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ABSTRACT

Selective Migration and Economic Development: A Generalized Approach*

International migration is a selective process that induces ambiguous effects on human capital and economic development in countries of origin. We establish the theoretical micro-foundations of the relationship between selective emigration and human capital accumulation in a multi-country context. We then embed this migration-education nexus into a development accounting framework to quantify the effects of migration on development and inequality. We find that selective emigration stimulates human capital accumulation and the income of those remaining behind in a majority of countries, in particular in the least developed ones. The magnitude of the effect varies according to the level of development, the dyadic structure of migration costs, and the education policy. Emigration significantly reduces cross-country income inequality and the proportion of the world population living in extreme poverty.

JEL Classification: J61, O15, E24, J24

Keywords: human capital, migration, selection, brain drain, brain gain, global inequality

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1 Introduction

International migration has become part of mainstream development thinking and international policy. This is best illustrated by the fact that the 2030 Agenda for Sustainable Development defines (well-managed) migration as a key driver of development for migrants and the communities they leave behind (United Nations, 2015). While it is undisputed that moving abroad brings significant benefits to the majority of migrants (as evidenced in Clemens and Pritchett, 2008), the implications for those remaining behind are more controversial. On the one hand, migrants act as development actors and contribute to inducing financial and political remittances, business links, and transfers of knowledge to their country of origin. On the other hand, highly educated people are more likely to emigrate than the less-educated. This positive selection is sometimes seen as depriving origin countries of vital human potential for boosting productivity, accumulating knowledge, and sound democratic values. Understanding the impact that international migration has on the economic development in countries of origin and on global inequality is therefore complex, given the multitude of transmission mechanisms at work. These mechanisms are well established in existing literature and have been subject to several literature surveys (Clemens et al., 2014, Commander et al., 2004, Docquier and Rapoport, 2012, Ozden and Rapoport, 2018). What is missing is a unified approach that allows a comparison of their strengths and highlights the role of country-specific characteristics. We propose a *generalized approach* – a micro-founded, multi-country, general equilibrium model that reconciles and extends existing empirical cross-country and case studies – to study the impact of selective migration on human and economic development in origin countries, global inequality, and extreme poverty.

We proceed in three steps. Our first objective is to revisit the link between selective emigration and human capital accumulation in the country of origin (a process we refer to as "*human development*" throughout this paper),[1] and establish its micro-foundations in a dyadic and multi-destination context. Focusing on migration to OECD countries only,[2] we develop a micro-founded and dyadic framework that fully accounts for the characteristics of each origin country and of all the potential destinations, including dyadic migration costs and access to education. After demonstrating that our *generalized framework* has desirable theoretical properties, we parameterize it to match migration and education data for 174 countries in the year 2010, as well as the average education response to migration prospects identified empirically for broad country income groups. We use this tool to quantitatively predict the net effect of selective emigration on human capital accumulation in the country of origin.

Our generalized approach reveals that selective emigration has heterogeneous effects with regard to expected returns on schooling, even within a broad country income group. This is because historical ties, as well as the geographic or linguistic characteristics of countries, govern the dyadic structure of emigration costs and the average wage gap with the most accessible destinations. In addition, access to education plays a major role, and country size influences the diversity in domestic jobs, thereby governing the gains resulting from diversifying employment opportunities through international migration. We find

[1]In the development literature, the term "*human development*" refers to a broader concept that goes beyond human capital accumulation and covers other aspects, such as health, life expectancy, poverty, etc.

[2]Migration to OECD destination countries is the best documented, fastest-growing, and most positively selected component of global migration.

that the incentive mechanism operates in virtually all countries. In line with existing case studies, however, the largest net benefits are observed in the poorest countries. Overall, our dyadic approach produces slightly more optimistic results than empirical estimates. It predicts that a net "brain gain" is at work in a majority of low and lower-middle income countries, though its overall effect on human capital disparities between countries is limited.

In the second step, we turn our attention to the effect of selective emigration on income per capita in the origin country (which we refer to here as "*economic development*"). This impact materializes through the human capital accumulation mechanism as well as additional channels. On the one hand, migrants remit financial resources and other non-material transfers that contribute to economic development and/or poverty reduction in their home country. On the other hand, emigration induces negative market size and fiscal externalities. Hence, it is likely that selective emigration produces winners and losers among developed and developing countries (in line with Biavaschi et al., 2020, Docquier and Rapoport, 2012). We estimate real disposable income responses to selective emigration country by country. To do so, we embed our micro-founded framework into a *development accounting* model in line with Hsieh and Klenow (2010) and Jones (2014). Our extended model accounts for the complementarity between high-skilled and low-skilled workers, schooling externalities, diaspora externalities, market size externalities, the fiscal impact of selective emigration, and remittances. We parameterize the different externalities incorporated into this *development accounting* framework using benchmark parameter values from the empirical literature, and alternatively considering a more conservative scenario.

Relying on this *development accounting* framework, we simulate a counterfactual no-migration scenario and show that selective emigration increases real disposable income per worker in a large majority of countries, in particular in the least developed ones. In spite of positive selection, emigration per se contributes to income convergence between countries. Most countries exhibit a gain in the range of 0 to 20 percent, but there is a non-negligible proportion of the sample for which the effect is larger. An adverse effect is found in a minority of (small) countries from which emigrants are negatively or too positively selected. Unsurprisingly, this convergence effect is even more pronounced if development is measured for people rather than for places (Clemens and Pritchett, 2008).

Our third objective is to analyze how global migration affects the *world distribution of income and extreme poverty.* We solve our model for all countries jointly, endogenizing wages and education responses to emigration and immigration in all parts of the world. We then compare a counterfactual no-migration scenario with the observed world economy equilibrium. Migration-driven changes in global inequality are driven by the per-worker income responses as well as by the geographic reallocation of the world's labor force. The pure income effect (i.e., convergence in average income levels between countries) is dominated by the effect of reallocating workers across countries. The movements from poor to rich countries increase the worldwide average level of disposable income by 4.5 percent, which is larger than the gain observed in the poorest countries of origin. Overall, global migration increases the Theil index of income inequality by 2.0 to 2.5 percent, meaning that the semi-elasticity of inequality to the proportion of international migrants is close to unity. The rise in inequality is not a problem in itself if the vast majority of people in general, and the extreme poor in particular, are better off (stochastic dominance). We find that global migration reduces extreme poverty by 5.3 to 8.1 percent depending on the parameter values, and is only harmful for a tiny proportion of the world's low-skilled population. We conclude that international migration can be considered as a driver of sustainable development that contributes, with a few exceptions, to improving the economic outcomes of both migrants and the communities left behind in the countries of origin.

Our paper addresses literature on the *brain drain* and its implications for economic development. The implications of international migration for economic development and global inequality are strongly (but not only) related to its effect on human capital disparities. International migration raises concerns about the *brain drain* of high-skilled workers from poorer to richer countries, as college and university graduates exhibit a much higher propensity to emigrate internationally than the less-educated, and tend to agglomerate in highly productive countries (Belot and Hatton, 2012, Docquier and Rapoport, 2012, Grogger and Hanson, 2011, Kerr et al., 2016). Positive selection results from migrants' self-selection (high-skilled people are more responsive to economic opportunities and political conditions abroad, have more transferable skills, have greater ability to gather information or finance emigration costs, etc.), and to the skill-selective immigration policies implemented in the major destination countries. Nearly one in five college graduates born in low-income countries live and work in an industrialized country, while the average emigration rate of the less-educated is below 1 percent. The emigration rate of college graduates even reaches 70 percent in some small island developing states.[3] As human capital is usually perceived as a proximate cause of development (Acemoglu et al., 2014, Glaeser et al., 2004, Jones, 2014), selective emigration could be seen as depriving poor countries of the necessary resources to drive economic growth, to provide key public services, and to articulate calls for greater democracy (Bhagwati and Hamada, 1974, Haque and Kim, 1995, Miyagiwa, 1991, Wong and Yip, 1999).

By contrast, selective emigration prospects also increases the expected returns on human capital, thus leading more people to invest (or people to invest more) in education at home before deciding whether to emigrate (Beine et al., 2001, Djajic, 1989, Mountford, 1997, Stark et al., 1997, Vidal, 1998). The latter effect has been identified empirically using cross-country regressions (Beine et al., 2008, 2010), enabling the assessment of the net education response to selective emigration. Under certain conditions, the stimulus for skill formation appears to be strong enough to bring the economy's stock of human capital to a higher level in the post-migration equilibrium. Evidence of such a "brain gain" mechanism is provided in several case studies exploiting quasi-natural experiments or long-lasting spatial variations in occupation-based or skill-biased migration prospects in low and lower-middle income countries (Abarcar and Theoharides, 2021, Chand and Clemens, 2008, Gibson and McKenzie, 2009, Khanna and Morales, 2017, Shrestha, 2017, Theoharides, 2018).[4] Additional related work has found an effect of increased exposure to migration on education that goes beyond the pure incentive effect (Antman, 2011, Batista et al., 2012, Caballero et al., 2021, Clemens and Tiongson, 2017, Dinkelman and Mariotti, 2016, Fernández Sánchez, 2022, Gibson et al., 2011, Khanna et al., 2022, Yang, 2008). These case studies are not properly comparable, as they rely on different proxies for human capital, cover countries sharing very different characteristics, and involve different mechanisms of transmission. By contrast, our micro-founded framework is better suited

[3]To a lesser extent, emigration is also a concern for high-income countries, where college graduates are 1.25 to 1.5 times more likely to emigrate than the less-educated.

[4]Consistently, shocks that mostly affect migration opportunities for low-skilled workers are shown to reduce human capital formation (de Brauw and Giles, 2017, Kosack, 2021, McKenzie and Rapoport, 2011, Pan, 2017).

for cross-country comparisons.

The impact of selective emigration on economic development goes beyond the human capital mechanism. Financial remittances are the less disputable compensating mechanism through which emigration affects income in the origin country (e.g., Bollard et al., 2011, Theoharides, 2020). Other studies show that migrant networks stimulate non-material transfers from destination to origin countries. They generate business links, stimulate trade and FDI, and induce political remittances and transfers of norms and values affecting the quality of institutions in the place of origin (e.g., Docquier et al., 2016). This, in turn, increases the level of the total factor productivity (e.g., Bahar and Rapoport, 2018, Felbermayr et al., 2010, Iranzo and Peri, 2009, Javorcik et al., 2011, Kugler and Rapoport, 2007, Parsons and Vezina, 2018). Conversely, emigration affects market sizes, the number of entrepreneurs, and the diversity of goods available to consumers (e.g., Aubry et al., 2016, di Giovanni et al., 2015), and can be at source of fiscal costs for those remaining behind (e.g., Alesina and Spolaore, 1997, Alesina and Wacziarg, 1998, Devesh et al., 2009, Egger et al., 2012, Teferra, 2007, World Bank, 2010). Our *development accounting* framework combines these mechanisms, allowing us to quantify their relative strengths.

The rest of this paper is organized as follows. Section 2, we focus on the link between selective emigration and human capital accumulation in the country of origin. We establish the micro-foundations of this link in a dyadic context and using this novel approach on our data. In Section 3, we go one step further and account for endogenous wages and several externalities reflecting the main feedback effects of emigration on income that are discussed in the existing literature. We describe our development accounting framework and apply it to the data. In Section 4, we quantify the effect of global migration on the world distribution of income, accounting for endogenous labor structures, income levels, and education responses in all countries. Section 5 concludes.

2 Selective Emigration and Human Development

We first focus on the relationship between selective emigration and human capital accumulation in the country of origin. The net effect of emigration on the share of high-skilled workers remaining in the origin country results from the combination of two opposite effects: a *composition effect*, in which highly educated people are more likely to migrate than the less-educated, and an *incentive effect*, in which the differential in emigration prospects raises the expected returns on education and thus leads more people to invest (or people to invest more) in education before deciding whether to emigrate.

The composition effect is illustrated in Table 1, which shows skill-specific emigration and selection rates for the year 2010 by income group and country size. Panel A illustrates that the average emigration rate of college graduates (Cols. (4-6)) exceeds the equivalent rate of the less-educated (Cols. (1-3)), a sign of positive selection in emigration along the (observable) schooling dimension. Emigration rates of high-skilled people strongly decrease with economic development, whilst the average emigration rates of the low-skilled increase with economic development.[5] Positive selection, as proxied by the ratio of emi-

[5] A deeper analysis reveals that the relationship between low-skilled emigration rates and income per capita shows an inverted U-shape: low-skilled emigration first increases and then decreases as a country experiences economic development. This relationship also holds for average emigration rates (Dao et al., 2018). Recent studies by Bencek and Schneiderheinze (2020), Clemens and Mendola (2020), and Clemens

gration rates in Cols. (7-9), thus decreases with development and is particularly prevalent in low-income countries. The average ratio of high-skilled to low-skilled emigration rates is between 16 and 33 in low-income countries, while it varies from 1.1 to 1.4 in high-income countries. High-skilled emigration rates decreased between 1990 and 2010 in all except the low-income group. Nevertheless, the worldwide average high-skilled emigration rate remained relatively stable across census rounds. This is due to the increasing demographic share of low-income countries – the group exhibiting the largest skilled emigration rates – in the world population. By contrast, low-skilled emigration rates increased in all groups. Hence, positive selection has decreased since 1990. Unlike emigrant populations (or stocks), all skill-specific emigration rates decrease with country size. This is due to the fact that large countries are economically more diverse and offer more internal migration opportunities. As highlighted in Panel B of Table 1, countries with the largest emigration rates are smaller countries with fewer than 2.5 million inhabitants.

Table 1: Emigration and selection rates to OECD destination countries
(Data by group of countries and education level for the years 1990, 2000, and 2010)

	Rate low-sk. ($m_{i,l,t}$) (As %)			Rate high-sk. ($m_{i,h,t}$) (As %)			Selection index ($m_{i,h,t}/m_{i,l,t}$)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	1990	2000	2010	1990	2000	2010	1990	2000	2010
World	1.3	1.5	1.7	5.2	4.7	5.1	4.0	3.1	3.0
A. By income group									
High-income	2.7	3.0	3.0	3.9	3.3	3.7	1.4	1.1	1.2
Upper-middle	0.9	1.3	1.6	6.4	5.5	5.1	7.1	4.2	3.2
Lower-middle	0.9	1.1	1.3	8.5	8.4	8.1	9.4	7.6	6.2
Low-income	0.5	0.8	1.1	16.4	16.2	18.0	32.8	20.3	16.4
B. By country size									
High-pop	0.9	1.1	1.2	4.0	3.8	4.2	4.4	3.5	3.5
Upper-middle	2.9	3.6	4.3	10.2	8.8	9.4	3.5	2.4	2.2
Lower-middle	4.7	5.5	6.2	12.1	10.5	10.4	2.6	1.9	1.7
Low-pop	8.0	9.3	9.9	28.2	24.5	22.1	3.5	2.6	2.2

Note: Table 1 focuses on emigration to OECD destination countries only. Data are obtained from Arslan et al. (2015) for the years 2000 and 2010, and from Artuc et al. (2014) for the year 1990. For income groups and regions, we follow the World Bank classification. For country size, we distinguish between countries with a population above 25 million (High-pop), between 10 and 25 million (Upper-middle), between 2.5 and 10 million (Lower-middle), and less than 2.5 million (Low-pop).

With regard to the incentive effect, the link between selective emigration rates and pre-migration human capital formation has been theoretically investigated in two-country settings with one poor origin country and one wealthy destination country (Beine et al., 2001, Mountford, 1997, Stark et al., 1997, Vidal, 1998). Under certain conditions, the stimulus for skill formation may be strong enough to bring the economy's stock of human capital to a higher level in the post-migration equilibrium, as evidenced in several case studies. In Section 2.1, we establish the micro-foundations of the link between emigration rates and human capital formation in a "generalized" multi-destination framework that

(2020) further discuss the relationship between economic development and emigration.

can be easily calibrated to conduct numerical experiments. In Section 2.2, we parameterize the model, compute the net human capital responses to selective emigration, and compare them with predictions of an empirical approach.

2.1 Generalized Approach: Theory

Existing literature analyzing the link between emigration and human capital formation mostly consists of country case studies – identifying a causal impact using natural experiment but raising external validity concerns – and cross-country regressions – identifying an average impact by country group at the expense of identification problems.[6] We propose a generalized approach that establishes the micro-foundations of the link between emigration rates and human capital formation, and combines the merits of existing empirical approaches. This means that our results are fully comparable across countries, and accounts for country-specific factors influencing the dyadic structure of migration (such as dyadic migration costs, income disparities with easily accessible countries, and the elasticity of migration to income) as well as access to education (such as the education policy, the distribution of individual ability to educate, and the elasticity of education to returns on schooling).

We consider a country of origin $i \in I$ with a working-age native population denoted by N_i, capturing the population that is old enough to decide whether to emigrate or stay in the country of origin. Our model is static: we investigate the relationship between emigration and education at the level of a given cohort, assuming that the implicit period of time represents the active life of one generation (say, 30 to 40 years). We therefore abstract from the time index t. We divide the population into two skill groups $s = (h, l)$, with $s = h$ for college graduates and $s = l$ for the less-educated, and we denote by $N_{i,s}$ the endogenous size of the type-s native population. Hence, the proportion of college graduates in the native population is given by:

$$H_i \equiv \frac{N_{i,h}}{N_{i,l} + N_{i,h}}.$$

Individuals have the choice between staying in their home country i or emigrating to a foreign country j. As the data do not allow us to distinguish between permanent and temporary migrants, we make the assumption that migrants pursue their whole working career in the foreign country. We denote by $M_{ij,s}$ the number of type-s individuals deciding to move from i to j.[7] Hence, the skill-specific emigration rate is defined as:

$$m_{i,s} \equiv \frac{\sum_{j \neq i} M_{ij,s}}{N_{i,s}},$$

implying that the number of non-migrants (or stayers) is given by
$M_{ii,s} \equiv N_{i,s} - \sum_{j \neq i} M_{ij,s} = N_{i,s}(1 - m_{i,s})$.

Our multi-country model jointly endogenizes H_i and $m_{i,s}$, and allows us to extract some static comparative properties. To do so, we model migration and education choices as outcomes of a Random Utility Model (RUM). The RUM is becoming the consensual tool to

[6] In Appendix A, we provide an update of the cross-country results discussed in Beine et al. (2011, 2008, 2010) by using better data, a more general specification, and an improved identification strategy.

