupled to RCP7.0 for each of the 16 regions in FUND, for the period 2015-2100. Color code indicates income quintiles; shapes indicate the three variants for the income elasticity of damages: damages proportional to income ($\xi = 1$, triangles), independent of income ($\xi = 0$, circles), and inversely proportional to income ($\xi = -1$, squares).

| | $\xi = 1$ | | $\xi = 0$ | | $\xi = -1$ | |
|----------------------|-----------|--------|-----------|--------|------------|--------|
| | Mig | No mig | Mig | No mig | Mig | No mig |
| <i>SSP1 – RCP1.9</i> | -0.25 | -0.31 | 14.47 | -0.25 | 39.69 | -0.18 |
| <i>SSP2 – RCP4.5</i> | 1.19 | 1.10 | 12.61 | 1.16 | 20.81 | 1.32 |
| <i>SSP3 – RCP7.0</i> | 4.55 | 4.40 | 22.08 | 6.54 | 78.31 | -19.19 |
| <i>SSP4 – RCP6.0</i> | 1.40 | 1.40 | 63.71 | 2.55 | 221.83 | -3.03 |
| <i>SSP5 – RCP8.5</i> | 0.85 | 0.84 | 372.36 | 0.85 | 346.87 | 0.12 |

Table B.1: Estimates for the social cost of carbon with (*Mig*) and without (*No mig*) the inclusion of international migration, using a version of FUND that includes within-region income distributions. Estimates for five scenarios of future development and climate change, and for three values of income elasticity of damages ($\xi \in \{1, 0, -1\}$). All values computed for the year 2020, over the period 2020–2200 with default FUND values for discounting parameters, expressed in 1995\$ per metric tonne of CO2.

becomes very high, the SCC is hard to pin down because the value varies enormously with the level of poverty that is reached.

C Supplementary tables for Methods and Materials

C.1 Regional disaggregation in FUND.

In FUND, the world is divided into 16 regions, two of them representing one country each: United States and Canada. All regions and corresponding countries are described in Table C.1.

C.2 Assumptions for extending the SSP to the FUND timeframe.

While FUND runs for the period 1950-3000 in yearly time steps, we make the migration dynamics explicit starting 2015 and present results for the period 2015-2100. Our SSP projections being available for the period 2015-2100 in 5-year time steps, we extend the projections as described in Table C.2.

D Supplementary tables for robustness checks

D.1 Estimation of our gravity model with another dataset for bilateral migration flows.

As a first check, we also estimate our gravity equation with bilateral migration flow data from [61]. The resulting estimation is presented in Table D.1. Compared to our main specification

| Code | Name | Countries |
|-------------|----------------------------|---|
| USA | USA | United States of America |
| CAN | Canada | Canada |
| WEU | Western Europe | Andorra, Austria, Belgium, Cyprus, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Liechtenstein, Luxembourg, Malta, Monaco, Netherlands, Norway, Portugal, San Marino, Spain, Sweden, Switzerland, United Kingdom |
| JPK | Japan and South Korea | Japan, South Korea |
| ANZ | Australia and New Zealand | Australia, New Zealand |
| CEE | Central and Eastern Europe | Albania, Bosnia and Herzegovina, Bulgaria, Croatia, Czech Republic, Hungary, FYR Macedonia, Poland, Romania, Slovakia, Slovenia, Yugoslavia |
| FSU | Former Soviet Union | Armenia, Azerbaijan, Belarus, Estonia, Georgia, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, Moldova, Russia, Tajikistan, Turkmenistan, Ukraine, Uzbekistan |
| MDE | Middle East | Bahrain, Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Oman, Qatar, Saudi Arabia, Syria, Turkey, United Arab Emirates, West Bank and Gaza, Yemen |
| CAM | Central America | Belize, Costa Rica, El Salvador, Guatemala, Honduras, Mexico, Nicaragua, Panama |
| LAM | South America | Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, French Guiana, Guyana, Paraguay, Peru, Suriname, Uruguay, Venezuela |
| SAS | South Asia | Afghanistan, Bangladesh, Bhutan, India, Nepal, Pakistan, Sri Lanka |
| SEA | Southeast Asia | Brunei, Cambodia, East Timor, Indonesia, Laos, Malaysia, Myanmar, Papua New Guinea, Philippines, Singapore, Taiwan, Thailand, Vietnam |
| CHI | China plus | China, Hong Kong, North Korea, Macau, Mongolia |
| MAF | North Africa | Algeria, Egypt, Libya, Morocco, Tunisia, Western Sahara |
| SSA | Sub-Saharan Africa | Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Cape Verde, Central African Republic, Chad, Congo-Brazzaville, Congo-Kinshasa, Cote d'Ivoire, Djibouti, Equatorial Guinea, Eritrea, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mozambique, Namibia, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, Somalia, South Africa, Sudan, Swaziland, Tanzania, Togo, Uganda, Zambia, Zimbabwe |

Table C.1: World regions used in our model, based on the 16 FUND regions.

| Period | Population growth | GDP per capita growth | Inequality growth | Energy intensity of GDP growth | Carbon intensity of energy growth | Carbon price |
|-----------|--|--|--|---|---|--------------|
| 2015-2100 | Linearize from 5-year periods to yearly values | | | | | |
| 1950-2015 | UN World Population Prospects 2019 | World Bank WDI when available, otherwise FUND scenario | World Bank WDI when available, otherwise interpolate | Default FUND scenario | 1990-2015: CMIP6 data 1950-1990: FUND scenario | 0 |
| 2100-2300 | Linear decline to 0 in 2200, then constant | Linear decline reaching 0 | | Fixed at 2090-2100 rate if < 0 in 2100, otherwise linear decline reaching 0 | | 0 |
| 2300-3000 | Steady state: growth rates = 0 | | | | | |

Table C.2: Assumptions used to extend SSP-based input scenarios to a FUND-compatible time frame. WDI stands for World Development Indicators.

with data from [42], we find that our estimation is little affected by the data source.

D.2 Estimation of our gravity model without contribution of remittances to income at origin.

As a second robustness check, we test for reverse causality of migration on income at origin, in particular through remittances, by using income minus remittances received as an independent variable (Table D.2); we find that the coefficients are not affected.

D.3 Estimation of our gravity model with non-linear effects of income at origin.

As a third set of robustness checks, we test for the presence of non-monotonicity in the role of income at origin on the migration decision, by including a quadratic (Table D.3) and a cubic specification (Table D.4) in our gravity equation. We do not find any significant non-monotonic effect of origin income. In the quadratic specification, the coefficient on squared origin income is positive and significant for all quintiles, while the coefficient on linear income is negative (and mostly insignificant). This suggests that the dampening effect of climate-induced income reduction on migration goes down when the shock is greater. Yet in the cubic specification, all coefficients on origin income become insignificant, and signs are reversed for linear and quadratic coefficients.

| Bilateral migrant flows for a given origin income quintile | | | | | |
|--|----------------------|----------------------|----------------------|----------------------|----------------------|
| | qorig1 | qorig2 | qorig3 | qorig4 | qorig5 |
| Origin population | 0.716*** (0.071) | 0.698*** (0.075) | 0.684*** (0.071) | 0.702*** (0.068) | 0.709*** (0.067) |
| Destination population | 0.726*** (0.061) | 0.721*** (0.061) | 0.722*** (0.061) | 0.724*** (0.061) | 0.726*** (0.061) |
| Origin quintile per capita income | 1.758*** (0.188) | 1.665*** (0.197) | 1.746*** (0.199) | 1.698*** (0.198) | 1.639*** (0.199) |
| Ratio of per capita incomes | 1.487*** (0.157) | 1.489*** (0.158) | 1.483*** (0.158) | 1.480*** (0.156) | 1.479*** (0.156) |
| Distance between locations | -0.952*** (0.107) | -0.922*** (0.110) | -0.933*** (0.107) | -0.910*** (0.104) | -0.926*** (0.101) |
| Residuals from share of income sent as remittances | 0.005 (0.005) | 0.005 (0.005) | 0.005 (0.005) | 0.006 (0.005) | 0.006 (0.005) |
| Cost of sending remittances | -13.805 (22.740) | -16.647 (22.917) | -15.139 (23.177) | -14.794 (22.496) | -14.319 (22.018) |
| Common official language | 1.188*** (0.289) | 1.293*** (0.280) | 1.247*** (0.281) | 1.280*** (0.281) | 1.245*** (0.273) |
| N | 15,765 | 15,765 | 15,765 | 15,765 | 15,765 |
| R^2 | 0.436 | 0.423 | 0.426 | 0.425 | 0.428 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.1: Results from OLS regression on country-level bilateral migration flows, separately for each origin income quintile. Specification estimated with data from [61]. Standard errors clustered at the origin and destination levels in parentheses.

| | Bilateral migrant flows for a given origin income quintile | | | | |
|--|--|----------------------|----------------------|----------------------|----------------------|
| | qorig1 | qorig2 | qorig3 | qorig4 | qorig5 |
| Origin population | 0.824*** (0.061) | 0.809*** (0.070) | 0.792*** (0.059) | 0.807*** (0.058) | 0.805*** (0.057) |
| Destination population | 0.719*** (0.062) | 0.717*** (0.062) | 0.719*** (0.062) | 0.718*** (0.062) | 0.720*** (0.062) |
| Origin quintile per capita income without remittances | 1.808*** (0.134) | 1.760*** (0.144) | 1.865*** (0.143) | 1.833*** (0.145) | 1.807*** (0.151) |
| Ratio of per capita incomes | 1.166*** (0.106) | 1.174*** (0.106) | 1.170*** (0.106) | 1.166*** (0.106) | 1.153*** (0.106) |
| Distance between locations | -1.100*** (0.097) | -1.081*** (0.102) | -1.099*** (0.097) | -1.086*** (0.094) | -1.120*** (0.091) |
| Residuals from share of income sent as remittances | -0.002 (0.008) | -0.002 (0.009) | -0.001 (0.009) | -0.000 (0.008) | 0.001 (0.007) |
| Cost of sending remittances | -22.619 (24.036) | -25.743 (24.308) | -24.567 (24.684) | -24.240 (24.055) | -24.614 (23.758) |
| Common official language | 1.433*** (0.251) | 1.490*** (0.245) | 1.422*** (0.247) | 1.436*** (0.253) | 1.320*** (0.254) |
| N | 24,100 | 24,100 | 24,100 | 24,100 | 24,100 |
| R^2 | 0.554 | 0.540 | 0.549 | 0.545 | 0.543 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.2: Results from OLS regression on country-level bilateral migration flows, separately for each origin income quintile. Specification estimated with income at origin quintile without remittances. Standard errors clustered at the origin and destination levels in parentheses.

| Bilateral migrant flows for a given origin income quintile | | | | | |
|--|----------------------|----------------------|----------------------|----------------------|----------------------|
| | qorig1 | qorig2 | qorig3 | qorig4 | qorig5 |
| Origin population | 0.851*** (0.059) | 0.830*** (0.068) | 0.810*** (0.057) | 0.826*** (0.054) | 0.810*** (0.051) |
| Destination population | 0.720*** (0.062) | 0.718*** (0.061) | 0.720*** (0.062) | 0.719*** (0.062) | 0.722*** (0.062) |
| Origin quintile per capita income | -0.151 (0.704) | -0.466 (0.984) | -0.826 (1.133) | -2.306 (1.358) | -4.977* (2.003) |
| Origin quintile per capita income squared | 0.128** (0.046) | 0.135* (0.060) | 0.155* (0.066) | 0.229** (0.076) | 0.350*** (0.104) |
| Ratio of per capita incomes | 1.176*** (0.106) | 1.182*** (0.107) | 1.177*** (0.107) | 1.176*** (0.106) | 1.165*** (0.107) |
| Distance between locations | -1.104*** (0.097) | -1.083*** (0.103) | -1.101*** (0.098) | -1.089*** (0.095) | -1.128*** (0.092) |
| Residuals from share of income sent as remittances | -0.001 (0.008) | -0.001 (0.009) | 0.000 (0.009) | 0.001 (0.008) | 0.004 (0.007) |
| Cost of sending remittances | -26.028 (24.405) | -28.520 (24.671) | -27.122 (25.071) | -27.068 (24.560) | -26.262 (24.562) |
| Common official language | 1.398*** (0.238) | 1.464*** (0.235) | 1.401*** (0.235) | 1.415*** (0.236) | 1.295*** (0.233) |
| N | 24,100 | 24,100 | 24,100 | 24,100 | 24,100 |
| R^2 | 0.561 | 0.545 | 0.554 | 0.555 | 0.557 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.3: Results from OLS regression on country-level bilateral migration flows, separately for each origin income quintile. Specification with quadratic effect of per capita income at origin (all columns). Standard errors clustered at the origin and destination levels in parentheses.