[7] In the calibration, $M_{ij,s}$ is measured as the skill-specific stock of migrants, permanent and temporary, living in each possible destination country at a given moment in time.

model dyadic migration decisions. The standard RUM assumes that the utility of a type-s individual λ born in country i and moving to a destination country j is composed of a deterministic component that accounts for the average income at destination ($w_{j,s} \in \Re^+$), the average level of moving costs ($c_{ij,s} < 1$), and of a random component ($\varepsilon^{\lambda}_{ij,s} \in \Re$) that captures heterogeneity between individuals (i.e., heterogeneity in preferences, in moving costs, in the ability to value work-related skills and experience abroad, etc.). To model interdependencies between migration and education decisions, we extend the standard RUM and introduce a second source of heterogeneity in the cost of college education, $e^{\lambda}_h \in [0, 1]$. There is no such cost if the individual chooses not to invest in human capital ($e^{\lambda}_l = 0$).

We allow the individual-specific effort to acquire education to decrease with the (exogenous) provision of public education, and to vary with other country-specific characteristics affecting access to basic (primary and secondary) and higher education (all of which are reflected in a scale variable G_i).[8] Highlighting the complementarity between public education and individual efforts to accumulate human capital is particularly relevant when considering the investment in education in poor, developing countries, in which credit markets for the purpose of funding private education are underdeveloped. As noted by the World Bank (2000), higher education systems in developing countries are heavily dominated by public universities, with the costs falling predominantly on the state. Hence, working-age individuals have heterogeneous abilities to acquire higher education, and heterogeneous preferences concerning destination countries. The utility function of an individual λ choosing education type s and moving from i to j has a logarithmic form and is expressed as:

$$U^{\lambda}_{ij,s} = \ln (w_{j,s}) + \ln (1 - c_{ij,s}) + \ln \left(1 - \frac{e^{\lambda}_s}{G_i}\right) + \varepsilon^{\lambda}_{ij,s}.$$

As is standard in the literature dealing with migration, we assume that the random component of utility $\varepsilon^{\lambda}_{ij,s}$ follows a Type I Extreme Value distribution, also known as the double-exponential cumulative distribution function:

$$\varepsilon^{\lambda}_{ij,s} \rightsquigarrow F_1(\varepsilon) = \exp\left[-\exp\left(-\frac{\varepsilon}{\mu} - \kappa\right)\right] \quad \forall i, j, s, t,$$

where $\mu > 0$ is a common scale parameter governing the responsiveness of migration decisions to income disparities and κ is Euler's constant.

With regard to the cost of the higher education, no effort is required if the individual does not acquire higher education (as stated above, $e^{\lambda}_l = 0$). By contrast, investing in higher education requires a positive level of effort ($e^{\lambda}_h \geq 0$). We assume that e^{λ}_h is distributed on $[0, 1]$ according to the following cumulative distribution function:

$$F_2(e_h) = e_h^{z+1},$$

where $z \in \Re^+$ is a parameter governing the slope of the density function, $f_2(e_h) = (1+z)e^z_h$, which is increasing in e_h. The greater the value of z, the smaller the proportion of

[8] Our framework is compatible with the fact that some individuals acquire education abroad. Our scale variable G_i can be seen as a weighted average of access to domestic and foreign education. Compared with domestically-trained individuals, the foreign-trained might encounter higher returns on schooling abroad and lower moving costs. This heterogeneity is captured by the random component of the utility function ($\varepsilon^{\lambda}_{ij,s}$).

individuals with a greater ability to acquire education (i.e., with a low education cost). In other words, z determines the scarcity of high-ability individuals, and/or the capacity of domestic agents to devote resources to education. The scale factor $(1+z)$ in $f_2(e_h)$ ensures that $\int_0^1 f_2\left(e_h^z\right) = 1$.[9]

Timing of decisions. The timing of decisions reflects the availability of information about the two random individual characteristics, e_h^λ and $\varepsilon_{ij,s}^\lambda$. First, individuals discover their ability to educate, e_h^λ. They do not know their migration type, $\varepsilon_{ij,s}^\lambda$, but they know its distribution. Given expectations about $w_{j,s}$ and $c_{ij,s}$, each individual decides whether to acquire higher education. Second, after the education decision is implemented, individuals discover their migration type, $\varepsilon_{ij,s}^\lambda$, and decide where to emigrate, or to stay in their home country.

Higher education decisions. In the first stage, individuals acquire higher education if the expected utility gain from being college educated exceeds the effort cost. Under the Type I Extreme Value distribution for $\varepsilon_{ij,s}^\lambda$, we can derive the expression for the ex-ante expected utility of choosing type s (see, for instance, de Palma and Kilani, 2007):

$$\begin{aligned}
\mathbb{E}\left(U_{i,s}\right) &= \ln \sum_{j=1}^{I} e^{[\ln(w_{j,s})+\ln(1-c_{ij,s})]/\mu} + \ln\left(1-\frac{e_s^\lambda}{G_i}\right) \\
&= \ln \sum_{j=1}^{I} \left(w_{j,s}\right)^{1/\mu}\left(1-c_{ij,s}\right)^{1/\mu} + \ln\left(1-\frac{e_s^\lambda}{G_i}\right).
\end{aligned}$$

Investing in college education is optimal if $\mathbb{E}\left(U_{i,h}\right) \geq \mathbb{E}\left(U_{i,l}\right)$. This condition can be expressed as:

$$\left(1-\frac{e_s^\lambda}{G_i}\right)\sum_{j=1}^{I}\left(w_{j,h}\right)^{1/\mu}\left(1-c_{ij,h}\right)^{1/\mu} \geq \sum_{j=1}^{I}\left(w_{j,l}\right)^{1/\mu}\left(1-c_{ij,l}\right)^{1/\mu} \tag{1}$$

A variable that plays a key role in this condition is the expected returns on higher education investment, which accounts for skill-specific migration prospects. It is defined as:

$$\begin{aligned}
\Lambda_i &\equiv \frac{\sum_{j=1}^{I}\left(w_{j,h}\right)^{1/\mu}\left(1-c_{ij,h}\right)^{1/\mu}}{\sum_{j=1}^{I}\left(w_{j,l}\right)^{1/\mu}\left(1-c_{ij,l}\right)^{1/\mu}} \\
&\equiv \frac{\left(w_{i,h}\right)^{1/\mu}+\left(W_{i,h}\right)^{1/\mu}}{\left(w_{i,l}\right)^{1/\mu}+\left(W_{i,l}\right)^{1/\mu}}
\end{aligned} \tag{2}$$

where $(W_{i,s})^{1/\mu} \equiv \sum_{j\neq i}(w_{j,s})^{1/\mu}(1-c_{ij,s})^{1/\mu}\ \forall s$ is the expected-income component related to emigration prospects for type-s individuals.

In a no-migration (or closed) economy, the expected returns on higher education investment are fully determined by the local wage ratio $(\Lambda_i^{NM} = \left(w_{i,h}/w_{i,l}\right)^{1/\mu})$. In an

[9] When $z = 0$, the distribution is uniform. When $z > 0$, the density is strictly increasing in e_h: there are more individuals facing larger education costs than individuals facing smaller education costs. Parameter z can be calibrated to match the semi-elasticity of human capital formation to the emigration differential estimated in Appendix A for broad income groups.

open-economy context, the influence of emigration prospects is large if the ratios $W_{i,s}/w_{i,s}$ are high. This is the case when foreign wages are high and migration costs are low. In an open economy (i.e., when $W_{i,s} > 0$), the expected return on higher education investment is therefore affected by emigration prospects. From (1) and (2), investing in college education is optimal when

$$e_h^{\lambda} \leq G_i \left[\frac{\Lambda_i - 1}{\Lambda_i}\right] \equiv \chi_i, \tag{3}$$

where χ_i is the (endogenous) critical level of cost below which investing in higher education is optimal. As in the two-country setting of Djajić et al. (2019), this critical level increases with the provision of public education (G_i) and with the expected college premium, which accounts for the wage structure in all potential destination countries and the dyadic-cum-skill structure of migration costs (Λ_i).

Given the cumulative distribution function $F_2(e_h)$ defined above, the proportion of natives deciding to invest in higher education can be expressed as:

$$H_i = F_2(\chi_i) = G_i^{1+z} \left[\frac{\Lambda_i - 1}{\Lambda_i}\right]^{1+z}. \tag{4}$$

This proportion depends on $w_{i,s}$ and G_i, the components of the expected utility affected by the home country characteristics (i.e, domestic wages and education policy), and on $W_{i,s}$, the component driven by emigration prospects (i.e., wages in destination countries and the migration costs). As already mentioned, the proportion of natives investing in education is high if wages in the country of origin are lower than in other countries, and if emigration costs are small. In a closed economy framework ($c_{ij,s} = 1 \; \forall s, j \neq i$), the critical level of effort below which college education is beneficial is determined locally; it increases with G_i and with the local skill premium ($w_{i,h}/w_{i,l}$). The no-migration level of human capital is denoted by H_i^{NM}.

The model has two properties that are in line with existing literature:

Proposition 1 *For a given education policy (G_i), emigration prospects stimulate incentives to acquire higher education if the expected education premium abroad is higher than in the country of origin* $\frac{W_{i,h}}{W_{i,l}} > \frac{w_{i,h}}{w_{i,l}}$.

Proof. Given Eq. (3), the condition $\frac{W_{i,h}}{W_{i,l}} > \frac{w_{i,h}}{w_{i,l}}$ is equivalent to $\Lambda_i > \Lambda_i^{NM}$. *QED*

Proposition 2 *When* $\frac{W_{i,h}}{W_{i,l}} > \frac{w_{i,h}}{w_{i,l}}$, *emigration prospects increase the marginal effect of education subsidies on human capital investments.*

Proof. From Eq. (4), the marginal benefit from education subsidies is given by $\frac{\partial H_i}{\partial G_i} = (1+z)G_i^z \left[\frac{\Lambda_i - 1}{\Lambda_i}\right]^{1+z} > 0$ if $\Lambda_i > 1$. This implies that $\frac{\partial^2 H_i}{\partial G_i \partial \Lambda_i} = (1+z)^2 G_i^z \left[\frac{\Lambda_i - 1}{\Lambda_i}\right]^z \frac{1}{\Lambda_i^2} > 0$. *QED*

This result is in line with Djajić et al. (2019), who highlight the complementarity between public spending on education, and students' efforts to acquire human capital. Nevertheless, this does not imply that the effectiveness of public education increases with selective emigration prospects. This is because a proportion of the domestically-produced human capital benefits a foreign country rather than the home country (which reduces the social returns on public education), and the relevant high-skilled emigrants leave the country without paying back into public finances. However, selective emigration prospects increase the enrolment response to public spending on education, as more individuals are incentivized to invest in education for a given public education policy (G_i).

Emigration decisions. In the second stage, education has been determined and individuals choose to emigrate to a country j if $\ln(w_{j,s}) + \ln(1 - c_{ij,s}) + \varepsilon^{\lambda}_{ij,s}$ exceeds the level attainable in any other location. In line with McFadden (1974), under the Type I Extreme Value distribution, the probability that a type-s individual born in country i moves to country j is given by a multinomial logit expression:

$$\frac{M_{ij,s}}{N_{i,s}} = \frac{e^{[\ln(w_{j,s})+\ln(1-c_{ij,s})]/\mu}}{\sum_{k=1}^{J} e^{\left[\ln\left(w_{k,s}\right)+\ln\left(1-c_{ik,s}\right)\right]/\mu}} = \frac{(w_{j,s})^{1/\mu}(1-c_{ij,s})^{1/\mu}}{\sum_{k=1}^{J}(w_{k,s})^{1/\mu}(1-c_{ik,s})^{1/\mu}}.$$

Skill-specific emigration rates are endogenous and lie between 0 and 1. The multinomial logit expression also implies that the emigration rate from i to j depends on the characteristics of all potential destinations k (e.g., a crisis in Greece affects the emigration rate from Romania to Germany). However, the staying rates ($M_{ii,s}/N_{i,s}$) are governed by the same multinomial logit expression. The emigrant-to-stayer ratio in Eq. (5) and the aggregation constraint in Eq. (6) fully characterize the equilibrium distribution of the population:

$$m_{ij,s} \equiv \frac{M_{ij,s}}{M_{ii,s}} = \frac{e^{[\ln w_{j,s}+\ln(1-c_{ij,s})]/\mu}}{e^{[\ln w_{i,s}]/\mu}} = \left(\frac{w_{j,s}}{w_{i,s}}\right)^{1/\mu}(1-c_{ij,s})^{1/\mu},\ \forall j \neq i \tag{5}$$

$$N_{i,s} = M_{ii,s} + \sum_{j\neq i} M_{ij,s} = \left(1 + \sum_{j\neq i} m_{ij,s}\right) M_{ii,s}. \tag{6}$$

From Eq. (5), it appears that $1/\mu$ can be interpreted as the elasticity of the migrant-to-stayer ratio to wage disparities. The ratio of emigrants to stayers only depends on the characteristics of the destination and origin countries: it increases with the income gap between the two countries and it decreases with dyadic migration costs. Heterogeneity in migration preferences implies that emigrants select all destinations for which $c_{ij,s} < 1$. If $c_{ij,s} = 1$, the corridor is empty. All corridors with $c_{ij,s}, c_{ji,s} < 1$ exhibit bi-directional migration flows.

Brain gain in a dyadic context. The aggregate emigration rate ($m_{i,s}$) and the ratio of emigration rates (ρ_i) from country i (an index of skill selection as illustrated in Table 1) are jointly determined and are given by the following expressions:

$$m_{i,s} \equiv \frac{\sum_{j\neq i} M_{ij,s}}{N_{i,s}} = \frac{(W_{i,s})^{1/\mu}}{(w_{i,s})^{1/\mu} + (W_{i,s})^{1/\mu}},$$

$$\rho_i \equiv \frac{m_{i,h}}{m_{i,l}} = \frac{(W_{i,h})^{1/\mu}}{(W_{i,l})^{1/\mu}} \left[\frac{(w_{i,h})^{1/\mu} + (W_{i,h})^{1/\mu}}{(w_{i,l})^{1/\mu} + (W_{i,l})^{1/\mu}}\right]^{-1}. \tag{7}$$

This implies:

Proposition 3 *Emigration-driven expected utility shocks ($\Delta W_{i,s}$) induce a positive correlation between human capital formation (H_i) and the ratio of emigration rates (ρ_i). Local expected utility shocks ($\Delta w_{i,s}$) induce a negative correlation between H_i and ρ_i.*

Proof. From Eq. (7), the ratio of high-skilled to low-skilled emigration rates increases with $W_{i,h}$ and $w_{i,l}$, and decreases with $W_{i,l}$ and $w_{i,h}$. From Eq. (4), the proportion of college graduates in the native population increases with $W_{i,h}$ and $w_{i,h}$, and decreases with $W_{i,l}$ and $w_{i,l}$. Consequently, we have $sgn\left(\frac{\partial H_i}{\partial W_{i,s}}\right) = sgn\left(\frac{\partial \rho_i}{\partial W_{i,s}}\right)$ and $sgn\left(\frac{\partial H_i}{\partial w_{i,s}}\right) \neq sgn\left(\frac{\partial \rho_i}{\partial w_{i,s}}\right)$. *QED*

In particular, a growth of the high-skilled wage at origin, $w_{i,h}$, increases the expected returns on higher education, Λ_i, and human capital formation, H_i, given Eqs. (3) and (4), while it decreases the ratio of high-skilled to low-skilled emigration rates ρ_i through lower incentives to emigrate for college graduates. Similarly, a rise in $w_{i,l}$ decreases the expected return on higher education and human capital formation, while it increases ρ_i through lower incentives to emigrate for the less-educated. Turning to shocks in foreign wages and/or migration costs, we find the opposite correlations. Shocks that increase the expected utility of college graduates abroad ($W_{i,h}$) have a positive effect on human capital formation (H_i) and on the positive selection of emigrants (as reflected by the ratio of high-skilled to low-skilled emigration rates, ρ_i) (e.g., Abarcar and Theoharides, 2021, Khanna and Morales, 2017, Shrestha, 2017, Theoharides, 2018). Shocks that increase the expected utility of the less-educated abroad ($W_{i,l}$) have a negative effect on both variables (e.g., de Brauw and Giles, 2017, Kosack, 2021, McKenzie and Rapoport, 2011, Pan, 2017). This establishes the micro-foundations of the link between emigration rates and pre-migration human capital formation in a multi-destination framework.

The post-migration proportion of college graduates in the resident labor force can be expressed as the ratio of college-educated non-migrants to total non-migrant populations, adjusted for the exogenous number of immigrants ($I_{i,s}$):

$$h_i \equiv \frac{(1-m_{i,h})H_iN_i + I_{i,h}}{(1-m_{i,h})H_iN_i + I_{i,h} + (1-m_{i,l})(1-H_i)N_i + I_{i,l}},$$

which increases with the proportion of remaining college graduates, $(1-m_{i,h})H_i$, and decreases with the proportion of remaining low-skilled workers, $(1-m_{i,l})(1-H_i)$. It follows that:

Proposition 4 *Emigration-driven expected utility shocks ($\Delta W_{i,s}$) induce ambiguous effects on ex-post (i.e., post-migration) human capital levels in the country of origin.*

Proof. A rise in $W_{i,h}$ increases H_i and $m_{i,h}$ jointly, leading to ambiguous net effects on the post-migration human capital levels of the non-migrant population (h_i). The same result holds after a rise in $W_{i,l}$, which decreases H_i and $m_{i,l}$ jointly. *QED*

Our final consideration relates to the importance of selection vs. the extent of emigration in governing human capital decisions. Biavaschi et al. (2020) compare the current world equilibrium with a counterfactual scenario, which assumes the same number of observed bilateral migrants but in which these migrants are neutrally selected (NS) from their countries of origin. In our context, this means a world with $m_{ij,h} = m_{ij,l} = \overline{m}_{ij}, \forall j$. The implications of neutrally selected emigration for human capital accumulation are governed by the following proposition:

Proposition 5 *In a world with neutral selection and exogenous wages, ($m_{ij,h} = m_{ij,l} = \overline{m}_{ij}, \forall j$), the expected return on education is identical to that of the no-migration counterfactual, $\Lambda_i^{NS} = \Lambda_i^{NM}$. It follows that $H_i^{NS} = H_i^{NM}$ whatever the migration intensity $\overline{m}_{ij}$.*

Proof. From Eq. (5), $m_{ij,h} = m_{ij,l}$ $\forall j$ implies that $\left(\frac{w_{j,h}}{w_{i,h}}\right)^{1/\mu}(1-c_{ij,h})^{1/\mu} = \left(\frac{w_{j,l}}{w_{i,l}}\right)^{1/\mu}(1-c_{ij,l})^{1/\mu}$. Summing over all possible destinations gives $\frac{w_{j,h}^{1/\mu}+W_{j,h}^{1/\mu}}{w_{i,h}^{1/\mu}} = \frac{w_{j,l}^{1/\mu}+W_{j,l}^{1/\mu}}{w_{i,l}^{1/\mu}}$, which implies that $\frac{(w_{i,h})^{1/\mu}+(W_{i,h})^{1/\mu}}{(w_{i,l})^{1/\mu}+(W_{i,l})^{1/\mu}} = \frac{(w_{i,h})^{1/\mu}}{(w_{i,l})^{1/\mu}}$, or equivalently, $\Lambda_i^{NS} = \Lambda_i^{NM}$. *QED*

Although the overall extent of migration likely influences the economic impact of emigration in the origin country through multiple channels (as discussed below), in a partial equilibrium framework with exogenous wages, the direct effect of emigration on human capital accumulation is entirely due to selection along the skill dimension (see Eq. (4)). In a general equilibrium context where the average emigration rate induces spillover effects on income (e.g., through remittances) and productivity (e.g., through business links), the effects of selection and migration are however not identical.[10]

2.2 Generalized Approach: Quantitative Applications

We parameterize the dyadic model for 174 countries and for the year 2010, and use this to assess the human capital response to selective emigration country by country. We compare the current situation with a counterfactual no-migration equilibrium (i.e. we assume $c_{ij,s} = 1$ for all s and for all $j \neq i$).[11] In this section, the analysis is conducted in a partial equilibrium context with constant wage rates.