| Bilateral migrant flows for a given origin income quintile | | | | | |
|--|----------------------|----------------------|----------------------|----------------------|----------------------|
| | qorig1 | qorig2 | qorig3 | qorig4 | qorig5 |
| Origin population | 0.851*** (0.059) | 0.829*** (0.070) | 0.809*** (0.058) | 0.825*** (0.055) | 0.811*** (0.052) |
| Destination population | 0.721*** (0.062) | 0.720*** (0.061) | 0.721*** (0.062) | 0.720*** (0.062) | 0.723*** (0.062) |
| Origin quintile per capita income | 2.281 (5.611) | 11.771 (10.616) | 13.343 (15.218) | 13.075 (21.310) | 16.413 (32.783) |
| Origin quintile per capita income squared | -0.204 (0.769) | -1.394 (1.343) | -1.522 (1.824) | -1.503 (2.430) | -1.872 (3.446) |
| Origin quintile per capita income cubed | 0.015 (0.034) | 0.062 (0.056) | 0.065 (0.072) | 0.064 (0.091) | 0.076 (0.120) |
| Ratio of per capita incomes | 1.176*** (0.106) | 1.183*** (0.107) | 1.178*** (0.107) | 1.176*** (0.106) | 1.164*** (0.107) |
| Distance between locations | -1.108*** (0.098) | -1.095*** (0.102) | -1.111*** (0.098) | -1.096*** (0.095) | -1.132*** (0.092) |
| Residuals from share of income sent as remittances | -0.002 (0.008) | -0.004 (0.010) | -0.002 (0.009) | -0.001 (0.008) | 0.002 (0.007) |
| Cost of sending remittances | -25.774 (24.412) | -27.621 (24.570) | -26.342 (24.926) | -26.474 (24.388) | -26.011 (24.349) |
| Common official language | 1.393*** (0.238) | 1.450*** (0.237) | 1.389*** (0.236) | 1.406*** (0.237) | 1.286*** (0.232) |
| N | 24,100 | 24,100 | 24,100 | 24,100 | 24,100 |
| R^2 | 0.561 | 0.547 | 0.556 | 0.556 | 0.558 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.4: Results from OLS regression on country-level bilateral migration flows, separately for each origin income quintile. Specification with cubic effect of per capita income at origin (all columns). Standard errors clustered at the origin and destination levels in parentheses.

| Bilateral migrant flows for a given origin income quintile | | | | | |
|--|----------------------|----------------------|----------------------|----------------------|----------------------|
| | qorig1 | qorig2 | qorig3 | qorig4 | qorig5 |
| Origin population | 0.837*** (0.066) | 0.820*** (0.072) | 0.799*** (0.060) | 0.808*** (0.058) | 0.786*** (0.059) |
| Destination population | 0.706*** (0.063) | 0.710*** (0.062) | 0.715*** (0.062) | 0.717*** (0.062) | 0.718*** (0.062) |
| Origin quintile per capita income | 1.449*** (0.128) | 1.546*** (0.136) | 1.753*** (0.136) | 1.805*** (0.142) | 1.806*** (0.156) |
| Ratio of per capita incomes | 1.065*** (0.102) | 1.130*** (0.102) | 1.156*** (0.103) | 1.165*** (0.105) | 1.087*** (0.102) |
| Distance between locations | -1.057*** (0.096) | -1.042*** (0.102) | -1.070*** (0.097) | -1.075*** (0.094) | -1.169*** (0.091) |
| Residuals from share of income sent as remittances | -0.002 (0.008) | -0.003 (0.009) | -0.002 (0.009) | -0.001 (0.008) | 0.004 (0.006) |
| Cost of sending remittances | -20.998 (23.453) | -24.285 (23.893) | -23.475 (24.434) | -23.813 (24.004) | -26.333 (24.042) |
| Common official language | 1.624*** (0.239) | 1.651*** (0.236) | 1.537*** (0.241) | 1.479*** (0.251) | 1.154*** (0.268) |
| N | 24,100 | 24,100 | 24,100 | 24,100 | 24,100 |
| R^2 | 0.540 | 0.533 | 0.547 | 0.545 | 0.533 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.5: Results from OLS regression on country-level bilateral migration flows, separately for each origin income quintile. Specification with ratio of average per capita incomes at origin and destination (all columns). Standard errors clustered at the origin and destination levels in parentheses.

D.4 Estimation of our gravity model with average and quintile-specific income ratios.

Fourth, we estimate our gravity equation using the ratio of average incomes levels $\ln(ypc_d/ypc_o)$ (Table D.5) and the ratio of quintile-specific income levels $\ln(ypc_{d,r}/ypc_{o,q})$ (Table D.6) in place of the income ratio $\ln(ypc_d/ypc_{o,q})$ used in our main specification. The former would illustrate a situation where the migrant would consider the general relative levels of development of her intended destination and her home region, rather than her specific economic situation; while the latter would illustrate a situation where the migrant has a clear and definite idea of how well she will fare once at destination. We find that both specifications display slightly weaker effects of income (both as a constraint and as a pull factor) on migration.

| | Bilateral migrant flows for a given origin income quintile | | | | |
|---|--|----------------------|----------------------|----------------------|----------------------|
| | qorig1 | qorig2 | qorig3 | qorig4 | qorig5 |
| Origin population | 0.811*** (0.061) | 0.797*** (0.069) | 0.779*** (0.058) | 0.795*** (0.058) | 0.794*** (0.056) |
| Destination population | 0.705*** (0.066) | 0.703*** (0.066) | 0.705*** (0.066) | 0.704*** (0.066) | 0.706*** (0.066) |
| Origin quintile per capita income | 1.381*** (0.111) | 1.327*** (0.122) | 1.430*** (0.121) | 1.399*** (0.123) | 1.375*** (0.131) |
| Ratio of per capita incomes | 0.785*** (0.074) | 0.791*** (0.075) | 0.788*** (0.075) | 0.786*** (0.074) | 0.777*** (0.075) |
| Distance between locations | -1.126*** (0.091) | -1.105*** (0.095) | -1.123*** (0.091) | -1.109*** (0.088) | -1.139*** (0.086) |
| Residuals from share of income sent as remittances | 0.005 (0.006) | 0.005 (0.006) | 0.006 (0.006) | 0.007 (0.006) | 0.008 (0.006) |
| Cost of sending remittances | -23.518 (25.723) | -26.612 (25.976) | -25.398 (26.334) | -25.029 (25.702) | -25.304 (25.403) |
| Common official language | 1.391*** (0.253) | 1.452*** (0.245) | 1.387*** (0.248) | 1.405*** (0.253) | 1.300*** (0.255) |
| N | 24,100 | 24,100 | 24,100 | 24,100 | 24,100 |
| R^2 | 0.517 | 0.502 | 0.511 | 0.507 | 0.505 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.6: Results from OLS regression on country-level bilateral migration flows, separately for each origin income quintile. Specification with ratio of quintile-specific per capita incomes at origin and destination (all columns). Standard errors clustered at the origin and destination levels in parentheses.

D.5 Estimation of our gravity model with inequality measures.

Fifth, we estimate our gravity equation including measures of inequality at origin and at destination – the Gini coefficients – as potential drivers of migration, both separately and as a ratio (see Tables D.7 and D.8). While we do not find any significant effect of inequality either at origin or at destination on migration flows, we find that the coefficients for inequality at destination are negative for all income quintiles, suggesting that people tend to move to more equal locations. Conversely, inequality at origin has a more contrasted effect: migrants from the poorest income quintiles tend to come from more unequal places, while migrants from the richest income quintiles tend to come from more equal places. Similarly, the effect of the Gini ratio is not significant either, but coefficients are negative for all income quintiles and strongest in magnitude for the poorest quintiles. This again suggests that people tend to move to more equal locations, and that it is especially true for the poorest populations, consistently with the Roy-Borjas model of migrants self-selection [68].

D.6 Estimation of our gravity model with shared border indicator.

Finally, we estimate our gravity equation including a dummy for shared border between two countries (see Table D.9). As documented in the literature [41], we find a somewhat significant and positive effect of common borders on migration, yet with little effect on the overall goodness-of-fit of our estimation.

D.7 Estimation of our gravity model with country fixed effects.

As an additional sensitivity analysis, we estimate our gravity equation including origin and destination fixed effects. When including origin and destination fixed effects, the inference is based on deviations of migration flows from origin and destination-specific averages. Compared to our main specification, when adding those fixed effects, the coefficients on destination population size and ratio of per capita GDP change sign, decrease magnitude, and lose significance. The destination population coefficient can be thought of summarizing the fact that more populous areas tend to be more attractive, potentially due to higher productivity (coefficient positive in Table 1) but are eventually subject to congestion effects (coefficients negative in with fixed effects). Similarly, the coefficient attached to the ratio of per capita GDP hints at the fact that individuals tend to move to countries with higher

| Bilateral migrant flows for a given origin income quintile | | | | | |
|--|----------------------|----------------------|----------------------|----------------------|----------------------|
| | qorig1 | qorig2 | qorig3 | qorig4 | qorig5 |
| Origin population | 0.819*** (0.060) | 0.805*** (0.069) | 0.790*** (0.058) | 0.807*** (0.058) | 0.817*** (0.057) |
| Destination population | 0.733*** (0.062) | 0.732*** (0.062) | 0.732*** (0.062) | 0.732*** (0.062) | 0.732*** (0.062) |
| Origin quintile per capita income | 1.809*** (0.143) | 1.746*** (0.152) | 1.832*** (0.150) | 1.791*** (0.149) | 1.751*** (0.151) |
| Ratio of per capita incomes | 1.122*** (0.113) | 1.127*** (0.113) | 1.126*** (0.113) | 1.122*** (0.113) | 1.122*** (0.113) |
| Gini at origin | 1.044 (1.235) | 0.687 (1.147) | 0.069 (1.087) | -0.281 (1.039) | -1.883 (0.969) |
| Gini at destination | -1.734 (1.648) | -1.857 (1.661) | -1.791 (1.655) | -1.846 (1.653) | -1.801 (1.650) |
| Distance between locations | -1.083*** (0.100) | -1.058*** (0.106) | -1.069*** (0.102) | -1.049*** (0.099) | -1.051*** (0.098) |
| Residuals from share of income sent as remittances | -0.000 (0.008) | -0.000 (0.008) | 0.000 (0.008) | 0.001 (0.008) | 0.001 (0.008) |
| Cost of sending remittances | -22.227 (24.836) | -25.248 (25.120) | -23.888 (25.377) | -23.404 (24.745) | -22.987 (24.416) |
| Common official language | 1.503*** (0.243) | 1.584*** (0.243) | 1.549*** (0.243) | 1.590*** (0.244) | 1.598*** (0.239) |
| N | 24,100 | 24,100 | 24,100 | 24,100 | 24,100 |
| R^2 | 0.517 | 0.502 | 0.511 | 0.507 | 0.505 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.7: Results from OLS regression on country-level bilateral migration flows, separately for each origin income quintile. Specification with Gini coefficients at origin and destination (all columns). Standard errors clustered at the origin and destination levels in parentheses.

| | Bilateral migrant flows for a given origin income quintile | | | | |
|---|--|----------------------|----------------------|----------------------|----------------------|
| | qorig1 | qorig2 | qorig3 | qorig4 | qorig5 |
| Origin population | 0.813*** (0.060) | 0.799*** (0.069) | 0.783*** (0.058) | 0.798*** (0.058) | 0.804*** (0.057) |
| Destination population | 0.731*** (0.062) | 0.728*** (0.062) | 0.727*** (0.062) | 0.726*** (0.062) | 0.721*** (0.062) |
| Origin quintile per capita income | 1.821*** (0.136) | 1.769*** (0.146) | 1.870*** (0.144) | 1.835*** (0.146) | 1.806*** (0.151) |
| Ratio of per capita incomes | 1.126*** (0.111) | 1.137*** (0.111) | 1.139*** (0.111) | 1.138*** (0.111) | 1.149*** (0.112) |
| Ratio of Gini | -0.529 (0.402) | -0.472 (0.383) | -0.380 (0.367) | -0.339 (0.355) | -0.041 (0.330) |
| Distance between locations | -1.081*** (0.097) | -1.066*** (0.101) | -1.089*** (0.097) | -1.078*** (0.094) | -1.119*** (0.091) |
| Residuals from share of income sent as remittances | -0.000 (0.008) | -0.001 (0.008) | 0.000 (0.008) | 0.001 (0.008) | 0.001 (0.007) |
| Cost of sending remittances | -22.814 (25.052) | -25.991 (25.226) | -24.803 (25.425) | -24.491 (24.717) | -24.648 (23.914) |
| Common official language | 1.454*** (0.250) | 1.501*** (0.244) | 1.426*** (0.248) | 1.436*** (0.254) | 1.320*** (0.255) |
| N | 24,100 | 24,100 | 24,100 | 24,100 | 24,100 |
| R^2 | 0.556 | 0.542 | 0.550 | 0.546 | 0.543 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.8: Results from OLS regression on country-level bilateral migration flows, separately for each origin income quintile. Specification with ratio of Gini coefficients between destination and origin (all columns). Standard errors clustered at the origin and destination levels in parentheses.

| | Bilateral migrant flows for a given origin income quintile | | | | |
|---|--|----------------------|----------------------|----------------------|----------------------|
| | qorig1 | qorig2 | qorig3 | qorig4 | qorig5 |
| Origin population | 0.814*** (0.062) | 0.799*** (0.071) | 0.782*** (0.060) | 0.798*** (0.059) | 0.796*** (0.058) |
| Destination population | 0.710*** (0.063) | 0.708*** (0.063) | 0.710*** (0.063) | 0.710*** (0.063) | 0.712*** (0.063) |
| Origin quintile per capita income | 1.806*** (0.134) | 1.758*** (0.145) | 1.862*** (0.143) | 1.831*** (0.145) | 1.805*** (0.151) |
| Ratio of per capita incomes | 1.165*** (0.106) | 1.173*** (0.106) | 1.169*** (0.106) | 1.165*** (0.106) | 1.152*** (0.106) |
| Distance between locations | -1.043*** (0.099) | -1.020*** (0.104) | -1.040*** (0.099) | -1.033*** (0.096) | -1.066*** (0.093) |
| Residuals from share of income sent as remittances | -0.002 (0.008) | -0.003 (0.009) | -0.002 (0.009) | -0.001 (0.008) | 0.001 (0.007) |
| Cost of sending remittances | -21.103 (23.323) | -24.129 (23.534) | -22.996 (23.923) | -22.825 (23.374) | -23.190 (23.081) |
| Common official language | 1.370*** (0.250) | 1.422*** (0.244) | 1.356*** (0.246) | 1.376*** (0.251) | 1.261*** (0.252) |
| Shared border | 0.737** (0.272) | 0.788** (0.277) | 0.766** (0.268) | 0.690** (0.259) | 0.695** (0.251) |
| N | 24,100 | 24,100 | 24,100 | 24,100 | 24,100 |
| R^2 | 0.556 | 0.542 | 0.551 | 0.547 | 0.544 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.9: Results from OLS regression on country-level bilateral migration flows, separately for each origin income quintile. Specification with indicator for shared border between origin and destination (all columns). Standard errors clustered at the origin and destination levels in parentheses.