Parameterization – We provide here a summary of our parameterization strategy for the migration and education technologies.[12] With regard to the migration technology, we use data from the ADOP (Artuc et al., 2014) and DIOC (Arslan et al., 2015) databases to characterize skill-specific emigration stocks and rates ($M_{ij,s}$ and $m_{ij,s}$), as summarized in Table 1. We restrict our sample to emigrants aged 25 and above who migrated to one of the OECD member states, and distinguish between college graduates ($s = h$) and the less-educated ($s = l$). The choice to focus on OECD destinations is guided by the fact that such migration is the best documented, fastest-growing, and most positively selected component of international migration.[13] It is the type of migration that is likely to govern differentials in emigration rates between high-skilled and low-skilled people, and to provide educational incentives. We combine data on GDP per worker in PPP value and the income ratio between skill groups to proxy wage rates by skill group ($w_{i,s}$), and assume an elasticity of migration to income, $1/\mu$, equal to 0.7, in line with Bertoli and Moraga (2013). Migration costs ($c_{ij,s}$) are calibrated as a residual from Eq. (5). In Appendix B.1, we show that the calibrated migration costs exhibit the expected correlations with standard determinants identified in the literature (such as distance, linguistic proximity, and colonial ties).

[10] We simulate and discuss a no-selection counterfactual scenario in Appendix D.

[11] Proposition 5 shows that the no-selection and no-migration counterfactuals induce the same changes in incentives to acquire education and human capital responses in the partial equilibrium framework.

[12] We detail the parameterization of the model in Appendix B.1.

[13] Migration to non-OECD countries is less prone to strong positive selection (see Artuc et al., 2014).

With regard to the training technology, we parameterize two unknown parameters per country, z_i and G_i to match data on emigration stocks and human capital, as well as semi-elasticities of pre-migration human capital (H_i) to selective migration prospects ($m_{i,h} - m_{i,l}$) identified empirically for broad income groups. These semi-elasticities are estimated in Appendix A, which updates and extends existing studies by using more recent data (covering three decades), a more general specification, and an improved identification strategy. We consider two scenarios:

- Our *conservative* scenario is based on the *short-run semi-elasticity* (SR), which captures the effect of migration shocks on human capital within a period of ten years. We obtain a semi-elasticity of 1.3 for low-income and lower-middle income countries, and values close to zero in upper-middle and high-income countries.

- Our *benchmark* scenario is based on the *long-run semi-elasticity* (LR), which better captures the effect of migration shocks on the long-term accumulation path. We obtain a long-run semi-elasticity of 3.2 for low-income and lower-middle income countries, and values close to zero in other countries.

We use a *Monte-Carlo* computational algorithm which works as follows. We combine wage rates and migration costs to compute Λ_i using Eq. (2). We assume that z_i is constant within an income group, whereas G_i is country-specific. We calibrate these two unknowns iteratively. For different vectors of z_i, we calibrate G_i to match H_i using Eq. (4), and then subject the model to various selective emigration shocks. We select the levels of z_i that match the four estimated semi-elasticities by country group (short-term or long-term level) of Table A.1. When fitting long-term levels (benchmark scenario), we find $z^*_{LOW} = 5.3$, $z^*_{LMI} = 3.8$ and $z^*_{UMI} = z^*_{HIC} = 0$ for low-income (LOW), lower-middle (LMI), upper-middle (UMI), and high-income countries (HIC), respectively. When matching the short-term elasticities (conservative scenario), we obtain $z^*_{LOW} = 1.7$, $z^*_{LMI} = 0.9$ and $z^*_{UMI} = z^*_{HIC} = 0$. This implies that the distribution of ability to educate is uniform in upper-middle and high-income countries, which limits incentive effects therein. However, as z is a proxy for the scarcity of talent (understood here as the ability to acquire education at low cost), it is reassuring that it decreases with the level of development. In addition, in Appendix B.1, we show that the calibrated levels of G_i are adequately correlated with traditional proxies for access to education (such as public education expenditure, urbanization rate, and GDP per capita). These differences in access to education are instrumental in predicting the human capital responses to selective emigration.

Results – Our quantitative findings are shown in Figure 1. Panel (a) depicts the density of the impact of (observed) selective migration on the expected returns on higher education, $(\Lambda_i - \Lambda_i^{NM})/\Lambda_i^{NM}$. The effect is positive in the great majority of countries. It is worth noting that ten countries in our sample exhibit negative emigration differentials (i.e. negative selection), implying that international migration reduces Λ_i and thereby the optimal investment in education in our framework. In the remaining 164 countries, we have $\Lambda_i > \Lambda_i^{NM}$, implying that selective emigration stimulates the pre-migration formation of human capital. The peak of the density is around 5 percent. However, the distribution is right-skewed and exhibits large variations between countries within each income group. For example, within a given income group, the returns on higher education in small countries are more sensitive to emigration than in larger countries. This is because small countries are highly economically specialized and offer limited diversity in domestic jobs. They benefit more from diversifying employment opportunities through international migration, which is reflected in our model by smaller net migration costs for both types of workers. The average level of development in the main destinations (governed by colonial links, and geographic and linguistic distances) also influences the gains from emigration. This clearly justifies why a dyadic approach that accounts for heterogeneity in migration costs and destination choices is likely to generate more accurate predictions than a framework that disregards these dimensions. The impact of selective emigration on Λ_i exceeds 20 percent in a non-negligible number of countries and is even above 40 percent in 21 countries.[14] The largest effects on Λ_i are observed in small and poor countries. The open economy level of Λ_i is at least 75 percent larger than the no-migration level in Mauritius, Guyana, Lebanon, Sao Tome and Principe, Haiti, Liberia, Trinidad and Tobago, Barbados, Tonga, Grenada, and Cape Verde.

To investigate whether emigration prospects induce convergence or divergence in the expected returns on higher education, Panel (b) compares the emigration-driven, relative change in Λ_i with the no-migration counterfactual level. The slope of the relationship is positive, which implies that selective emigration leads to divergence in the distribution of Λ_i. The effect is stronger in poor countries where the no-migration levels of Λ_i^{NM} are already at the highest levels.[15]

Panels (c) and (d) show the variations in human capital ($\Delta h_{i,t}$ on the vertical axis) as a function of the no-migration level of human capital ($h_{i,t}^{NM}$ on the horizontal axis). In the *conservative scenario* (Panel (c)), selective emigration induces an increase in human capital in 101 countries (58% of our sample), and a short-term decrease in 73 countries. The short-term gain is greater than one percentage point (p.p.) in 23 countries. These include small upper-middle and high-income countries where the emigration differential is limited (Norway, New Zealand, Czech Republic, Luxembourg, Israel, etc.). A gain is observed in 44 lower-middle and low-income countries, out of 58 in our sample. The short-term loss is greater than 1 p.p. in 14 countries. These include Guyana, a lower-middle income countries characterized by a high level of positive selection, as well as 13 upper-middle and high-income countries where the emigration differential is either negative (e.g. Georgia, Finland, Ireland, Lithuania) or positive and very large (Grenada, Trinidad and Tobago, Tonga, Barbados, Mauritius, etc.).

The magnitude of the short-term effect is not informative with regard to the actual human capital changes driven by selective migration. The short-term thought experiment quantifies the effect of moving from a no-migration scenario to the current state of the world in ten years. In practice, emigration differentials change slowly, implying that most countries are close to their long-term accumulation path. When using the *benchmark scenario*, we identify a net "brain gain" in 128 countries (74% of our sample), and a human capital loss in 46 countries. The effects are identical to those of the conservative scenario in upper-middle and high-income countries, and entirely driven by the change in population structure – as the same uniform distribution of ability ($z^*_{UMI} = z^*_{HIC} = 0$) is

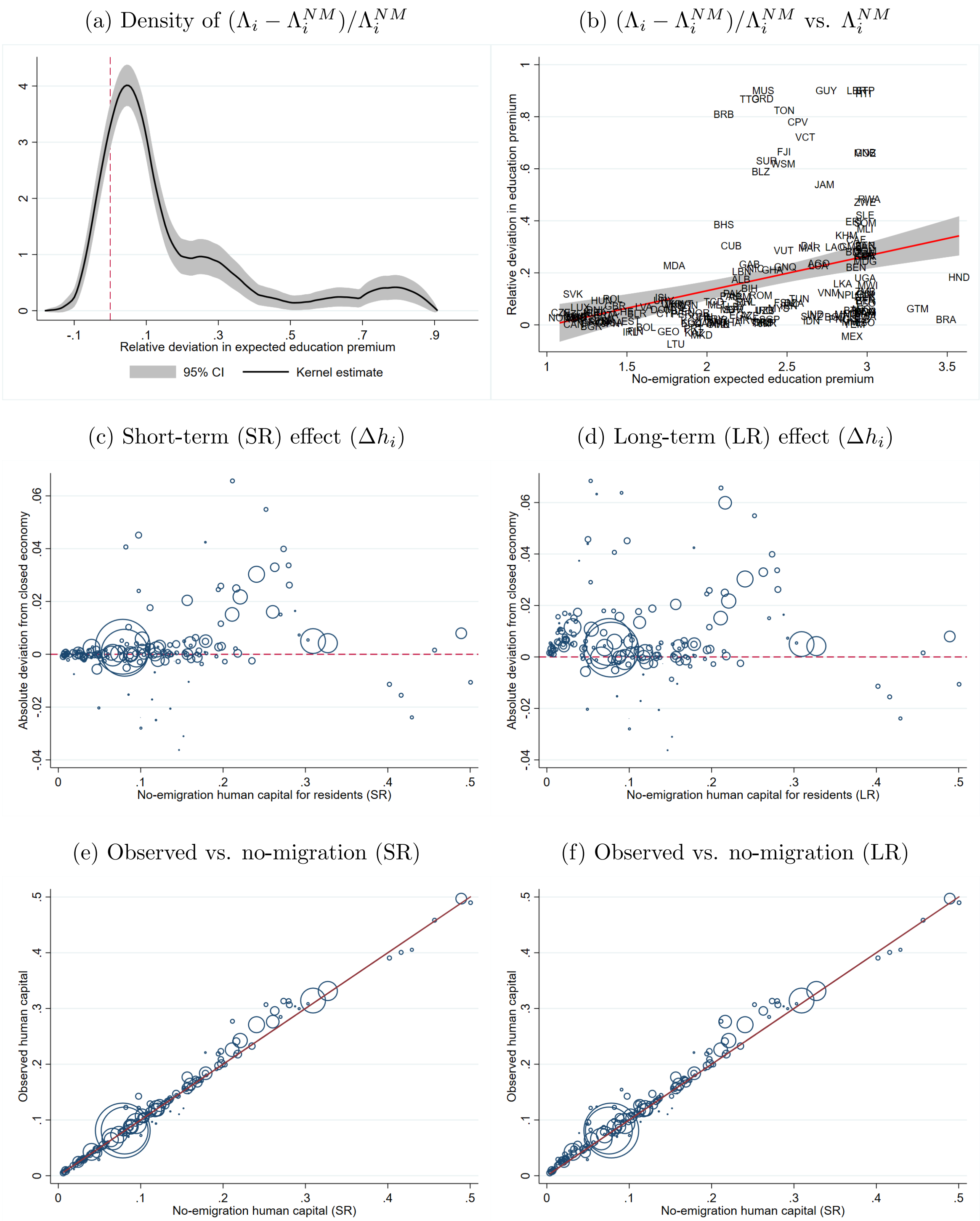
[14]These countries are: Sierra Leone, Zimbabwe, Rwanda, Jamaica, Belize, Lebanon, Samoa, Suriname, Fiji, Mozambique, Saint Vincent and the Grenadines, Cape Verde, Barbados, Tonga, Trinidad and Tobago, Grenada, Mauritius, Guyana, Liberia, Haiti, Guinea Bissau, Sao Tome and Principe.

[15]It is worth emphasizing that $(\Lambda_i - \Lambda_i^{NM})/\Lambda_i^{NM}$ is independent of the level of μ when the model is properly calibrated (i.e., when migration costs are re-calibrated to match the current state of the economy). This is because, from Eq. (7), $(W_{i,s})^{1/\mu}$ can be written as $\frac{m_{i,s}}{1-m_{i,s}}(w_{i,s})^{1/\mu}$. Plugging this expression into Eq. (2) and comparing with the no-migration equilibrium, we have that $\Lambda_i/\Lambda_i^{NM} = (1-m_{i,l})/(1-m_{i,h})$.

assumed in both scenarios. However, the effect is more optimistic in the group of lower-middle and low-income countries, where we now identify 57 winners and 1 loser only. The latter exception is Bolivia, the only lower-middle income country in our sample where the emigration differential is negative. The net gain exceeds 1 p.p. in 48 countries, and the largest effects are observed in Moldova (6.8 p.p.), Norway (6.6 p.p.), Jamaica (6.4 p.p.), Fiji (6.3 p.p.), the Philippines (6.0 p.p.), New Zealand (5.5 p.p.), Cuba (4.6 p.p.), the Czech Republic (4.5 p.p.), Guyana (4.4 p.p.), the Slovak Republic (4.1 p.p.) and Sweden (4.0 p.p.).

These long-term responses better reflect the actual impact of selective migration on human development. Overall, however, the human capital responses to selective emigration are somewhat limited. In Panel (e) and (f) in Figure A.1, we compare the observed and counterfactual levels of human capital. All the observations are close to the 45-degree line in the conservative scenario in Panel (e), suggesting that the human capital responses to selective emigration are rather limited in the short-run. Greater effects on cross-country disparities in human capital are observed in Panel (f), when focusing on the *benchmark scenario*. This is particularly the case in poor countries – although human capital remains low, selective emigration almost doubles the share of college graduates in Cape Verde, Cuba, Fiji, Guyana, Haiti, Liberia, Moldova or Zimbabwe – and in small states belonging to the top quartile of the human capital distribution.

Figure 1: Effect of selective emigration on human capital accumulation (h_i)
Insights from the generalized approach



(a) Density of $(\Lambda_i - \Lambda_i^{NM})/\Lambda_i^{NM}$

(b) $(\Lambda_i - \Lambda_i^{NM})/\Lambda_i^{NM}$ vs. Λ_i^{NM}

(c) Short-term (SR) effect (Δh_i)

(d) Long-term (LR) effect (Δh_i)

(e) Observed vs. no-migration (SR)

(f) Observed vs. no-migration (LR)

Note: Panel (a) gives the density of the migration-driven relative change in expected returns to schooling (Λ_i), under the benchmark scenario. Panel (b) compares the relative change in expected returns to schooling with the no-migration counterfactual level. Panels (c) and (d) compare the variation Δh_i (i.e. the difference between the observed proportion of college graduates (h_i) and the no-migration proportion (h_i^{NM})) as a function of the no-migration counterfactual level (h_i^{NM}). Panels (e) and (f) compare the observed proportion of college graduates h_i with the no-migration proportion h_i^{NM}. Panels (c) and (e) present the results obtained with the conservative scenario, while Panels (d) and (f) present those obtained with the benchmark scenario.

3 Selective Emigration and Economic Development

In this section, we supplement the dyadic framework of Section 2, with a production function and a set of externalities reflecting the main feedback effects of emigration discussed in existing literature (Clemens et al., 2014, Commander et al., 2004, Docquier and Rapoport, 2012, Ozden and Rapoport, 2018). These include neo-classical effects on marginal productivity, financial remittances as well as schooling, diaspora, market size and fiscal externalities. We thus embed our micro-founded model of migration and human capital accumulation into an extended *development accounting* framework (Hsieh and Klenow, 2010, Jones, 2014). We use this framework to estimate the net impact of emigration on real disposable income for the individuals remaining in the origin countries. The *development accounting* framework is described in Section 3.1. In Section 3.2, we explain its calibration and provide lower-bound and upper-bound estimates of the disposable income responses to selective emigration.

3.1 Development Accounting: Theory

The core of our *development accounting* framework is a constant elasticity of substitution (CES) production function. Such a framework has been used in labor/growth literature to explain disparities in macroeconomic performance between countries and the patterns of wage inequality between skill groups. The CES technology determines the aggregate real output/income level in country i:

$$Y_i = \frac{A_i}{P_i}\left[\frac{\Gamma_i}{1+\Gamma_i}L_{i,h}^{\frac{\sigma-1}{\sigma}} + \frac{1}{1+\Gamma_i}L_{i,l}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{8}$$

where $L_{i,s}$ denotes the number of workers of type s (such that $L_i = L_{i,h} + L_{i,l}$), A_i denotes total factor productivity (TFP), P_i is the ideal/average price index in the economy, Γ_i determines the relative productivity and firms' preference for college-educated workers, and σ is the elasticity of substitution between skill groups. Such a production function without physical capital features a globalized economy with a common international interest rate.

We focus on the real disposable income of those remaining behind, which is affected by the average income-tax rate (τ_i), and by the proportion of remittance inflows in domestic income (r_i). Given constant returns to scale in Eq. (8), the level of real disposable income per worker ($y_i \equiv \frac{(1-\tau_i+r_i)Y_i}{L_i}$) is given by:

$$\begin{aligned} y_i &= \frac{(1-\tau_i+r_i)A_i}{P_i}\left[\frac{\Gamma_i}{1+\Gamma_i}h_i^{\frac{\sigma-1}{\sigma}} + \frac{1}{1+\Gamma_i}(1-h_i)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} && (9)\\ &= \frac{(1-\tau_i+r_i)A_iQ(\Gamma_i,h_i)}{P_i}, && (10)\end{aligned}$$

where $h_i \equiv L_{i,h}/L_i$ is the proportion of college-educated workers in the resident labor force, and $Q(\Gamma_i, h_i)$ is the CES labor composite.

By affecting human capital accumulation (h_i), selective emigration influences disposable income via the complementarity between high-skilled and low-skilled workers (neo-classical forces), as reflected in the term $Q(\Gamma_i, h_i)$. In particular, income per worker increases with human capital if the marginal productivity of college-educated workers exceeds that of less-educated workers. However, the total impact on disposable income goes beyond this pure "neo-classical" mechanism and depends on a wider variety of effects.

Schooling externalities. First, an additional contribution of human capital to productivity can be obtained by assuming positive technological externalities. Recent studies show that college-educated workers are instrumental in supporting democratization (e.g., Bobba and Coviello, 2007, Castelló-Climent and Mukhopadhyay, 2013, Docquier et al., 2016, Murtin and Wacziarg, 2014), and in facilitating innovation and technology diffusion when knowledge becomes economically useful (e.g., Benhabib and Spiegel, 1994, Caselli and Coleman, 2006, Ciccone and Papaioannou, 2009). We consider two education-driven externalities: an aggregate productivity externality and directed technical changes:

$$A_i = \overline{\overline{A}}_i \left(\frac{h_i}{1-h_i} \right)^{\epsilon}, \tag{11}$$

$$\Gamma_i = \overline{\Gamma}_i \left(\frac{h_i}{1-h_i} \right)^{\kappa}. \tag{12}$$

The aggregate externality in Eq. (11) formalizes a simple Lucas-type effect of human capital on TFP (see Lucas, 1988); it assumes that the scale of the TFP is a concave function of the skill ratio in the resident labor force with an elasticity ϵ, whereas $\overline{\overline{A}}_i$ is a scale factor. The skill-biased technical change in Eq. (12) affects the relative productivity of high-skilled workers with an elasticity κ, whereas $\overline{\Gamma}_i$ is a residual scale factor (see Acemoglu, 2002, Autor et al., 2003, Restuccia and Vandenbroucke, 2013). As the supply of high-skilled labor increases, the relative labor demand for non-routine tasks increases to the detriment of the demand for routine and manual tasks. The observed relative demand shift favors highly-educated workers over their less-educated counterparts.[16]

Diaspora externalities. Second, it has been empirically shown that the diaspora abroad contributes to reducing transaction costs between countries, and to easing trade and foreign direct investment (FDI). To capture the size of these diaspora effects, we combine two strands of literature. The first has identified a causal impact of migration on trade and FDI, with respective elasticities of 0.1 and 0.2 (e.g., Felbermayr et al., 2010, Iranzo and Peri, 2009, Javorcik et al., 2011, Kugler and Rapoport, 2007, Parsons and Vezina, 2018). The other strand of literature has identified a causal effect of trade and FDI on TFP, with respective elasticities of 0.3 and 0.01 (see Bahar and Rapoport, 2018, Feyrer, 2019, Larch et al., 2017). Combining these findings gives a conservative elasticity of total factor productivity to emigration of approximately 0.032. Starting from Eq. (11), we allow $\overline{\overline{A}}_i$ to depend on the emigration rate and modify the TFP function as follows:

$$A_i = \overline{A}_i \left(\overline{m} + m_i \right)^{\rho} \left(\frac{h_i}{1-h_i} \right)^{\epsilon}, \tag{13}$$

where ρ is the elasticity of TFP to the diaspora abroad (proxied by the average emigration rate, m_i), $\overline{m}$ is a constant added to avoid having TFP equal to zero when the average emigration rate is nil, and $\overline{A}_i$ is the adjusted scale factor, considered as exogenous.

Remittances. The least disputable mechanism is the remittance channel. Data on the proportion of remittance inflows in domestic income, r_i, is obtained from the World

[16]When comparing low-income, middle-income, and high-income countries, skill-biased technical changes also capture the transition from agriculture to non-agriculture, or from the traditional to the modern sector (see Ciccone and Papaioannou, 2009, Gollin et al., 2014, Vollrath, 2009).

Development Indicators. Remittances reallocate income from donor to recipient countries, and reinforce (or attenuate/compensate, respectively) the income gain (loss, respectively) due to selective emigration, as shown in di Giovanni et al. (2015) and Theoharides (2020). In the no-migration counterfactual, r_i is equal to zero.

Market size externalities. Selective emigration affects the total demand for goods and services in the origin country, by reducing aggregate income and consumption. In a monopolistic competition context, the aggregate demand determines firms' entry and exit decisions, and in turn, the number of entrepreneurs and the extent of goods available to consumers. The market size and country size are uncorrelated in a world of completely free trade. In practice, trade is costly and the magnitude of market size effects depends both on the country size and on trade openness. When the domestic market size decreases, fewer entrepreneurs can operate in it, the number of goods decreases, and the ideal price index increases (Aubry et al., 2016, di Giovanni et al., 2015, Krugman, 1980). For simplicity, we account for market size effects by dividing our CES production aggregate by an endogenous equilibrium price index P_i, which can be expressed as a non-linear function of the total demanded output (for private goods):

$$P_i = \overline{P}_i \left[A_i L_i Q(\Gamma_i, h_i)(1 - \tau_i + r_i)\right]^{\frac{-1}{\lambda-1}}, \tag{14}$$

where λ is the elasticity of substitution between goods in the utility function, and $\overline{P}_i$ is normalized to generate a unitary equilibrium price in the observed equilibrium, without loss of generality.

Fiscal effects of emigration. Migration scholars have long focused on the fiscal impact of immigration and the cost of selective emigration is paid little attention in existing literature. We account for two sources of fiscal costs in our model. First, education systems are heavily dominated by public institutions. This is particularly the case in developing countries, in which education costs are largely subsidized (Devesh et al., 2009, Djajić et al., 2019, Egger et al., 2012, Teferra, 2007, World Bank, 2010). Most emigrants have benefited from education subsidies and leave the country without paying their way. Second, Alesina and Spolaore (1997) and Alesina and Wacziarg (1998) argue that sharing the cost of non-rival goods and services over a larger pool of taxpayers reduces the fiscal burden on residents. These authors show that government consumption per person decreases with population size. We start from a government budget constraint imposing that a proportional tax on nominal income is levied to finance the education expenditure of stayers and emigrants, as well as public consumption. This budget constraint can be written as $\tau_i L_i A_i Q(\Gamma_i, h_i) = \hat{g}_i P_i N_i + \hat{c}_i P_i L_i^{1-\eta}$, where $1-\eta$ is the elasticity of public consumption to population, $\hat{c}_i$ is a scale factor governing public consumption per resident, and $\hat{g}_i$ is the average level of education expenditures (all levels) per native expressed in real terms.

We can define $g_i \equiv \frac{\hat{g}_i P_i}{A_i Q(\Gamma_i, h_i)}$ as the ratio of education expenditure per person to income per worker, and $c_i \equiv \frac{\hat{c}_i P_i}{N_i^{\eta} A_i Q(\Gamma_i, h_i)}$ as the ratio of public consumption per person to income per capita in the no-migration economy. For simplicity, we assume that these two ratios are exogenous. When a proportion m_i of the native labor force leaves the country, the equilibrium tax rate becomes:

$$\tau_i = \frac{g_i}{1-m_i} + \frac{c_i}{(1-m_i)^{\eta}}.$$

The first term captures the fact that education expenditures are now supported by a smaller number of resident taxpayers, whereas the second term accounts for the rise in public consumption per resident due to the smaller population size.

3.2 Development Accounting: Quantitative Application

The *development accounting* block is used to estimate the relative variations in disposable income per worker due to selective emigration, $(y_i - y_i^{NM})/y_i^{NM}$, for each country. We calibrate the income block of the model to exactly match the observed level of disposable income in the year 2010, and use estimated elasticities from empirical studies. In the benchmark case, we consider the long-term effect of selective emigration on human capital accumulation (see Section 2.2), and we use intermediate elasticity levels from existing literature. In the conservative case, we consider the short-term human capital response to emigration, and double or halve elasticity levels so as to generate lower income gains or greater income losses. Table 2 reports consensus parameter values used in the benchmark simulations and their main sources, as well as the conservative values that we combine with our short-term human capital responses. We detail the calibration of the technological parameters in Appendix B.2, and alternative values are considered in Appendix C.

Table 2: Calibration of the income block

Parameter		Conservative	Benchmark	Source
Change in human capital	Δh_i	SR	LR	Section 2.2
Substitution HS/LS	σ	2.0	2.0	Ottaviano and Peri (2012)
Migration-income elasticity	$1/\mu$	0.7	0.7	Bertoli and Moraga (2013)
Schooling ext. aggregate	ϵ	0.05	0.10	Caselli and Ciccone (2013)
Schooling ext. skill-biased	κ	0.05	0.10	Burzyński et al. (2020)
Diaspora externality	ρ	0.016	0.032	Feyrer (2019), Larch et al. (2017)
Substitution between goods	λ	4.0	8.0	Feenstra (1994)
Fiscal externality	η	0.112	0.056	Alesina and Spolaore (1997)

Conservative scenario. Figure 2 presents the results obtained under the conservative scenario. This scenario considers the human capital effect of moving from a no-migration scenario to the current state of the world in only ten years, together with a parameter set that minimizes the income gains and/or maximizes the income losses due to emigration and changes in education. Panel (a) shows that the density of the net impact of emigration is right-skewed. The unweighted average income response to selective emigration equals 3.6 percent. We identify 151 winners and only 23 losers. The losses exceed 5 percent in seven small island states with large emigration differentials: Barbados (-5.7%), Sao Tome and Principe (-7.2%), Mauritius (-8.1%), Saint Vincent and the Grenadines (-8.4%), Trinidad and Tobago (-9.3%), Grenada (-9.6%), and Suriname (-12.0%). By contrast, the gains exceed 15 percent in eleven countries: Lebanon (32.2%), Comoros (29.9%), Madagascar (25.8%), Tajikistan (21.8%), Haiti (21.0%), Slovenia (21.0%), Lesotho (18.8%), Jamaica (17.0%), Serbia and Montenegro (16.4%), and Zimbabwe (15.0%).[17]

[17] We also find a large gain in Luxembourg (20.2%) but this result rings false. It is driven by a large amount of recorded remittances, which are likely to include financial transfers to individual bank accounts whose owners do not physically reside in the country, thereby inflating the amount of remittances received per worker. In the data, remittances represent more than 10 percent of the average worker's net income, while in reality the flows of migration-related transfers are presumably low.

These gains can be driven by large inflows of remittances, large "brain gain" responses, or large diaspora externalities. Panel (b) shows the density of each mechanism of transmission taken in isolation: the neo-classical effects and schooling externalities (ambiguous effects), diaspora externalities (positive), fiscal externalities (negative), market size effects (negative), and remittances (positive). The effect of remittances is dominant in a large number of countries. On average, recorded remittances only represent 3 percent of GDP in developing countries, but 135 countries exhibit a proportion above the mean. These include Tajikistan (38%) , Tonga (36%), Lesotho (34%), Bosnia (29%), Jordan (22%), Samoa (20%), Palestine (17%), Albania (16%), Haiti, Yemen and, Cape Verde (all 15%). The median intensity of the other mechanisms is relatively small, but their variability and their combined effect on disposable income can be large.

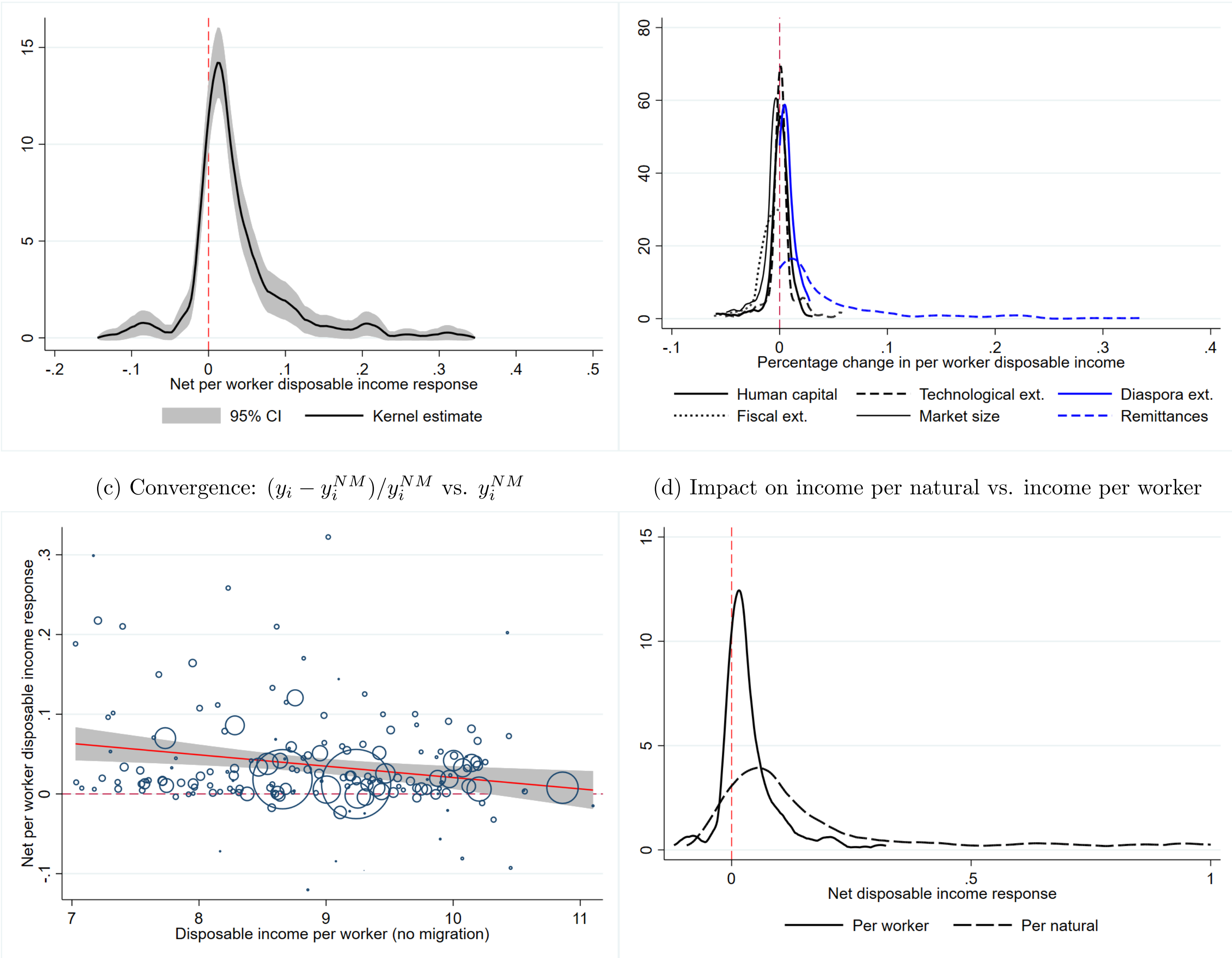
Panel (c) compares the income response to emigration with the no-migration counterfactual income level (in logs). The curve is above zero. This means that on average and with a few exceptions, emigration increases income per worker at all levels of development. As the slope is negative, the income response is larger in poor countries (around +5% in the least developed countries, against +1% at the top end of the distribution). Although selective, emigration *per se* tends to reduce cross-country disparities in disposable income per worker and contributes to income convergence.

This convergence effect is even more pronounced if development is measured for people rather than for places. Defining income per natural as the mean annual income of all people born in a given country, regardless of where they live, Clemens and Pritchett (2008) emphasize the role of emigration in boosting the world production frontier and reducing cross-country income disparities. In Panel (d), we aggregate the income of non-migrants and emigrants from all countries, and compute the variation in income per natural. The density shifts to the right compared with that of income per worker. Most countries exhibit a gain in the range of 0-20 percent, and there is a non-negligible proportion of the sample for which selective emigration increases income per natural by more than 40 percent.

Figure 2: Effect of selective emigration on disposable income (y_i)
Results obtained under the conservative scenario (short-term human capital responses and conservative elasticity values)

(a) Density of $(y_i - y_i^{NM})/y_i^{NM}$ (b) Decomposition by channel

(c) Convergence: $(y_i - y_i^{NM})/y_i^{NM}$ vs. y_i^{NM} (d) Impact on income per natural vs. income per worker



Note: Each circle represents a country, and its size represents the size of the labor force.

Benchmark scenario. These income responses are magnified in the benchmark scenario. The benchmark better captures the human capital responses to emigration along the long-term accumulation path, and relies on more consensual parameter values. The results are summarized in Figure 3. In Panel (a), the density of the net impact of emigration on disposable income shifts to the right compared with the conservative scenario. The peak and median of the distribution are around +3.5 percent, whereas the unweighted average income response equals 5.7 percent.[18] Unsurprisingly, Panel (b) shows that the magnitude of neo-classical effects and, to a lesser extent, of schooling externalities is stronger than in the conservative scenario. The convergence forces are also stronger; the convergence effect – proxied by the absolute value of the slope of the fitted curve – driven by selective emigration is twice as large as in the conservative case. In Panel (c), we observe that the average income gain is around 10 percent in the least developed countries, against 1 percent at the top end of the distribution. The effect on income per natural, which is mostly governed by emigrants' income gains (i.e. income disparities between countries), is less dependent on parameter values, as shown in Panel (d).