| | Share of migrants to a given tercile at destination | | |
|-----------------------------|---|---------------------|----------------------|
| | tdest1 | tdest2 | tdest3 |
| Ratio of per capita incomes | 0.115*** (0.017) | 0.063*** (0.013) | -0.110*** (0.016) |
| N | 14,460 | 14,460 | 14,460 |
| R^2 | 0.239 | 0.154 | 0.188 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.10: Results from OLS regression on share of migrants arriving in a given income tercile at destination, separately for each destination income tercile. Standard errors clustered at the origin and destination levels in parentheses.

incomes (positive coefficient in Table 1) but might require a minimum level of resources to be able to move (negative coefficients with fixed effects). The standard errors become very large for the population and income coefficients due to the limited availability of migrant’s income data. As discussed in the main manuscript, those short- to medium-term elasticities are not suited for our projection exercise.

D.8 Estimation of the distribution of migrants onto income terciles at destination.

We also estimate the distribution of migrants onto income quantiles at destination using terciles instead of quintiles (Table D.10). We find rather similar coefficients for all quantiles, with an increased significance of the coefficient on income per capita ratio as well as a better goodness-of-fit for the middle tercile. This result suggests that we appropriately distribute migrants onto middle income quintiles at destination.

E Literature review

Migration events are often multi-causal and do not always result from a desire to move. In a similar, albeit less discussed fashion, immobility can happen as a choice or as the involuntary consequence of a given context. In order to reflect reality, the role of aspiration in mobility is best discussed along continuous scales: agency in (im)mobility decisions is, indeed, a matter of degree [8, 10, 9]. Still, resource constraints can unequivocally limit one’s ability to migrate: as migration requires resources, whether economic, social or health-related, those who move are those who can afford to do so [11, 12, 13, 15]. The migration literature has discussed

involuntary immobility in contexts of conflict [78], poverty [10] and/or decline in wellbeing and mental health derived from environmental degradation [79], labeling people in a situation of involuntary immobility due to resources constraints as “trapped populations”.

The role of environmental change in (im)mobility events is multi-faceted and complex. Migration decisions are rarely due to environmental stress alone. Climate change may influence migration both directly and indirectly through various channels: economic, political, social, demographic, and environmental [16]. Migration patterns can respond to extreme weather events (projected to increase in intensity in the future) and long-term climate variability or change (droughts, sea-level rise [80]). Those changes might both enhance and reduce migration flows. Migration is expected to be increasingly used as an adaptation strategy to climate change [18, 19, 20]. At the individual or household level, (im)mobility might not directly reflect such environmental changes for several reasons. Remittances from earlier migrants may reduce incentives to move. In contrast, established migration networks may increase an individual’s propensity to move. Second, either through lack of information about risks at destinations or as the outcome of a balancing of risks, migrants might move to areas that are more or less exposed to climate change impacts than those where they came from, undermining its value for adaptation. Third, climate change is likely to lead to resource depletion in some of the most deprived areas, thereby trapping individuals who cannot afford to move [22, 23, 24, 25]. Therefore, higher levels of climate change will likely reduce people’s ability to move on their own terms, inducing both an increasing number of people who are forced to move (displacement), and an increasing number of people who are forced to stay in their origin locations [81]. The latter category of affected populations reflects, in essence, the effect of climate change on resource-constrained immobility [16, 19, 26].

Resource deprivation caused by climate change impacts, and potentially responsible for immobility, can be quantified in the form of climate change damages computed with Integrated Assessment Models (IAM). IAM couple a single climate model to one of the global economy, by representing greenhouse gas emissions as well as damages on the economy resulting from climate change. Some IAM provide a representation of mitigation costs and impacts as a single economic metric through their monetary-equivalent value (e.g. DICE, FUND,

PAGE). Such IAM are used for cost-benefit analyses centered on maximizing welfare in order to identify optimal climate change policies, calculations of marginal effect of emissions on social welfare – also called the Social Cost of Carbon (SCC), as well as sensitivity analyses aiming at weighing the relative importance of various climate change drivers, impacts and policies. Both the Intergovernmental Panel on Climate Change (IPCC) and the National Academy of Sciences have called for improvements in IAMs’ damage functions [82, 48].

Migration is at this point hardly included in commonly used IAM. For most models, migration is absent from the IAM itself and only considered implicitly, as part of required input population growth scenarios. However, recent efforts have been deployed by the authors and others to study climate-migration interactions using a variety of IAM and other models [27, 28, 80, 30, 29, 31]. In a previous project we proposed a model of international migration and remittances dynamics and included it in an IAM [27]. Yet we did not consider any income heterogeneity within regions, needed to identify resource-constrained immobility. Furthermore, [83] propose migration projections across 17 world regions using an overlapping generations model, focusing on migration effects on within-region inequality, as well as effects of between-region inequality on migration. [28] use a dynamic spatial model to analyze effects of climate change on production, migration and trade. They find that in a climate change context, migration restrictions have significant effects on welfare as well as on spatial inequities. [80] use a similar model to quantify the economic costs of climate change-driven coastal flooding, inducing mainly internal moves. [29, 31] use an overlapping generations model in the continuous space, and focus on migration projections along climate change scenarios.

Resource deprivation contributing to immobility is distinct from, yet directly related to inequality and poverty. A recent and upcoming strand of literature has been focusing on considerations of inequality in damages assessments [33, 34, 35], albeit without specifying migration dynamics. The extent to which damages from climate change are and will be regressive, i.e. affect the poor disproportionately, is still unclear. Recent empirical literature suggests that damages have been [84, 85, 86] and will continue to [87, 88, 89] exacerbate between-country inequality. Yet the evidence relating damages effects on within-country

(or region) inequality is both less documented and less conclusive. Some studies suggest an increasing effect of damages on within-country inequality [90, 91], for instance in Brazil [92] and in the United States [93], while others document a decrease in inequality, resulting from destroyed assets following a cyclone in Bangladesh [94], or through increased return on acquiring skills [95]. Note that the regressive character of climate change damages is necessarily influenced by adaptation measures now and in decades to come.