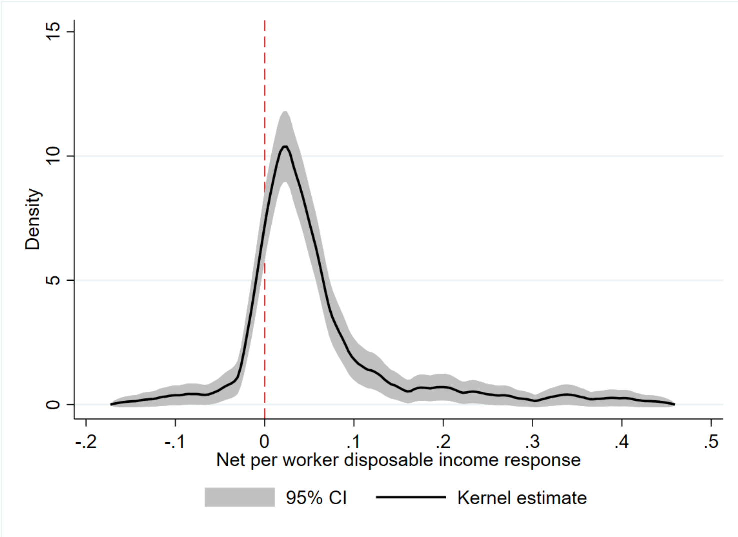
Under the benchmark scenario, we identify 156 winners and 18 losers. The losses are in the same order of magnitude as in the conservative scenario. They exceed 5 percent in six small island states: Mauritius (-6.1%), Barbados (-6.5%), Trinidad and Tobago (-9.0%), Saint Vincent and the Grenadines (-9.5%), Grenada (-11.2%), and Suriname (-14.2%). By contrast, the gains are larger than in the conservative scenario, and exceed 20 percent in 13 countries: Jamaica (42.8%), Madagascar (39.4%), Comoros (38.4%), Haiti (34.6%), Lebanon (33.6%), Guyana (33.3%), Samoa (29.4%), Fiji (27.2%), Slovenia (25.4%), Zimbabwe (24.9%), Tajikistan (22.7%), Lesotho (21.9%), and the Philippines (21.7%).

[18] In Appendix C, we show that results are robust to alternative values for the elasticity of bilateral migration to the wage ratio (by changing μ) and the elasticity of substitution between skill groups, σ, in the production function.

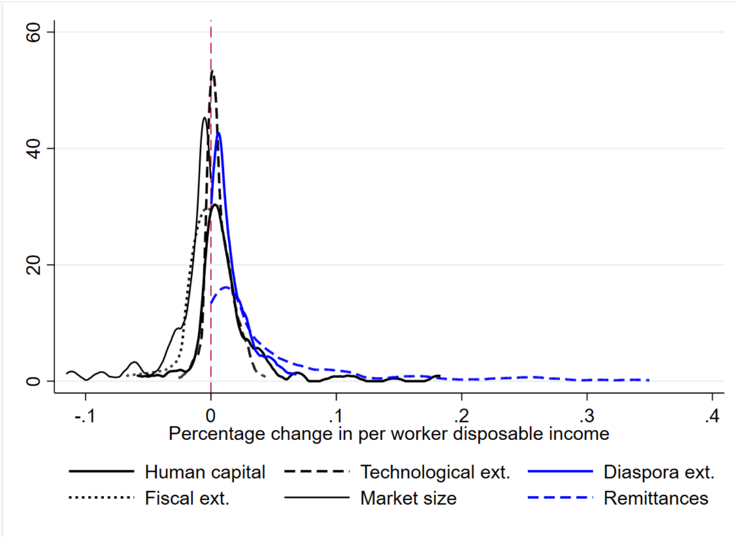
Figure 3: Effect of selective emigration on disposable income (y_i)

Results obtained under the benchmark scenario (long-term human capital responses and benchmark elasticity values)

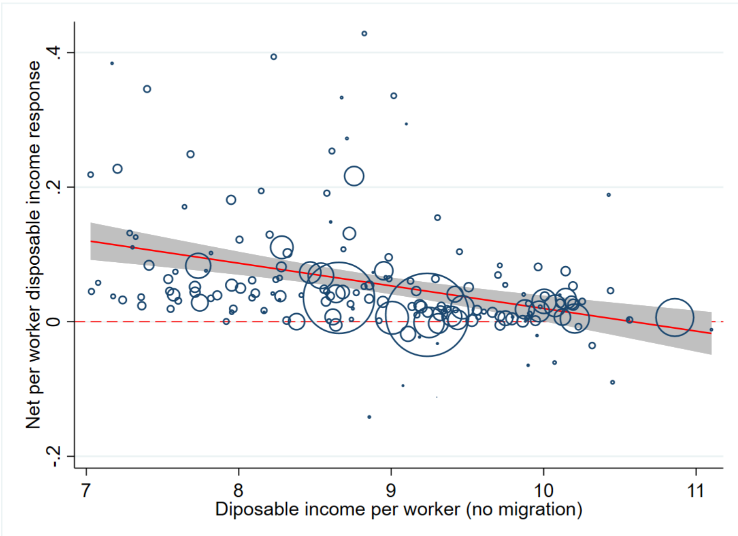
(a) Density of $(y_i - y_i^{NM})/y_i^{NM}$



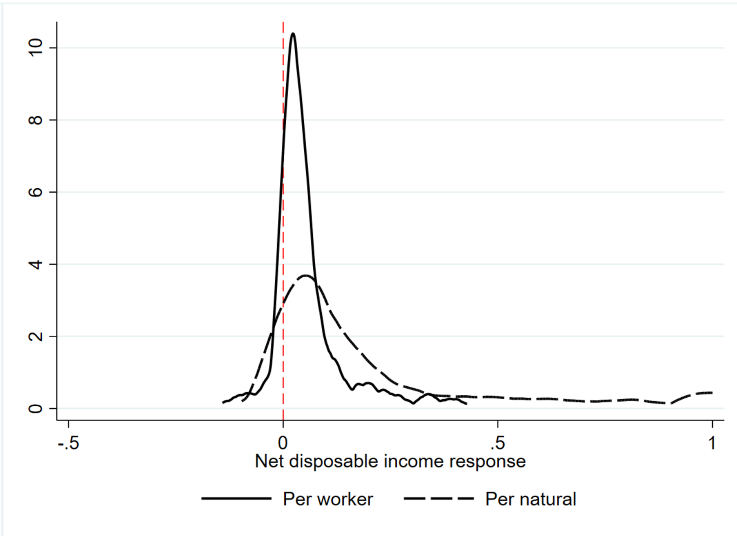
(b) Decomposition by channel



(c) Convergence: $(y_i - y_i^{NM})/y_i^{NM}$ vs. y_i^{NM}



(d) Impact on income per natural vs. income per worker



Note: Each circle represents a country, and its size represents the size of the labor force.

Synthetic overview. Figure 4 provides an overview of our results. Panel (a) shows the population-weighted average disposable income response to selective emigration per worker (left-hand bars), and per natural (right-hand bars) worldwide. The average effect per worker varies from 1.7 percent in the conservative scenario to 1.9 percent in the benchmark scenario. The effect on income per natural, which accounts for migrants' income gains, varies between 4.5 percent and 4.6 percent. Given that the average fraction of emigrants is small (around 2.25 percent of the total population), the semi-elasticity of real disposable income to migration is in the vicinity of 2.0 in our model.[19]

Panel (b) decomposes these effects by income group. The largest gains for non-migrants are observed in lower-middle and low-income countries, and vary between 2.7 and 6.1 percent. These results are more optimistic than those reported in di Giovanni et al. (2015) and Biavaschi et al. (2020). Focusing only on remittances and market size effects, di Giovanni et al. (2015) find an average gain from emigration of around 2.0 percent for non-migrants in non-OECD countries. Although our benchmark assumes more conservative market size effects, we account for the "brain gain" mechanism and induced schooling externalities. Accounting for similar mechanisms but less-optimistic education responses, Biavaschi et al. (2020) find a gain of 0.3 percent in non-OECD countries. This confirms that the magnitude of the "brain gain" mechanism is a key determinant of the development impact of selective emigration. Our micro-founded model, calibrated to match updated empirical elasticities and country-specific drivers of education and migration decisions, substantially reinforces the predictions of less sophisticated approaches. When accounting for migrants' income gain, the average effect measured by the income per natural decreases with the level of development of the origin country. It amounts to 31-35 percent in low-income countries and 11-14 percent in lower-middle income countries. The average gain is below 5 percent in upper-middle and high-income countries. This evidences that the "place premium" plays a key role in governing the economic gains from emigration, in line with Clemens and Pritchett (2008).

4 Selective Migration and Global Inequality

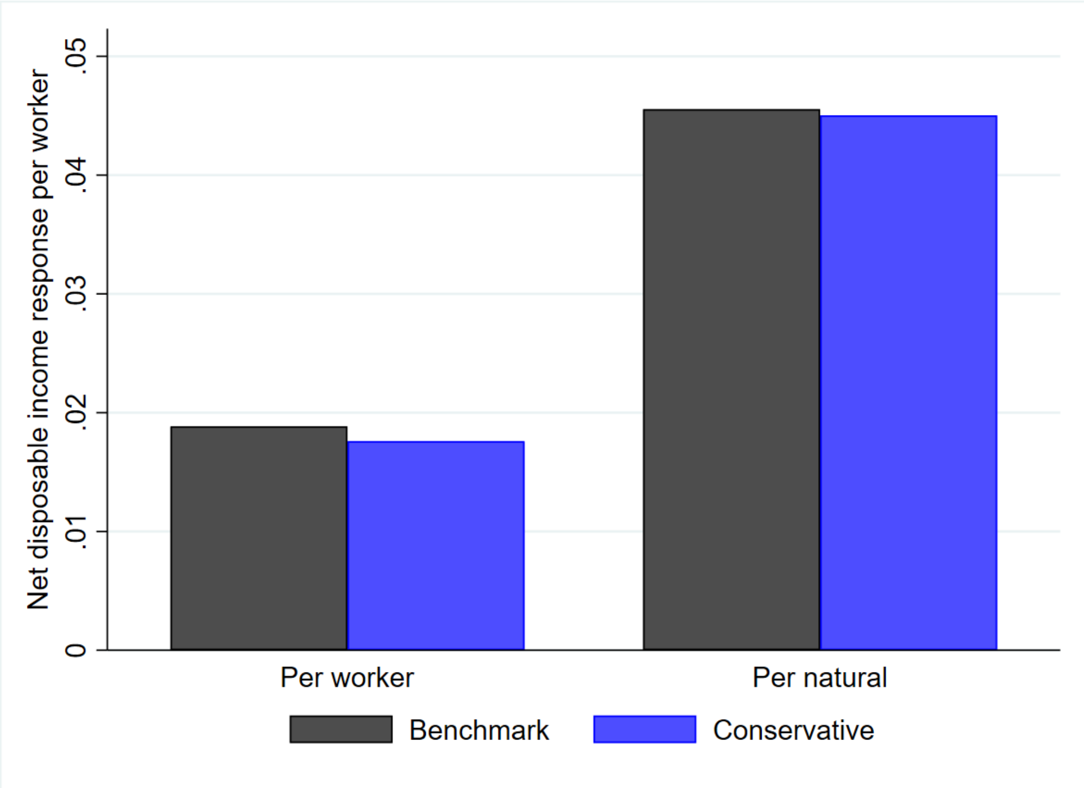
In the previous section, we computed the effect of selective emigration on real disposable income per worker in each origin country (one at a time), taking foreign income levels as given and thus disregarding the fact that an emigrant from one origin country is at the same time an immigrant in a different destination country. We now turn our attention to inequality and extreme poverty responses to global migration in a world economy context. These effects are ambiguous. On the one hand, we show in Section 3.2 that selective emigration induces convergence in disposable income per worker between countries. On the other hand, international migration reallocates people from poor to rich countries, increases the worldwide average income level, and induces uncertain redistributive effects within countries (between low-skilled and high-skilled workers).

To quantify the effect of global migration on the world distribution of income, we simulate a no-migration counterfactual for all countries jointly, endogenizing income and education responses in all parts of the world. Hence, we account for the fact that stopping

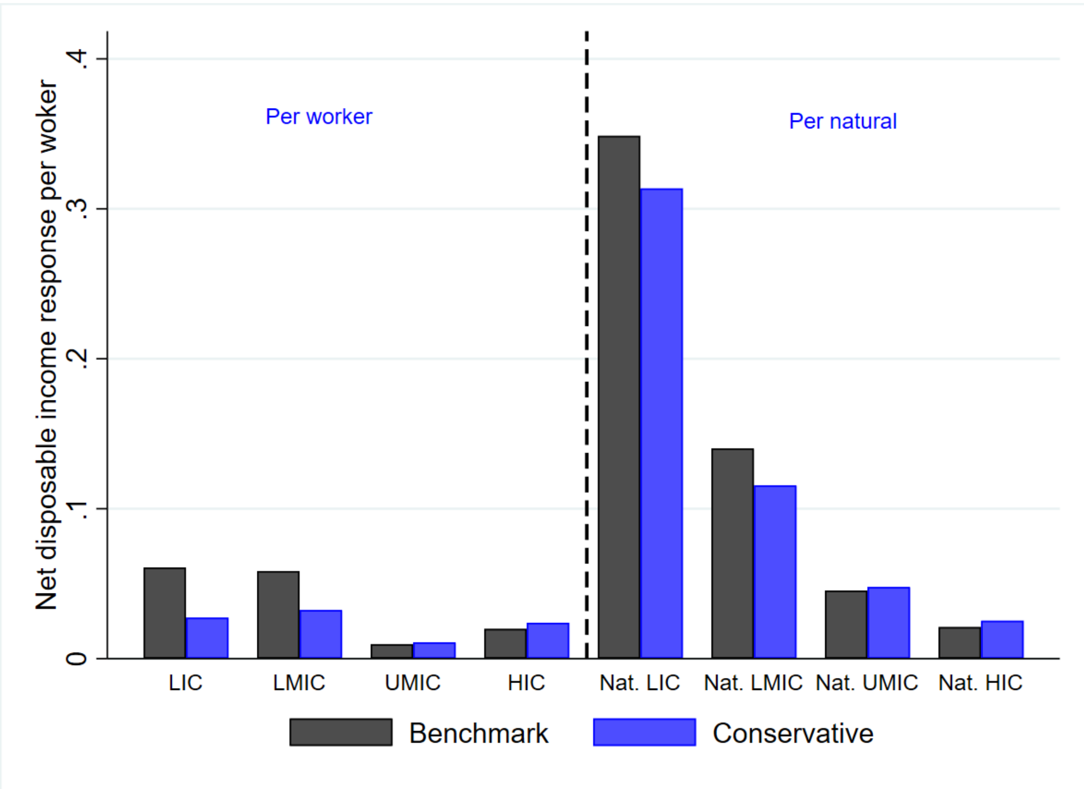
[19] Delogu et al. (2018) estimated the worldwide gain from observed migration at 3.8 percent in the short term, and a "secular" gain of 19 percent when accounting for the cumulative effect of South-North migration on the world population growth (changes in the fertility rate and in access to education for future generations).

Figure 4: Average disposable income responses to selective emigration

(a) Average response worldwide (weighted average of all countries)



(b) Average response by income group (weighted average of all countries)



emigration changes the size and structure of the labor force in destination countries, with consequences for productivity, prices, taxes, and income levels. The resident labor force in country i is given by:

$$L_{i,s} = \sum\nolimits_j M_{ji,s}, \tag{15}$$

which implies that when $M_{ji,s}$ varies, it directly affects both sending and receiving countries, and indirectly affects education decisions in all the other countries. In this global setting, the world economy equilibrium is an allocation of labor $\{L_{ij,s}\}_{\forall i,j,s}$ and a vector of income levels $\{y_{j,s}\}_{\forall j,s}$ satisfying the utility and profit maximization conditions, as well as worldwide aggregation constraints. We use this setting to simulate the impact of global migration on the world distribution of income.

We first measure global income inequality using the Theil index:

$$T = \sum_i \sum_s \frac{y_{i,s} L_{i,s}}{\bar{y} L} \ln \left(\frac{y_{i,s}}{\bar{y}} \right) \tag{16}$$

Where $L \equiv \sum_i \sum_s L_{i,s}$ and $\bar{y} \equiv \left(\sum_i \sum_s y_{i,s} L_{i,s} \right) / L$ denote the total working-age population of the world and the worldwide average level of disposable income, respectively. The ratio $y_{i,s}L_{i,s}/\bar{y}L$ is the proportion of world income that is earned by type s workers living in country i. This index can be expressed as the sum of two components:

(i) an across-country component: $T_A \equiv \sum_i \frac{y_i L_i}{\bar{y} L} \ln \left(\frac{y_i}{\bar{y}} \right)$, where y_i and L_i stand for the average level of disposable income and working-age population in country i, respectively;

(ii) a within-country component: $T_W \equiv \sum_i \frac{y_i L_i}{\bar{y} L} \sum_s \frac{y_{i,s} L_{i,s}}{y_i L_i} \ln \left(\frac{y_{i,s}}{y_i} \right)$.

Table 3 compares the observed and counterfactual levels of the Theil index under the conservative and benchmark scenarios. Col. (1) reports the observed levels in income disparities. These levels are smaller than the usual estimates because we focus on the working-age population, and we only distinguish between two types of workers by country. We thus disregard the residual (or unexplained) heterogeneity within these broad groups of workers. In Cols. (2) and (3), we compute the Theil index in the no-migration (NM) counterfactual under the conservative scenario. Changes are driven by the income responses to global migration, as well as by the geographic reallocation of the world labor force ($L_{i,s}$ is endogenous). Col. (2) abstracts from population reallocation and isolates the income effects. It shows that global migration reduces the across-country component of the Theil index (reflecting the convergence in disposable income per worker between countries, as highlighted in Figures 2 and 3), and increases the within-country component (as it increases the income gap between high-skilled and low-skilled workers in receiving countries). Overall, these pure income mechanisms tend to generate a decrease in global inequality of approximately 0.5 percent.

When accounting for the reallocation effects, the results are inverted. Global migration increases the across-country component of the Theil index. This is generated by the huge "place premium" effect: migrants' income gains tend to increase the worldwide average income level more rapidly than the income level of those remaining behind, as illustrated in Figure 4. This is partly attenuated by a decrease in the within-country component of the Theil index, and is driven by the fact that migrants move from high-inequality to low-inequality countries. Overall, the Theil index increases by 1.94 percent due to the composition effect. In Cols. (4) and (5), we conduct the same exercise under the benchmark scenario. The changes are magnified but qualitatively similar. The Theil index increases by 2.5 percent, spurred by the across-country component. This may appear to be a small effect; however, it is worth emphasizing that international migrants represent about 2.25 percent of the world's working-age population. Hence, the elasticity of the Theil index to migration slightly exceeds unity.