F Additional details on Methods

F.1 Choice of values for the income elasticity of damages

In our model, we add income distributions in the form of quintiles to the FUND IAM. Following the approach developed by [34], each region is split into population quintiles. The damage distribution over income quintiles depends on the income distribution through the income elasticity of damages ξ (equation 12). Elasticity values of 1, 0, and -1 correspond to damages being proportional, independent, and inversely proportional to income. Since the regressive character of damages is still unsettled (see Section Literature review), we provide results with all three variants.

While our choice of values for the income elasticity of damages remains illustrative, the three selected elasticities correctly illustrate the range of preliminary values that can be inferred from the existing literature.

Hsiang et al. [93] provide estimates of damages from climate change in the United States at the county level. When ranking counties by 2012 income per capita level, they find that for a RCP8.5 scenario, current socioeconomic conditions, and the period 2080-2099, the poorest 5% of counties face damages of 5.5–27.8% of county income (90% interval), while the richest 5% of counties face damages of only -1.1–4.2% of county income. Given that the poorest 5% of counties receive 0.2% of national income, while the richest 5% receive 27.4% (data for 2012 from the U.S. Bureau of Economic Analysis), this yields an average income elasticity of damages of 0.54, with a maximum value of 0.95 and a minimum value well below -1.

Hallegatte and Rozenberg [32] assess five types of climate change impacts (agricultural productivity and prices, food prices, natural disasters, labor productivity, child stunting/malaria/diarrhea)

and their effect on poverty in 92 countries. They find that impacts on the bottom 40% are 70% larger than those on the average population. They do not provide information on damages for other percentiles, keeping us from inferring the resulting elasticity of damages.

Finally, Park et al. [90] focus on 52 developing countries to analyze the sole effects of heat stress on households across income levels. They find that in many hot (often poor) countries, warmer temperatures are strongly negatively associated with household wealth, with an exposure to temperatures in the hottest month up to 5degC higher for the poorest quintile than for the richest. They do not provide information on damages resulting from heat stress, keeping us from inferring the resulting elasticity of damages.

Note that further studies are available when considering the effect of climate change impacts on inequality between countries. Diffenbaugh and Burke [86] provide evidence that climate change already has increased income inequality between countries, with low-latitude (often poorer) countries having suffered cumulative losses of up to 40% of GDP per capita in the period 1961-2010 due to climate change, while higher-latitude (often richer) countries having enjoyed cumulative gains of up to similar magnitudes. Mendelsohn et al. [87], in an early study of distributional climate change impacts across countries, found that in a pessimistic climate scenario, the poorest quartile of countries (largely located in Sub-Saharan Africa) would endure damages of 23.8% of GDP by 2100.

F.2 Effect of changes in perceptions of future climate change on mobility decisions.

A crucial channel through which climate change impacts might affect international migration decisions is the income channel, as income levels and differences across countries are key drivers of international movements, and as climate change affects income levels differently in different countries. Other channels could also be at play. For instance changing perceptions of future climate change might affect mobility decisions. Our migration model does not include individual agents' perceptions of the future. It is not designed to analyze such perceptions, contrary to other model types (e.g., Agent-Based Models [96, 97, 98]. Yet we note that gravity models of migration such as the one we use do have a micro foundation. If one models an individual's decision to migrate that involves comparing potential income

gains in all places, amenities, costs to get there, and idiosyncratic preferences, and if one then aggregates all individuals' decisions, one ends up with a similar gravity equation [99].

The literature documenting whether and how agents update their beliefs about climate change and other environmental conditions suggests that individuals often change their behavior in order to reduce their personal [100] or financial exposure [101], although they sometimes do not [102]. The consequence for income growth appears to be detrimental, as agents refrain from investing into now riskier ventures and have fewer resources available to invest in learning [103, 104]. This detrimental effect on growth might perhaps be more pronounced in lower income regions. If that were the case, the resulting consequence on our migration model would take place both as an increased resource constraint and as an increased pull factor towards richer regions. The overall effect is unclear.

Looking more directly at the effect of perceptions of environmental change on migration decisions, without going through the income channel, the literature suggests that said effect is quite heterogeneous and depends on whether environmental changes at play are gradual or sudden. Koubi et al. [105], in a study focusing exclusively on internal migration in five countries, find that sudden-onset events such as floods increase migration, yet slow-onset events such as droughts lower the likelihood of migration. Yet the evidence on migration responses to environmental change is, as discussed in the introduction, quite mixed. Mueller et al. [106] find that migration decisions in rural Pakistan are more sensitive to some sudden-onset events (heat stress) than to others (flooding), while Bohra-Misra et al. [107] find that internal migration decisions in Indonesia are little responsive to sudden events yet are affected by temperature and precipitation variations.

Given the nature of our study which is based on a projection exercise, we would need to rely not only on individuals' current perception of climate change, but also on how that perception might change over time. We do not think that we are in a position to determine how such perceptions might evolve, but we consider it a great avenue for future research.

F.3 Input Scenarios: the Shared Socioeconomic Pathways (SSP) without migration.

In order to avoid double counting of migration, we use versions of those scenarios without migration, which some of us developed in a previous project [71]. The corresponding approach goes as follows. First, population projections for zero migration were developed by Samir KC, who ran a zero migration scenario based on [108, 109], using a demographic model of population dynamics. Second, we developed GDP projections for zero migration, using a similar gravity model with remittances to trace the migration effect on GDP. Third, we derived projections of final energy consumption and emissions for zero migration by assuming, for a given SSP narrative, that migration dynamics do not affect the energy consumption, respectively emissions path along GDP per capita levels. Note that for the energy consumption and emissions projections, we select relevant combinations of SSP with climate scenarios, the Representative Concentration Pathways, among the ones selected for the upcoming IPCC Assessment Report (see Fig. A.4): SSP1-RCP1.9, SSP2-RCP4.5, SSP3-RCP7.0, SSP4-RCP6.0, SSP5-RCP8.5. Fourth, we derived projections of Gini coefficients for zero migration using [66], who estimate their empirical model of Gini using global panel data for the period 1980-2010. Their data sources are the World Income Inequality Database, the Luxembourg Income Study and Eurostat measures for Western European countries, Transmonee (UNICEF) for countries in transition, the Social and Economic Database for Latin American Countries for Latin American countries, and either individual country or World Bank sources (Deininger and Squire, or the Poverty Monitoring Database) for Asian and African countries. In particular, we used the specification proposed in [66] (see equation (1) in their contribution) and computed changes in Gini coming exclusively from migration-driven changes in education drivers (education levels and share of public spending), using their estimated coefficients (see Table 2 in [66]). For this exercise we employ the SSP population projections without migration, available with detailed education levels. As in [66], we also use data on educational attainment levels by age and sex in 2010 from [110], as well as data on per capita education spending from [111]. For the latter, we use regional averages for countries with missing data. We get income quintiles from Gini coefficients by assuming that

the underlying income distribution can be fitted by a lognormal distribution. Conversely, we obtain Gini coefficients from income quintiles by using the Lorenz curve, a commonly used graphical representation of the cumulative income distribution [112]. We get missing values of the Lorenz curve by linear interpolation of values corresponding to the income quintiles, which allows us to approximate the Gini. We then correct this approximation using the error derived for known values of Gini.