Table 3: Theil index

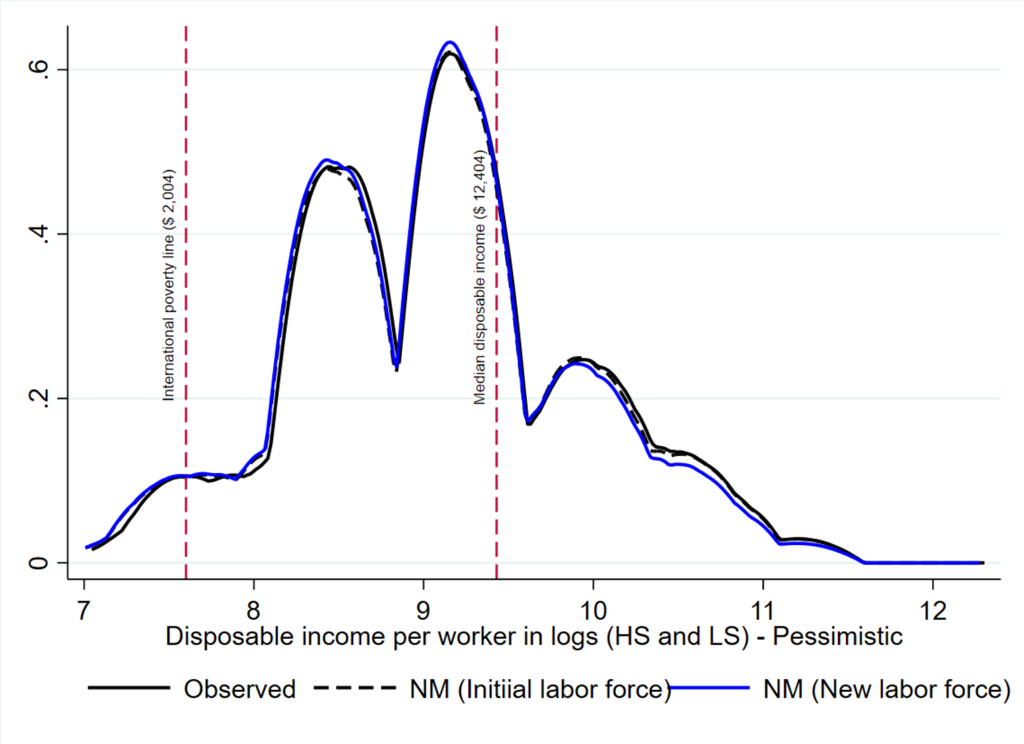
	Obs.	NM Pessim.		NM Bench.	
		Cst. pop	New pop	Cst. pop	New pop
Total	0.355	0.357	0.349	0.363	0.351
Across	0.294	0.299	0.284	0.303	0.287
Within	0.061	0.059	0.064	0.059	0.064
		Rel. dev.		Rel. dev.	
Total		-0.51%	+1.94%	-0.68%	+2.50%
Across		-1.49%	+3.51%	-1.28%	+4.17%
Within		+4.51%	-5.00%	+2.40%	-4.96%
		Acr/With		Acr/With	
Across	82.8%	83.6%	81.5%	83.6%	81.8%
Within	17.2%	16.4%	18.5%	16.4%	18.2%

The rise in inequality is not a problem in itself if the vast majority of people in general – and the extreme poor in particular – are better off. In Figure 5, we pool all the countries and skill groups, and compare the counterfactual distribution of income (shown in blue) with the observed one (shown in black). The vertical lines represent the United Nations poverty line (5.5 USD per day or 2,000 USD per year in PPP values) and the median of the income distribution observed in the year 2010 (34 USD per day or 12,404 USD per year in PPP values). Panel (a) shows the results obtained under the conservative scenario, while Panel (b) focuses on the benchmark scenario. Changes in the distribution are qualitatively similar, albeit unsurprisingly larger under the benchmark scenario. Global migration shifts the density to the right. This is the case at low income levels (i.e., below 5,000 USD), as well as at high-income levels (i.e., above the median). There is a quasi-perfect relationship of quasi-perfect stochastic dominance between the observed and counterfactual densities. Importantly, the proportion of people living below the poverty line decreases by 5.3 percent under the conservative scenario, and by 8.1 percent under the benchmark scenario (i.e., 66.7 and 104.6 million people, respectively).

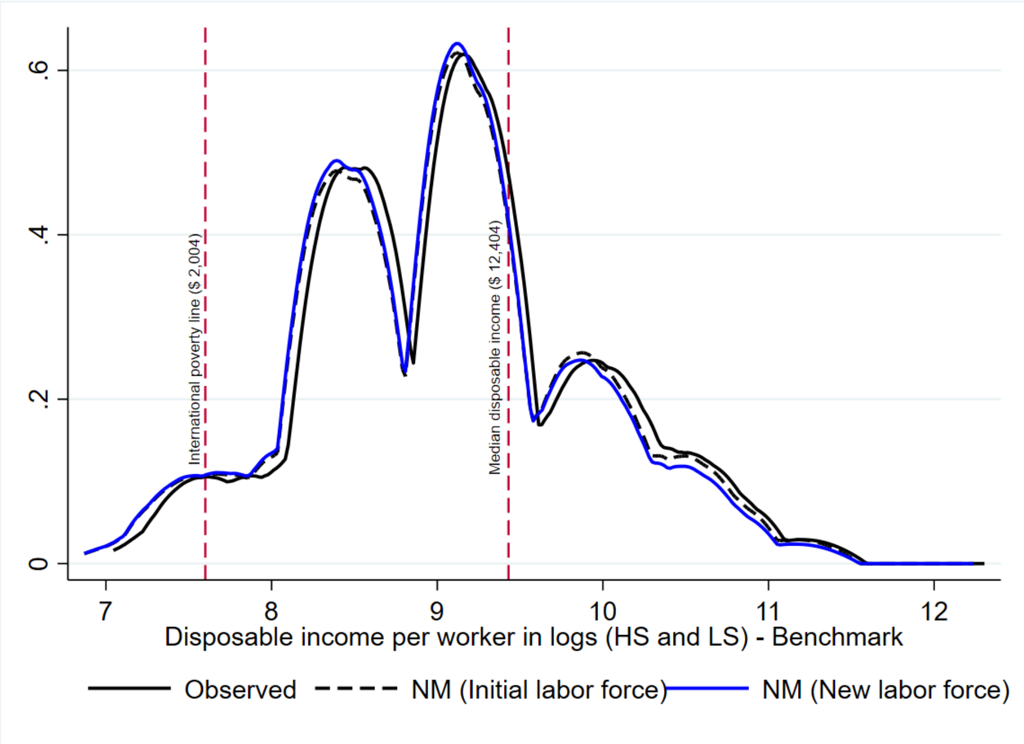
Compared with the no-migration counterfactual, we compute the world income distribution by accounting for the reallocation of people (the black continuous curve in Figure 5a) or, in line with the Theil index, by considering a constant population allocation (the dotted black line). Most of the effect in developing countries is governed by changes in the level of income per worker; this is due to the fact that the average proportion of emigrants is very small (around 2 percent). By contrast, when focusing on the countries at the top end of the distribution (i.e., the main OECD destination countries), changes are dominated by the composition effect: the proportion of immigrants in the working-age population is around 15 percent in the main destinations.

Figure 5: Emigration and world distribution of income

(a) Conservative scenario



(b) Benchmark scenario



5 Conclusion

International migrants are positively selected in terms of education, and the movement of highly educated workers from developing to advanced countries has been the subject of extensive research over the last four decades. Selective emigration has long been viewed as beneficial for migrants, but as having an ambiguous impact on the growth potential of origin countries and the welfare of those remaining behind. Earlier literature emphasizes the risk of harmful effects for the least developed countries where positive selection is substantial. This view has been challenged by recent literature, which demonstrates that limited high-skilled emigration can be beneficial for growth and development. The standard empirical approach suggests that sizeable "brain gain" effects can occur if high-skilled emigration rates are not overly high (Beine et al., 2008). While these findings are globally confirmed when pooling old and recent data on skill-specific emigration rates, the standard approach disregards the cross-country heterogeneity in migration opportunities, development differentials, and access to education.

We expand the traditional approach of quantifying the impact of selective international migration on human capital accumulation, economic development in the origin country, and global inequality. We propose a new dyadic approach that is compatible with updated empirical findings and that fully accounts for the characteristics of each origin country and of all the potential OECD destinations. We establish the micro-foundations of the relationship between selective emigration and human capital accumulation in this dyadic context. Parameterized on the year 2010, our model first shows that selective emigration prospects stimulate human capital formation and induce brain gain effects in the great majority of countries (74 percent of them in our sample), including small states and a few industrialized countries.

We then embed the migration-education nexus into a development-accounting framework that takes into consideration the main transmission mechanisms through which emigration affects economic development in each origin country separately. The quantitative analysis suggests that emigration increases income per worker in most countries, and particularly so in low-income ones. Despite strong selection patterns, international migration tends to reduce disparities in average income between countries. It shifts the world distribution of income to the right and reduces the proportion of extreme poor in the world population. We estimate that selective migration reduces the proportion of people living on less than USD 5.5 a day from 5 percent to 8 percent (which represents 67 to 105 million people), and increases the worldwide average income per worker by 1.9 percent. These estimates may actually be conservative. This is because (i) we are probably not capturing the full benefits linked to temporary migration and brain circulation, and (ii) we disregard potential mechanisms such as transfers of behavioral norms (fertility, education, gender-egalitarian, culture, etc.) or political remittances (the influence of diasporas on the number of voters and on political preferences). Adding these effects to our quantitative framework would be a challenging task. However, our study gives credit to the 2030 Agenda for Sustainable Development, which considers (regular and well-managed) international migration as a phenomenon that improves the lives of migrants and communities in their countries of origin.

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Online Appendix

A Selective Emigration and Human Development: Updated Empirical Estimations

The empirical literature shows that incentives for human capital accumulation in developing countries increase with selective migration opportunities. Micro-level evidence of a positive impact of selective emigration on the *net* stock of human capital in the source country has been provided by several case studies.[20] Although causation is harder to establish with aggregate data, the macro-level literature provides evidence of the same relationship. Beine et al. (2008) estimate a dynamic β-convergence model that analytically boils down to a Cobb-Douglas relationship between human capital and emigration: $H_{i,t+1} = A_{i,t} H_{i,t}^{1+\gamma_1} m_{i,h,t}^{\gamma_2}$, where $H_{i,t}$ is the proportion of college graduates in the native labor force of country i in year t, and $A_{i,t}$ is a country-specific scale factor.[21] The coefficient γ_2 is the short-term elasticity of human capital to emigration prospects. The model is stable if $\gamma_1 \in]-1,0[$, and the human capital stock converges toward $H_i = A_i^{-1/\gamma_1} m_{i,h}^{-\gamma_2/\gamma_1}$, so that the long-term elasticity of human capital to emigration equals $-\gamma_2/\gamma_1$. They show that if a country's emigration rate of high-skilled workers doubles, it is associated with a 20 percent increase in the natives' long-term stock of human capital (including emigrants), and with a 4.5 percent increase in the short-term (within one decade in their context).[22]

In addition to the inherent limitations of using cross-sectional data, the β-convergence specification described above suffers from three main limitations. First, in the absence of skilled emigration ($m_{i,h,t} = 0$), this specification implies that human capital is equal to zero ($H_{i,t+1} = 0$). Second, it disregards the role played by low-skilled emigration.[23] Third, it assumes that the elasticity of education to emigration prospects (γ_2) is identical across countries and independent of a country's level of economic development.

Here, we revisit the empirical analysis of the "brain gain" hypothesis using more recent data, a more general specification, and an improved identification strategy. First, we pool data over two decades for which comparable data exist (1990-2000 and 2000-2010). Second, to overcome the limitations faced by previous approaches, we test whether the

[20] These case studies are surveyed in Section 1. To identify causation, they exploit survey data on education choices and migration intentions, micro data on education and exposure to migration by region, or quasi-natural experimental methods.

[21] Their specification is written as $\Delta \ln H_{i,t} = \gamma_0 + \gamma_1 \ln H_{i,t} + \gamma_2 \ln(m_{i,h,t}) + X_{i,t}^{'}\Gamma + \epsilon_{i,t}$. The vector of controls ($X_{i,t}^{'}$) include population density, a dummy for sub-Saharan African countries and for Latin American countries; $\epsilon_{i,t}$ is the error term. Hence, the scale factor is given by $A_{i,t} = \exp\left(\gamma_0 + X_{i,t}^{'}\Gamma + \epsilon_{i,t}\right)$.

[22] Beine et al. (2010) find that the brain gain mechanism holds when using alternative brain drain measures controlling for whether migrants acquired their skills in the home or host country, or when using alternative specifications and/or indicators of human capital formation. Beine et al. (2011) confirm these effects in a panel setting covering 147 origin countries and 6 destination countries for the period 1975-2000.

[23] Beine et al. (2010) consider a specification with the ratio of emigration rates ($m_{i,h,t}/m_{i,l,t}$) but arrive at results with less significance. They also consider a specification with $1 + m_{i,h,t}$, which is compatible with a no-migration situation.

emigration differential between high-skilled and low-skilled workers is associated with human capital formation in the origin countries, allowing this incentive mechanism to vary with the level of development. Third, in an attempt to identify a causal impact, we use a gravity-based identification strategy, exploiting exogenous variations in dyadic and destination-specific factors to predict emigration populations and rates, and to instrument the emigration differential. Details of the instrumentation strategy are provided in Section A.3.

Our extended empirical model can be written as:

$$\begin{aligned}\Delta \ln H_{i,t} =& \gamma_0 + \gamma_1 \ln H_{i,t} + \gamma_2 \left(m_{i,h,t} - m_{i,l,t}\right) + \sum_{k=2,3,4} \gamma_3^k D_i^k + \\ & \sum_{k=2,3,4} \gamma_4^k \left(m_{i,h,t} - m_{i,l,t}\right) \times D_i^k + X_{i,t}^{'}\Gamma + \Phi_t + \epsilon_{i,t},\end{aligned} \tag{17}$$

where $\Delta \ln H_{i,t} \equiv \ln H_{i,t+1} - \ln H_{i,t}$ stands for the change in the logged proportion of college-educated natives; D_i^k is a dummy variable indicating the income group k to which country i belongs, in which low-income countries constitute the reference group and groups 2, 3 and 4 stand for lower-middle, upper-middle, and high-income countries respectively (as defined in 2010); $X_{i,t}'$ is the set of explanatory variables used in Beine et al. (2008), excluding regional dummies that we replace by income-group dummies; and Φ_t is a decade fixed effect.

Our Eq. (17) improves existing estimation strategies along three dimensions. First, we allow for a heterogeneous effect of selective emigration on human capital formation across country income groups, keeping in mind that poorer countries are characterized by greater migration *premiums* and more severe financial constraints. The total impact of selective emigration is the combination of the effect of the emigration differential ($\delta_{i,t} \equiv m_{i,h,t} - m_{i,l,t}$) and of its interaction with income-group dummies.[24] The semi-elasticity of human capital formation to emigration differentials thus varies with the level of economic development. Second, using emigration differentials neutralizes the influence of other channels of transmission that usually relate to the average level of openness of the origin country, such as transfers of norms and preferences regarding higher education. Third, the fact that the emigration differential is not expressed in logs allows us to overcome the limitations discussed above. In particular, the Cobb-Douglas form underlying our specification can be written as: $H_{i,t+1} = A_{i,t} H_{i,t}^{1+\gamma_1} \exp\left[\left(\gamma_2 + \gamma_4^k D_i^k\right)\left(m_{i,h,t} - m_{i,l,t}\right)\right]$. It is compatible with the no-migration, no-selection, and negative-selection cases.

A.1 Data and OLS estimates

We first estimate Eq. (17) using standard OLS techniques. Our data on migration and human capital are taken from the ADOP and DIOC databases, which characterize the evolution of emigration stocks and rates across the years 1990, 2000, and 2010. We restrict our sample to emigrants aged 25 and above who migrated to one of the OECD member

[24] Specification (17) has advantages over commonly-used alternatives, such as the ratio of skill-specific emigration rates, $\ln(m_{i,h,t}/m_{i,l,t})$, or a log-log specification, $\ln\left(m_{i,h,t} - m_{i,l,t}\right)$. First, $m_{i,h,t}/m_{i,l,t}$ is incompatible with zero emigration rates and is neutral with respect to the size of emigration. For instance, two countries with $(m_{i,h,t}, m_{i,l,t})$ equal to $(0.06, 0.03)$ or to $(0.6, 0.3)$ exhibit an identical ratio of skill-specific emigration rates. Second, the β-convergence specification with the log difference in emigration rates between the two skill groups can be derived from a Cobb-Douglas function of the form $H_{i,t+1} = A_{i,t} H_{i,t}^{1+\gamma_1}\left(m_{i,h,t} - m_{i,l,t}\right)^{\gamma_2+\gamma_4^k I_i^k}$, which is incompatible with $m_{i,h,t} \leq m_{i,l,t}$ as it leads to $H_{i,t+1} \leq 0$.

states, and distinguish between college graduates ($s = h$) and the less-educated ($s = l$). Data on emigration for the year 1990 are taken from the ADOP database. For the years 2000 and 2010, we use the DIOC. We denote by $M_{ij,s,t}$ the populations of migrants from any origin country i to an OECD destination country j in the skill group s at time t. In order to obtain the emigration rates, we have to proxy the size and skill structure of the native (pre-migration) population of the origin country, denoted by $N_{i,s,t}$. For this purpose, we combine data on the resident population aged 25 years and above with data on the proportion of college-educated individuals from different data sources,[25] and obtain the resident labor force by skill group, denoted by $L_{i,s,t}$. Subtracting the number of immigrants, $I_{i,s,t}$, from the resident labor force gives the number of native stayers by skill group.

For virtually all the countries in the world, the skill-specific emigration rates ($m_{i,s,t}$) are proxied by the ratio of emigrants to OECD destination countries ($M_{i,s,t} \equiv \sum_{j \neq i} M_{ij,s,t}$) to the sum of the emigrant and native-stayer populations ($L_{i,s,t} - I_{i,s,t}$). We write:

$$m_{i,s,t} \equiv \frac{M_{i,s,t}}{N_{i,s,t}} \equiv \frac{\sum_{j \neq i} M_{ij,s,t}}{\sum_{j \neq i} M_{ij,s,t} + L_{i,s,t} - I_{i,s,t}}. \tag{18}$$

OLS results are shown in the first four columns of Table A.1. In the table, Cols. (1) and (2) focus on developing countries only – as in Beine et al. (2008) – whilst Cols. (3) and (4) show the results for the full sample, including high-income countries. Although our database on skill-specific emigration rates includes 174 countries pooled over the decades 1990-2000 and 2000-2010 (a total of 348 observations), we lose two countries (Belize, and Serbia and Montenegro) for which data on bilateral skill-specific emigration stocks are missing for some years. Hence, our full sample includes 129 developing countries and 43 high-income countries (i.e., 344 observations). In the second column of each country-group specification, we add a dummy variable to control for the 11 countries for which the emigration differential is badly predicted by the zero-stage of the gravity model (see IV strategy below).