As a result, the way we remove migration from the original SSP projections is almost the exact mirror of the way we include migration effects on each quantity in the IAM. As such, we represent migration along various socioeconomic scenarios in a broadly consistent manner. The only exception to this consistency relates to the population projection. As discussed above, its zero-migration version is obtained by forcing the international migration component of a demographic model of population dynamics to zero, which affects the ulterior location-specific fertility and mortality rates. When including migration in an IAM with our approach, we do not re-modify these fertility and mortality rates as they are not featured explicitly in our model — only overall population growth is explicit. This is equivalent to assuming that migrants adopt fertility and mortality patterns of the host country, while fertility and mortality at origin are not affected by emigration. This assumption likely induces a downward bias on population growth in destination countries as immigrants tend to have higher fertility rates than native populations. The direction of the bias on population growth in origin countries is less clear: on the one hand, emigrants tend to be healthier on average than the overall population, hinting at a lower mortality; yet on the other hand, emigrants also tend to be more educated, which is often linked to lower fertility rates. Overall, the effect of both biases on our main result on immobility is unclear. In order to add robustness to our findings, we now also perform runs using as input the original SSP projections — not modified for migration. Our central finding on immobility holds as quantitative results are minimally affected (see Fig. B.10).

Furthermore, to project consistent mitigation costs, we use carbon prices projections corresponding to the respective SSP–RCP combinations selected. These projections are computed using the process-based IAM described in [73]. They feature narrative-specific global carbon

prices. We illustrate those carbon price projections in Fig. A.5.

Finally, as FUND runs for the period 1950-3000 in yearly time steps while our SSP projections are available for the period 2015-2100 in 5-year time steps, we extend the projections as described in Table C.2.

F.4 Derivation of weights on remittances shares for aggregation from country to region level.

We use coefficients estimated at the country level in our remittance model, itself at the regional level. Residuals ϵ , used both in our remittance and our gravity models (equations 1 and 5), are aggregated at the region level just like the share of income sent as remittance ρ .

The flow of remittances *remit* sent from region d to region o is a function of the number of migrants from region o present in region d which we name $stock_{od}$, their income per capita level $ypc_{mig,od}$, and the corridor-specific parameter ρ . It is also, by construction, the sum of remittances sent from all countries j in region d to countries i in region o . Hence:

$$\begin{aligned} remit_{od} &= \rho_{od} \times ypc_{od}^m \times stock_{od} \times (1 - \phi_{od}) \\ \sum_{(i,j) \in (o,d)} remit_{ij} &= \sum_{(i,j) \in (o,d)} \rho_{ij} \times ypc_{ij}^m \times stock_{ij} \times (1 - \phi_{ij}) \end{aligned} \quad (14)$$

So

$$\begin{aligned} \rho_{od} &= \sum_{(i,j) \in (o,d)} w_{ij} \times \rho_{ij} \\ \text{and } exp(\epsilon_{od}) &= \sum_{(i,j) \in (o,d)} w_{ij} \times exp(\epsilon_{ij}) \end{aligned} \quad (15)$$

with

$$\begin{aligned} w_{ij} &= stock_{ij} / (\sum_{(i,j) \in (o,d)} stock_{ij}) \times ypc_{ij}^m / ypc_{od}^m \times (1 - \phi_{ij}) / (1 - \phi_{od}) \\ ypc_{ij}^m &= \max((ypc_i + ypc_j) / 2, ypc_j) \\ ypc_{od}^m &= \max(1/2((\sum_{i \in o} ypc_i \times pop_i) / (\sum_{i \in o} pop_i) + (\sum_{j \in d} ypc_j \times pop_j) / (\sum_{j \in d} pop_j)), \\ &\quad (\sum_{i \in o} ypc_i \times pop_i) / (\sum_{i \in o} pop_i)) \end{aligned} \quad (16)$$

References

- [73] Brian C. O'Neill et al. "The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6". In: *Geoscientific Model Development* 9 (2016), pp. 3461–3482. DOI: <http://dx.doi.org/10.5194/gmd-9-3461-2016>.
- [74] Matthew J. Gidden et al. "Global emissions pathways under different socioeconomic scenarios for use in CMIP6: a dataset of harmonized emissions trajectories through the end of the century". In: *Geoscientific Model Development* 12 (2019), pp. 1443–1475. DOI: <http://dx.doi.org/10.5194/gmd-12-1443-2019>.
- [75] R E Kopp et al. "The Influence of the Specification of Climate Change Damages on the Social Cost of Carbon". In: *Economics: The Open-Access, Open-Assessment E-Journal* 6 (2012), pp. 1–40. DOI: <https://doi.org/10.5018/economics-ejournal.ja.2012-13>.
- [76] Kevin Rennert et al. *The Social Cost of Carbon: Advances in Long-term Probabilistic Projections of Population, GDP, Emissions, and Discount Rates*. Tech. rep. BPEA Conference Draft, 2021.
- [77] Martin L. Weitzman. "On modeling and interpreting the economics of catastrophic climate change". In: *The review of economics and statistics* 91.1 (2009), pp. 1–19.
- [78] Stephen C. Lubkemann. "Involuntary Immobility: On a Theoretical Invisibility in Forced Migration Studies". In: *Journal of Refugee Studies* 21 (4 2008). DOI: <https://doi.org/10.1093/jrs/fen043>.
- [79] Sonja Ayeb-Karlsson, Dominic Kniveton, and Terry Cannon. "Trapped in the prison of the mind: Notions of climate-induced (im)mobility decision-making and wellbeing from an urban informal settlement in Bangladesh". In: *Palgrave Communications* 6.62 (2020). DOI: <https://doi.org/10.1057/s41599-020-0443-2>.
- [80] Klaus Desmet et al. "Evaluating the Economic Cost of Coastal Flooding". In: *American Economic Journals: Macroeconomics* 13.2 (2021), pp. 444–86.