There are two main parameters of interest. First, we focus on the short-term impact of the emigration differential on human capital formation, as well as on the impact of the country's development level on this emigration-education nexus. This is captured by the coefficient of the emigration differential (γ_2) for the reference group (i.e., low-income countries), and by summing the coefficient of the reference group and those for the other income groups (i.e., lower-middle, upper-middle, and high-income countries) as $\gamma_2 + \gamma_4^k D_i^k \;\; \forall k = 2, 3, 4$. Second, we are also interested in the long-term effect of the emigration differential, which can be obtained by dividing the short-term impact by the convergence parameter ($-\gamma_1$). The long-term effects by income groups are reported in Panel B of Table A.1.

The results are robust with regard to the treatment of outliers and to the sample, as our specification includes income group dummies and interaction terms. The short-term semi-elasticity γ_2 in the reference group of low-income countries is between 1.03 and 1.13 when the sample is restricted to developing countries, and between 1.06 and 1.16 when we use the full sample. These coefficients are statistically significant at the 1 percent level. In addition, the coefficient γ_1 related to the lagged dependent term belongs to $]-1, 0[$,

[25] For the years 1990, and 2000, we use population data by education level from Docquier et al. (2009). For the year 2010, we use a combination of data from Docquier et al. (2009) and the *Wittgenstein* database.

which ensures that the model is stable and that the stock of human capital converges toward equilibrium in the long term. For the reference group of low-income countries, the long-term semi-elasticity is between 2.71 and 3.15 when using the sample of developing countries, and between 2.61 and 3.01 when using the full sample. These coefficients are significant at the 1 percent level. Compared with low-income countries, we find that the short-term and long-term semi-elasticities are not statistically different for the group of lower-middle income countries. They are, however, lower for the upper-middle and high-income countries (see the interaction terms in Table A.1).

These empirical findings suggest that there is a positive and significant association between selective emigration prospects and human capital formation in countries belonging to the bottom of the income-per-capita distribution (i.e., low-income and lower-middle income countries), in line with existing case studies. By contrast, when summing the effects of $\delta_{i,t}$ and of its interaction with the dummies for upper-middle and high-income countries, we find that the sum of the two effects is not statistically different from zero in both groups (although it is positive in upper-middle income countries). Lastly, we obtain intuitive estimates for the income-group dummies. Human capital formation increases with the level of development, which may be due to less severe financial constraints and/or more ambitious education policies. Population density at the national level has a positive but negligible effect when considering the full sample. The dummy for the 2000-2010 period is negative, suggesting that the average growth rates (not the levels) of human capital decreased between the two decades.

A.2 Instrumentation Strategy

A positive association between the emigration differential and human capital formation does not necessarily imply a causal relationship. It can be argued that our variable of interest ($\delta_{i,h,t} \equiv m_{i,h,t} - m_{i,l,t}$) is endogenous due to potential reverse causality, unobserved heterogeneity, or measurement errors. Reverse causality risks are mitigated due to the fact that emigration rates are computed using migration stock rather than flow data. This implies that $\delta_{i,h,t}$ results from the accumulation of emigration flows over the 40 to 50 years preceding time t. These past migration flows are unlikely to be directly affected by human capital accumulation after time t. However, we cannot ignore the fact that a fast-growing stock of human capital may reduce the local skill premium and make high-skilled people more likely to emigrate, leading to positive reverse causality. An opposite bias is expected if fast-growing human capital translates into skill-biased technological changes, greater local skill premiums, and lower emigration pressures. Bias can also occur if low levels of human capital growth rates generate negative externalities (e.g., low levels of democracy, political instability, violent conflicts, etc.), which encourage the more-educated to leave the country.

With regard to unobserved heterogeneity, a rise in the quality of education in the origin country can stimulate people to educate themselves and facilitate their access to work permits and visas in wealthier countries. Alternatively, a sudden exodus of low-skilled workers to non-OECD countries can also artificially increase the proportion of skilled workers among natives, while being only partially reflected in the emigration differential as we disregard non-OECD destinations. Hence, unobserved heterogeneity can induce upward or downward biased estimations of the causal impact of emigration prospects on human capital formation.

Table A.1: Emigration differential and education incentives: short-term and long-term effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Developing		Full sample		Developing		Full sample	
	Least Squares				Instrumental variables			
A – Short-term estimates								
$\ln(H_{i,t})$	-0.360***	-0.378***	-0.387***	-0.405***	-0.361***	-0.379***	-0.387***	-0.405***
	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
$m_{i,h,t} - m_{i,l,t} \equiv \delta_{i,t}$	1.132***	1.026***	1.164***	1.060***	1.262**	1.340**	1.211**	1.311**
	(0.38)	(0.37)	(0.38)	(0.38)	(0.50)	(0.55)	(0.51)	(0.55)
Lower-Middle	0.422***	0.403***	0.450***	0.431***	0.463***	0.463***	0.491***	0.495***
	(0.11)	(0.11)	(0.11)	(0.11)	(0.12)	(0.12)	(0.12)	(0.12)
Upper-Middle	0.677***	0.672***	0.731***	0.726***	0.722***	0.752***	0.763***	0.798***
	(0.11)	(0.11)	(0.11)	(0.11)	(0.12)	(0.12)	(0.12)	(0.12)
High-Income	-	-	0.919***	0.913***	-	-	0.919***	0.947***
	-	-	(0.12)	(0.12)	-	-	(0.12)	(0.13)
Lower-Middle × $\delta_{i,t}$	-0.640	-0.543	-0.656	-0.566	-0.924	-0.934	-0.973	-1.006
	(0.47)	(0.47)	(0.48)	(0.48)	(0.67)	(0.71)	(0.67)	(0.70)
Upper-Middle × $\delta_{i,t}$	-0.860*	-0.650	-0.880*	-0.645	-1.253*	-1.320*	-1.217*	-1.281*
	(0.47)	(0.48)	(0.48)	(0.50)	(0.64)	(0.68)	(0.66)	(0.68)
High-Income × $\delta_{i,t}$	-	-	-1.335***	-1.264**	-	-	-1.262**	-1.410**
	-	-	(0.49)	(0.49)	-	-	(0.64)	(0.67)
Population density	0.000	0.000	0.000**	0.000***	0.000	0.000	0.000**	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
2000-2010 dummy	-0.862***	-0.846***	-0.816***	-0.800***	-0.870***	-0.853***	-0.825***	-0.808***
	(0.10)	(0.10)	(0.08)	(0.08)	(0.10)	(0.10)	(0.08)	(0.08)
Outliers	-	-0.214**	-	-0.232**	-	-0.192*	-	-0.208*
	-	(0.10)	-	(0.11)	-	(0.10)	-	(0.11)
B – Long-term estimates								
Low and Lower-Middle	3.146***	2.713***	3.010***	2.614***	3.492**	3.541**	3.126**	3.238**
	(1.03)	(0.97)	(0.98)	(0.93)	(1.40)	(1.46)	(1.31)	(1.36)
Upper-Middle	0.756	0.994***	0.734	1.022	0.026	0.053	-0.015	0.076
	(0.87)	(0.88)	(0.78)	(0.81)	(1.02)	(0.99)	(0.98)	(0.93)
High-Income	-	-	-0.442	-0.504	-	-	-0.131	-0.243
	-	-	(0.77)	(0.73)	-	-	(0.92)	(0.87)
Obs.	258	258	344	344	258	258	344	344
F-first stage	-	-	-	-	75.03	73.61	72.03	70.67
R^2	0.596	0.600	0.602	0.606	0.595	0.599	0.601	0.605

Note: Robust standard errors in parentheses are clustered at country level. Significant coefficients are denoted with stars as follows: *** p<0.01, ** p<0.05, and * p<0.1. Outliers are 11 countries for which our zero-stage, gravity model poorly predicts the emigration rates differential. These include ALB, COM, GNB, FSM, LBN, MDV, MLI, MOZ, NER, PAN, and STP.

Although causation is always hard to establish with cross-country data, we propose an IV strategy relying on a pseudo-gravity approach and destination-specific factors. Our approach is inspired by, among others, Boustan (2010), Kleemans and Magruder (2018), Munshi (2003), and Monras (2020), who propose instruments for dealing with immigration shocks. They rely on push factors in origin countries that are not directly linked to shocks affecting the receiving country. We transpose this approach to emigration and rely on pull factors of destination countries that can be reasonably assumed as exogenous from the point of view of the origin country. Our IV strategy consists of three steps.

First Step: Zero-Stage Gravity Model. – We predict skill-specific bilateral migration populations ($\hat{M}_{ij,s,t}$) using a pseudo-gravity model. On the right-hand side, we mostly include destination and time fixed effects and exogenous dyadic controls. The gravity-based prediction of skill-specific bilateral migration stocks $\hat{M}_{ij,s,t}$ is obtained using the following pseudo-gravity model:

$$\begin{aligned}\ln M_{ij,t,s} = {} & \beta_0^s + \beta_1^s \ln Pop_{i,t} + \beta_2^s \ln Dist_{ij} + \beta_3^s \ln w_{j,t} + \beta_4^s \ln Network_{ij,t-20} \\ & + \beta_5^s Guest_{ij,t} + \beta_6^s Lang_{ij} + \beta_7^s Col_{ij} + \beta_8^s Cont_{ij} \\ & + \sum_{t=00,10} \beta_9^s \delta_t + \sum_{t=00,10} \beta_{10}^s \rho_t \times \ln Dist_{ij} + \mu_j + \epsilon_{ij,t} \,,\end{aligned} \tag{19}$$

where $\ln Dist_{ij}$ is the log of weighted distance between i and j based on bilateral distances between the most populated city in each of the two countries weighted by the share of the city in the country's total population; alternatively, to capture the fact that the cost of distance may have changed over time, we use $\rho_t \times \ln Dist_{ij}$, the interaction between distance and time dummies; $\ln w_{j,t}$ is the log wage in the OECD destination country j; $Guest_{ij,t}$ is a dummy variable taking the value 1 if a guest-worker program between i and j was in place during the decade prior to the census and 0 otherwise; $Lang_{ij}$ is a dummy variable equal to 1 if the same language is spoken by at least 9% of the population in both countries and 0 otherwise; Col_{ij} and $Cont_{ij}$ are two dummy variables that equal 1 if countries i and j have a colonial link and share common borders respectively and 0 otherwise; μ_j and δ_t are destination and time fixed effects.

Hence, we avoid using variables pertaining to the origin country. We only control for the log of total population at origin at time t ($\ln Pop_{i,t}$), to capture country size. We also include $\ln Network_{ij,t-20}$, the log of network size in the destination country j proxied by the total stock of migrants from i to j twenty years earlier. The network variable is not skill-specific and includes young foreign-born individuals below age 25, which mitigates endogeneity concerns.

We estimate Eq. (19) after pooling dyadic migration data for the years 1990, 2000 and 2010. We use Poisson Pseudo-maximum likelihood (PPML) *à la* Silva and Tenreyro (2011) to deal with the large number of zeroes in the dependent variable and the heteroskedasticity.[26] Standard errors are robust and clustered at country level. Since most of our determinants of the skill-specific emigration rate are time invariant (except for time pattern and the network in $t-20$), we follow Feyrer (2009) and move to a panel setting in which we add time fixed effects and interaction terms between time fixed effects and weighted distance between i and j, capturing gradual changes in migration costs.

Results of the zero-stage gravity regressions are provided in Table A.2. Cols. (1) and (2) use a specification with the log of distance for college-educated and less-educated migrants, respectively. Cols (3) and (4) supplement this specification with the interaction between distance and year dummies for 2000 and 2010 (1990 being the reference period). Migration stocks decrease with geographic distance, and the effect of distance decreases over time. This suggests that migration costs have decreased over time, in line with Feyrer (2009). The size of dyadic migration stocks increases with the population size of the origin country, with dyadic network in $t-20$, and with the wage rates in the destination country. The dyadic network variable absorbs much of the effects of distance, colonial links and common language. Yet, in line with existing empirical findings, college-educated workers are sensitive to linguistic proximity, which is a key factor governing the transferability of human capital across countries; this is not the case for low-skilled workers.

[26] This approach is relevant as the proportion of zeroes in the migration data is quite important (26.6 to 39.01% for less-educated and 27.4 to 40.8% for college-educated migrants).

Table A.2: Pseudo-Gravity model for dyadic migration stocks ($M_{ij,s}$)

	(1)	(2)	(3)	(4)
	$M_{ij,h,t}$	$M_{ij,l,t}$	$M_{ij,h,t}$	$M_{ij,l,t}$
population size (log)	0.313***	0.122***	0.313***	0.122***
	(0.0306)	(0.0305)	(0.0305)	(0.0305)
distance (log) ×1990	-0.228***	-0.216*	-0.0922*	-0.180
	(0.0558)	(0.122)	(0.0546)	(0.127)
distance (log) ×2000			-0.117***	-0.0557**
			(0.0263)	(0.0243)
distance (log) ×2010			-0.205***	-0.0432
			(0.0547)	(0.0557)
wage at destination (log)	0.145**	0.179	0.147**	0.180*
	(0.0652)	(0.109)	(0.0665)	(0.109)
Network 20 years ago (log)	0.503***	0.729***	0.504***	0.728***
	(0.0237)	(0.0450)	(0.0230)	(0.0449)
Guest worker program last 10 years	0.125	-0.186	0.121	-0.190
	(0.0840)	(0.175)	(0.0818)	(0.172)
Common language	0.546***	-0.116	0.552***	-0.114
	(0.0416)	(0.212)	(0.0424)	(0.212)
colony	0.182**	0.122	0.175**	0.123
	(0.0827)	(0.289)	(0.0858)	(0.289)
Contiguity	-0.168*	0.322	-0.162*	0.324
	(0.0932)	(0.310)	(0.0930)	(0.308)
Obs	17,612	17,612	17,612	17,612
Intercept	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes	Yes
R^2	0.851	0.779	0.847	0.782

Note: PPML regressions. Robust standard errors in parentheses. Significant coefficients are denoted with stars as follows: *** p<0.01, ** p<0.05, and * p<0.1.

Second Step: Building Instruments. – In the second step, we aggregate predicted emigration stocks and divide them by the native population to predict skill-specific emigration rates ($\hat{m}_{i,s,t} \equiv \sum_j \hat{M}_{ij,s,t}/N_{i,s,t}$) and the aggregate emigration differential ($\hat{\delta}_{i,t} \equiv \hat{m_{i,h,t}} - \hat{m_{i,l,t}}$) for each corresponding year.

Third Step: First-Stage Regressions. – In the third step, we use the (gravity based) predicted emigration rates differentials ($\hat{\delta}_{i,t}$) to instrument the observed gap in emigration rates ($\delta_{i,t} \equiv m_{i,h,t} - m_{i,l,t}$) in our first stage regression, which writes as:

$$\begin{aligned}\delta_{i,t} =& a_0 + a_1\hat{\delta}_{i,t} + a_2 \ln(H_{i,t}) + \sum_{k=2,3,4} a_3^k I_i^k \\ &+ \sum_{k=2,3,4} a_4^k \hat{\delta}_{i,t} \times I_i^k + X'_{i,t} b + \Phi_t + \epsilon_{i,t},\end{aligned} \tag{20}$$

where we combine the external instruments and the set of controls used in the second stage regression.

Table A.3: First-stage regression (instrumenting $\delta_{i,t}$ in 1990 and 2000)

	(1)	(2)	(3)	(4)	(5)	(6)
	Developing Countries			All		
$\ln(H_{i,t})$	0.050***	0.047***	0.041***	0.050***	0.047***	0.042***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\hat{\delta_{it}}$	0.946***	0.964***	1.074***	0.962***	0.981***	1.098***
	(0.14)	(0.12)	(0.06)	(0.14)	(0.12)	(0.06)
Lower-Middle	0.003	0.003	0.012	0.008	0.009	0.018
	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)
Upper-Middle	-0.026	-0.020	-0.008	-0.021	-0.015	-0.004
	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)
High-Income				-0.038	-0.034	-0.014
				(0.03)	(0.03)	(0.02)
Lower-Mid $\times$ $\hat{\delta_{it}}$	-0.106	-0.111	-0.175*	-0.126	-0.133	-0.200*
	(0.16)	(0.14)	(0.10)	(0.16)	(0.14)	(0.10)
Upper-Mid $\times$ $\hat{\delta_{it}}$	0.058	0.044	-0.104	0.070	0.060	-0.102
	(0.16)	(0.15)	(0.09)	(0.16)	(0.15)	(0.10)
High-Inc $\times$ $\hat{\delta_{it}}$				0.109	0.082	-0.046
				(0.17)	(0.16)	(0.12)
Pop. density	0.000	0.000*	0.000*	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
2010 Dummy	-0.063***	-0.060***	-0.060***	-0.055***	-0.052***	-0.052***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Outliers		-0.046			-0.041	
		(0.04)			(0.04)	
Obs	256	256	237	340	340	321
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.721	0.729	0.803	0.753	0.758	0.813

Note: Robust standard errors in parentheses. Standard error are clustered at country level. Significant coefficients are denoted with stars as follows: *** p<0.01, ** p<0.05, and * p<0.1.

The first stage estimates in Table A.3 show that the predicted emigration rate differential ($\hat{m}_{i,h,t} - \hat{m}_{i,l,t}$) is a very good predictor of $m_{i,h,t} - m_{i,l,t}$. The coefficient of the external instrument is close to unity. Interactions between country income-group dummies and the external instrument are weakly significant. The R^2 of the first-stage regression is in the range of 0.7 to 0.8. With regard to the internal instrument, $\delta_{i,t}$ is significantly correlated with the lagged level of human capital and with the time dummy. The other internal instruments are insignificant.