- [81] Francois Gemenne. “Climate-induced population displacements in a 4C+ world”. In: *Philosophical Transactions of the Royal Society A* 369 (2011), pp. 182–195. DOI: <http://dx.doi.org/10.1098/rsta.2010.0287>.
- [82] Kolstad C. et al. “Social, Economic and Ethical Concepts and Methods”. In: *Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Ed. by Edenhofer O. et al. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 2014.
- [83] Soheil Shayegh, Johannes Emmerling, and Massimo Tavoni. “International Migration Projections across Skill Levels in the Shared Socioeconomic Pathways”. In: *Sustainability* 14.8 (2022).
- [84] Melissa Dell, Benjamin F. Jones, and Benjamin A. Olken. “Temperature shocks and economic growth: Evidence from the last half century”. In: *American Economic Journal: Macroeconomics* 4.3 (2012). DOI: <https://doi.org/10.1257/mac.4.3.66>.
- [85] Marshall Burke, Solomon M. Hsiang, and Edward Miguel. “Global non-linear effect of temperature on economic production”. In: *Nature* 527 (2015). DOI: <https://doi.org/10.1038/nature15725>.
- [86] Noah S. Diffenbaugh and Marshall Burke. “Global warming has increased global economic inequality”. In: *Proceedings of the National Academy of Sciences* 116.20 (2019), pp. 9808–9813. DOI: <https://dx.doi.org/10.1073/pnas.1816020116>.
- [87] Robert Mendelsohn, Ariel Dinar, and Larry Williams. “The distributional impact of climate change on rich and poor countries”. In: *Environment and Development Economics* 11.2 (2006), pp. 159–178. DOI: <https://dx.doi.org/10.1017/S1355770X05002755>.
- [88] E. De Cian et al. “Alleviating inequality in climate policy costs: an integrated perspective on mitigation, damage and adaptation”. In: *Environmental Research Letters* 11.074015 (2016). DOI: <https://dx.doi.org/10.1088/1748-9326/11/7/074015>.
- [89] Nicolas Taconet, Aurélie Méjean, and Céline Guivarch. “Influence of climate change impacts and mitigation costs on inequality between countries”. In: *Climatic Change* 160 (2020), pp. 15–34. DOI: <https://doi.org/10.1007/s10584-019-02637-w>.

- [90] Jisung Park et al. “Households and heat stress: estimating the distributional consequences of climate change”. In: *Environment and Development Economics* 23.3 (2018), pp. 349–368. DOI: <https://doi.org/10.1017/S1355770X1800013X>.
- [91] Nazrul Islam and John Winkel. *Climate change and social inequality*. Tech. rep. 152. United Nations Department of Economic and Social Affairs, 2017.
- [92] Emmanuel Skoufias. *The poverty and welfare impacts of climate change: quantifying the effects, identifying the adaptation strategies*. Tech. rep. The World bank, 2012.
- [93] Solomon Hsiang et al. “Estimating economic damage from climate change in the United States”. In: *Science* 356.6345 (2017), pp. 1362–1369. DOI: <https://dx.doi.org/10.1126/science.aal4369>.
- [94] Abu Nasar Mohammad Abdullah et al. “A short-term decrease in household income inequality in the Sundarbans, Bangladesh, following Cyclone Aila”. In: *Natural Hazards* 83 (2016), pp. 1103–1123. DOI: <https://dx.doi.org/10.1007/s11069-016-2358-1>.
- [95] Soheil Shayegh. “Outward migration may alter population dynamics and income inequality”. In: *Nature Climate Change* 7 (2017), pp. 828–832. DOI: <https://dx.doi.org/10.1038/NCLIMATE3420>.
- [96] Dominic R. Kniveton, Christopher D. Smith, and Richard Black. “Emerging migration flows in a changing climate in dryland Africa”. In: *Nature Climate Change* 2 (2012).
- [97] Behrooz Hassani-Mahmooei and Brett W. Parris. “Climate change and internal migration patterns in Bangladesh: An agent-based model”. In: *Environment and Development Economics* 17 (2012).
- [98] A. R. Bell et al. “Migration towards Bangladesh coastlines projected to increase with sea-level rise through 2100”. In: *Environmental Research Letters* 16.2 (2021).
- [99] Michel Beine, Simone Bertoli, and Jesús Fernández-Huertas Moraga. “A practitioners’ guide to gravity models of international migration”. In: *The World Economy* 39.4 (2016), pp. 496–512.
- [100] Matthew Neidell. “Information, avoidance behavior, and health the effect of ozone on asthma hospitalizations”. In: *Journal of Human resources* 44.2 (2009), pp. 450–478.
- [101] Wolfram Schlenker and Charles A. Taylor. “Market expectations of a warming climate”. In: *Journal of Financial Economics* (2021).

- [102] Marshall Burke and Kyle Emerick. “Adaptation to climate change: Evidence from US agriculture”. In: *American Economic Journal: Economic Policy* 8.3 (2016), pp. 106–40.
- [103] Anna Ciesielski. *Climate Change Expectations and Endogenous Economic Growth in the Dice Model*. Working Paper 7761. CESifo, 2019.
- [104] Alexander Dietrich, Gernot J. Müller, and Raphael Schoenle. *The Expectations Channel of Climate Change: Implications for Monetary Policy*. Discussion Paper DP15866. CEPR, 2021.
- [105] Vally Koubi et al. “The role of environmental perceptions in migration decision-making: evidence from both migrants and non-migrants in five developing countries”. In: *Population and Environment* 38.2 (2016), pp. 134–163.
- [106] Valerie Mueller, Clark Gray, and Katrina Kosec. “Heat stress increases long-term human migration in rural Pakistan”. In: *Nature Climate Change* 4.3 (2014), pp. 182–185.
- [107] Pratikshya Bohra-Mishra, Michael Oppenheimer, and Solomon M. Hsiang. “Nonlinear permanent migration response to climatic variations but minimal response to disasters”. In: *Proceedings of the National Academy of Sciences* 111.27 (2014), pp. 9780–9785.
- [108] W. Lutz et al. *Demographic and human capital scenarios for the 21st century: 2018 assessment for 201 countries*. Tech. rep. Publications Office of the European Union, Luxembourg, 2018.
- [109] Samir KC. *Updated demographic SSP4 and SSP5 scenarios complementing the SSP1-3 scenarios published in 2018*. Working Paper WP-20-016. Laxenburg Austria: IIASA, 2020.
- [110] *Wittgenstein Centre Data Explorer Version 2.0*. 2018. URL: <http://www.wittgensteincentre.org/dataexplorer>.
- [111] *Statistics on Public Expenditures for Economic Development (SPEED)*. International Food Policy Research Institute (IFPRI), 2015. DOI: <http://dx.doi.org/10.7910/DVN/INZ3QK>.

- [112] Michel Lubrano. *The econometrics of inequality and poverty. Lecture 4: Lorenz curves, the Gini coefficient and parametric distributions*. 2013. URL: <http://www.vcharite.univ-mrs.fr/PP/lubrano/cours/Lecture-4.pdf>.

E

Figure E.1

Figure E.2

Figure E.3

Figure E.4

Figure E.5

Figure E.6