A.3 IV estimates

The results of the IV regressions are presented in the last four columns of Table A.1, in which Cols. (5) and (6) restrict the sample to developing countries only, whilst Cols. (7) and (8) provide the results for the full sample. Compared with the OLS estimates, the short-term semi-elasticity of human capital formation to selective emigration prospects is inflated by around 20 percent. This is also the case for the long-term semi-elasticity, as the convergence rate is almost identical to that obtained with OLS estimations. Similar relative changes are found for the coefficients of interaction with income-group dummies. These findings confirm that selective emigration prospects are likely to have a positive impact on human capital formation in countries belonging to the bottom of the income-per-capita distribution, with a short-term elasticity varying between 1.2 and 1.3, and a long-term semi-elasticity between 3.1 and 3.5 in lower-middle and low-income countries. Hence, an increase of 10 percentage points in the emigration differential translates into a 12-13 percent increase in the stock of human capital within ten years, and a 31-35 percent increase in the long term. Assuming a poor country with an initial proportion of college graduates equal to 5 percent, this selective emigration shock brings the proportion to 5.5 percent after ten years, and to 6.8 percent in the long term.

A.4 Net Human Capital Response: Numerical Assessment

In line with the generalized approach of Section 2, the findings of the empirical model can be used to quantify the effect of selective emigration on human capital accumulation in the country of origin. Human capital is proxied by the proportion of college graduates in the resident population, which is linked to emigration rates, pre-migration human capital levels, and immigration through the following relationship:

$$h_{i,t} \equiv \frac{(1-m_{i,h,t})H_{i,t}N_{i,t} + I_{i,h,t}}{(1-m_{i,h,t})H_{i,t}N_{i,t} + I_{i,h,t} + (1-m_{i,l,t})(1-H_{i,t})N_{i,t} + I_{i,l,t}}, \tag{21}$$

where $N_{i,t}$ denotes the total native population in year t, and $I_{i,s,t}$ is the population of immigrants of type s. These two variables are assumed to be exogenous.

Using the estimated semi-elasticity of human capital formation to emigration, we can simulate the counterfactual proportions of educated natives and residents that would be observed in a no-migration counterfactual scenario (i.e., when $m_{i,h,t} = m_{i,l,t} = 0$), as if no native would have left their home country.[27] Compared with the observed level ($H_{i,t}$), the counterfactual proportion of educated natives ($H_{i,t}^{NM}$) varies when migration rates are set equal to zero. When focusing on the short-term human capital response in country i belonging to the income group k, we have:

$$\ln H_{i,t}^{NM} = \ln H_{i,t} - \left(\gamma_2 + \gamma_4^k D_i^k\right)(m_{i,h,t} - m_{i,l,t}),$$

while the long-term human capital response to selective emigration is given by:

$$\ln H_{i,t}^{NM} = \ln H_{i,t} - \frac{\left(\gamma_2 + \gamma_4^k D_i^k\right)}{-\gamma_1}(m_{i,h,t} - m_{i,l,t}).$$

[27]Since we aim to identify the effect of emigration on human capital accumulation, we assume that the stock of immigrants ($I_{i,s,t}$) is left unchanged. In our computations, immigrants are assimilated to natives. We will relax this assumption in the last section of the paper.

Under the stability condition ($\gamma_1 \in]-1, 0[$), the counterfactual no-migration proportion of educated is smaller (greater, respectively) than the observed one if the migration differential is positive (negative, respectively). This is at least the case in lower-middle and low-income countries, where the incentive effect is significant and positive ($\gamma_2+\gamma_4^k D_i^k > 0$). In the upper-middle and high-income countries, we have $H_{i,t}^{NM} = H_{i,t}$. Then, from Eq. (21), we have

$$h_{i,t}^{NM} \equiv \frac{H_{i,t}^{NM} N_{i,t} + I_{i,h,t}}{N_{i,t} + I_{i,h,t} + I_{i,l,t}} \tag{22}$$

in the no-migration scenario.

For the 174 countries included in our sample, we simulate the counterfactual proportions of college graduates obtained in the no-migration scenario, and define the human capital response to selective emigration as the difference between the observed and counterfactual proportions of college graduates in the labor force: $\Delta h_{i,t} \equiv h_{i,t} - h_{i,t}^{NM}$. The results are shown in Figure A.1. The three figures in the left-hand panel give the effects observed within a decade (when $H_{i,t}^{NM}$ is computed using short-term semi-elasticity), while figures in the right-hand panel depict the long-term human capital responses.

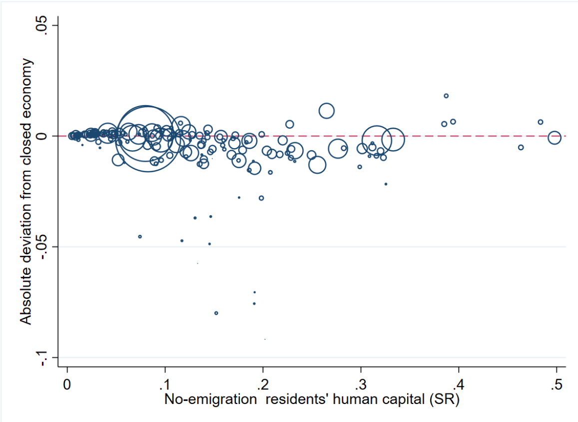
Panels (a) and (b) show the variations in human capital ($\Delta h_{i,t}$ on the vertical axis) as a function of the no-migration level of human capital ($h_{i,t}^{NM}$ on the horizontal axis). Selective emigration induces a short-term increase in human capital in 78 countries, and a short-term decrease in 96 (compared with 101 winners and 73 losers when using the micro-founded approach in Figure 1). When using the long-run semi-elasticity level, a gain is obtained in exactly half of the sample (i.e. 87 countries out of 174, compared to 128 winners and 46 losers when using the micro-founded approach). Relative to the micro-founded approach depicted in Figure 1, the gains are smaller and the losses are greater. A negative effect is found in upper-middle and high-income countries where the emigration differential is positive. It should be noted that the emigration differential is negative (i.e., emigrants are negatively selected) in only ten countries (Bolivia, Bulgaria, Finland, Georgia, Ireland, Kazakhstan, Lithuania, Mexico, Macedonia, and Portugal).

Panels (c) and (d) compare the predictions of the cross-country and micro-founded approaches under both scenarios. We identify *three major differences*. First, the micro-founded approach predicts a positive effect in some upper-middle and high-income countries, while the empirical approach predicts a human capital loss, at least when the emigration differential is positive. Second, a few upper-middle and high-income countries that benefited from negative emigration differentials in the empirical setting suffer from smaller incentives to acquire human capital under the micro-founded approach. This is the case for Finland, Georgia, Ireland, Kazakhstan, Lithuania, and Mexico. Third, for the reason explained above, small states lose less or gain more in the micro-founded framework.

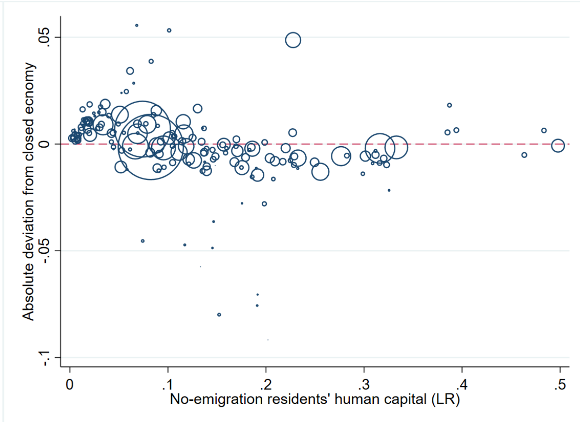
Panel (e) and (f) compare the kernel density of the migration-driven change in human capital under the two approaches. While the density is left-skewed under the empirical approach, it is almost symmetric under the micro-founded approach.

Figure A.1: Effect of selective emigration on human capital accumulation (h_i)
Insights from the empirical model

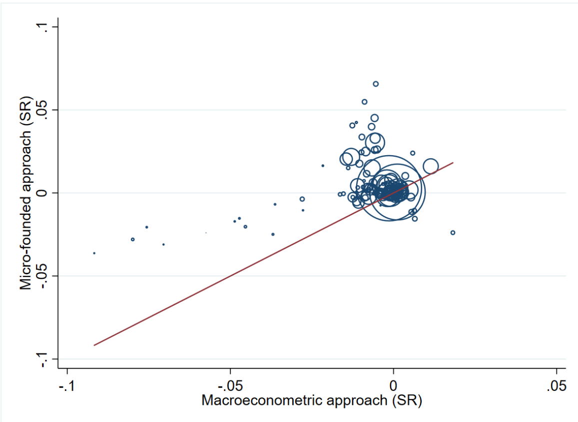
(a) Short-term (SR) effect (Δh_i)



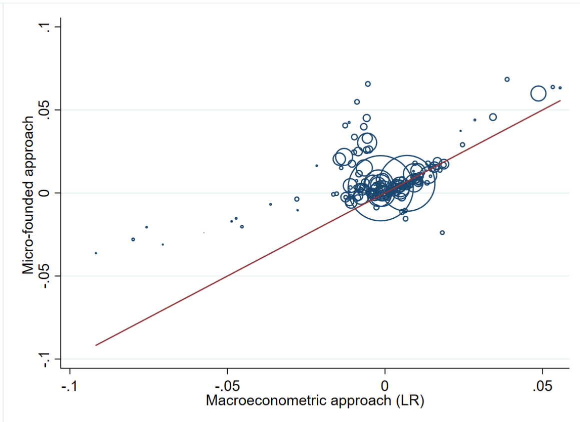
(b) Long-term (LR) effect (Δh_i)



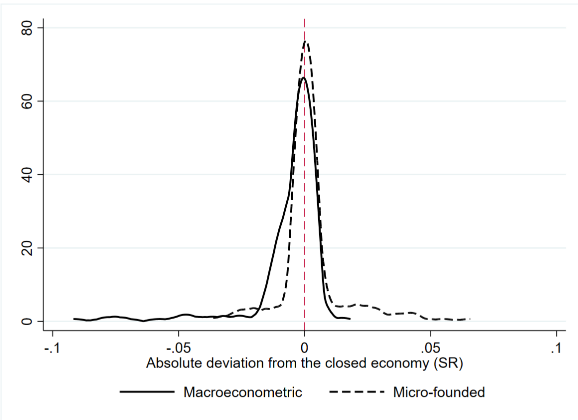
(c) Generalized vs. Empirical (Δh_i in SR)



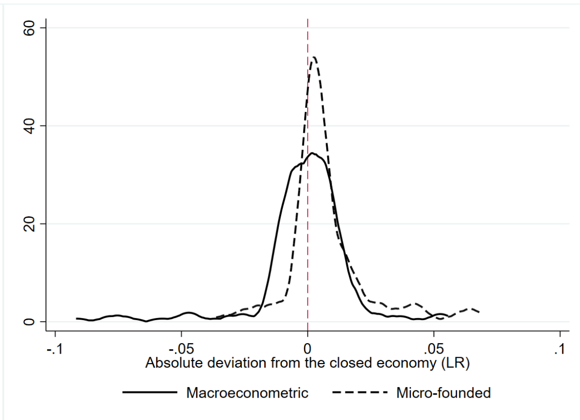
(d) Generalized vs. Empirical (Δh_i in LR)



(e) Density of Δh_i (SR)



(f) Density of Δh_i (LR)



Note: Panels (a) and (b) compare the variation in resident human capital, Δh_i, (i.e. the difference between the observed proportion of college graduates, h_i, and the no-migration proportion, h_i^{NM}) as a function of the no-migration counterfactual human capital level (h_i^{NM}). Panels (c) and (d) compare the variation in resident human capital, Δh_i, obtained with the cross-country empirical approach (X-axis, labeled as "Macroeconometric approach") and with the structural approach (Y-axis, labeled as "Micro-founded approach"). Panels (e) and (f) compare the density of Δh_i obtained with the two approaches. Panels (a), (c), and (e) present the results obtained with the short-term (SR) elasticity, $\gamma_2 + \gamma_4^k D_i^k$. Panels (b), (d), and (f) present the results obtained with the long-term (LR) elasticity, $(\gamma_2 + \gamma_4^k D_i^k)/(-\gamma_1)$.

B Generalized Approach: Parameterization

In this section, we detail the parameterization of our model. In Section B.1, we start by calibrating the dyadic model to exactly match the dyadic size and skill structure of international migration and the observed level of human capital. We then explain the parameterization of the general equilibrium framework and its extensions in Section B.2.

B.1 Human Development Block

We parameterize the dyadic model of Section 2.1 for 174 countries and for the year 2010.

B.1.1 Migration technology

We use proxies for skill-specific wages and calibrate migration costs to exactly match the observed structure of the labor force and international migration stocks. We use the same data on dyadic emigration stocks ($M_{ij,s}$) and size of stayers ($N_{ii,s}$) by education level as in Section A. As in Eq. (18), we define the native population as $N_{i,s} = \sum_{j \neq i} M_{ij,s} + M_{ii,s}$. Then, Eqs. (5) and (6) show that dyadic migration stocks, $M_{ij,s}$, depend on wage disparities between countries ($w_{j,s}/w_{i,s}$) and on migration costs ($c_{ij,s}$).

To produce estimates of the skill-specific wages, we use data on GDP in PPP value from the Maddison project described in Bolt and Van Zanden (2014), and data on the wage ratio between college graduates and less-educated workers ($R_i \equiv w_{i,h}/w_{i,l}$) from Hendricks (2004). The data are available for 143 out of the 174 countries in our larger sample. We obtain the GDP in PPP by multiplying the GDP per capita by the population size. For missing observations, we use rescaled GDP data from the *World Development Indicators* (WDI) provided by the World Bank.[28] Assuming total labor income (W_i) equals 2/3 of the GDP, we have $W_i = L_{i,h}w_{i,h} + L_{i,l}w_{i,l} = w_{i,l}(L_{i,h}R_i + L_{i,l})$. We identify $w_{i,l}$ from this equation and use $w_{i,h} = w_{i,l}R_i$ for the high-skilled wage.

Migration costs ($c_{ij,s}$) are calibrated as a residual from Eq. (5), assuming an elasticity of bilateral migration to the wage ratio, $1/\mu$, where μ is set to 0.7 (in line with Bertoli and Moraga, 2013). Alternative values for $1/\mu$ are considered in the robustness analysis (see Figure C.1). As a validation exercise, we show below that the calibrated levels of migration costs are positively correlated with distance and negatively correlated with colonial links, common language and migrant stocks in the 90's. Furthermore, in a former version of this work (Deuster and Docquier, 2018), we gauged the ability of our model to replicate past emigration rates (i.e., to predict the skill structure of emigration stocks by education level in the years 1990 and 2000). The correlation between actual and predicted stocks equals 0.907 for college graduates and 0.905 for the less-educated in the year 2000, and 0.766 and 0.803 in the year 1990. The correlation unsurprisingly decreases with the time distance from the year 2010. This is because we do not account for past variations in migration policies (e.g., the Schengen agreement in the European Union, changes in the H1B visa policy in the US, etc.), for conflicts, etc. Nevertheless, the correlations are large, a proof of concept that our model does a good job at explaining migration patterns.

[28] The data are rescaled in a way that matches the GDP in the United States. For this, the GDP obtained from the Maddison project is divided by the GDP obtained from the WDI for the United States. The GDP from the WDI is then multiplied by this quotient for the missing observations in order to retrieve comparable GDP measures.

B.1.2 Calibration of Migration Costs: Validation

The calibrated migration costs $c_{ij,s}$ capture disparities in amenities and other residual factors not explicitly controlled for in the utility term of our model. Their values should therefore not be over-interpreted. Nevertheless, analyzing the correlation between the calibrated level of the migration costs and control variables that are found to be determinants of the size of migration flows and stocks in the literature allows to verify whether the between-corridor variation seems empirically valid. Hence, we regress the values of our calibrated migration costs, $c_{ij,s}$, on origin - and destination country fixed effects as well as bilateral control variables, including: a binary indicator for a shared colonial link, a shared common language, log of distance between countries and log of bilateral migrant stocks in 1990. Migration costs are expected to be positively correlated with distance and negatively correlated with colonial links, common language and migrant stocks in the 1990s.

We also add two different proxies for migration policies. The first is provided by DEMIG (2015) Visa data, which construct an indicator for entry visa requirements based on data reported in the Travel Information Manuals published by the International Air Transport Association (IATA). The indicator is equal to 1 in case a destination country j requires nationals from origin i to be in possession of visa to enter the country. We calculate the average intensity of requirement for each corridor as the long term average over the period for which data are available, going from 1973 to 2010.[29] Even though this variable is merely a proxy, it is fair to assume that countries with more stringent migration laws might also impose more restrictive conditions on travelers' entrance. A visa requirement for travelers can be seen as a first tool for destination countries to control (legal) entries into the country. Hence, we expect the visa indicator to be positively correlated to our calibrated migration cost, $c_{ij,s}$. The second indicator that we rely on is a binary variable with value equal to 1 if a guest-worker program was in place at destination country j for origin country i. We expect bilateral migration corridors with guest-worker programs in the past to exhibit, on average, lower migration costs.

Table B.1 confirms that migration costs are on average lower for high-skilled migrants (Cols. (1) and (2)) compared to low-skilled immigrants (Cols. (3) and (4)), as reported by the values of the constant terms. For both education groups, migration costs are negatively correlated with shared colonial links, a shared common language and bilateral migrant stocks in 1990. They are positively correlated with distance, as expected. Regarding the two proxies for visa costs, we find a counter-intuitive negative correlation with the long-term average visa requirement, which is significant for the low-skilled only (at the 5% level). This result can be explained by several factors. First, the requirement of a visa at entry is, at best, an imperfect measure of actual visa restrictions. Indeed, it just stipulates one specific type of legal rules that a visitor from a given origin country is required to meet in order to legally enter a specific destination country. It does not say anything about other aspects, such as the duration of stay allowed or whether individuals can search for a job. Second, visa policies are endogenous and evolve as migrant inflows and the desired migration levels in destination countries change. Destinations that were particularly attractive in the past might have opted for more stringent visa policies in order to control/limit the immigration flows, leading to a positive correlation between high immigrant stocks (translated into low migration costs in our calibration strategy)

[29] We tried alternative definitions, using for example the year 2009 instead of an average value or the average over the period 2000 and 2010. Results are robust and available upon request.

and increased visa restrictions. Hence, issues of reverse causation and collinearity might arise in our regressions.

As expected, the indicator for the existence of guest-worker programs in the 90's is negatively correlated to migration costs, albeit not significantly. However, this indicator suffers from the fact that most guest-worker programs occurred in the 1960's and 1970's and only a few persisted thereafter. In addition, the issues of reverse causality and collinearity that affect the visa requirements are also likely to impact guest-worker programs.

Table B.1: Validating the calibrated migration costs

	(1)	(2)	(3)	(4)
	$c_{ij,h}$	$c_{ij,h}$	$c_{ij,l}$	$c_{ij,l}$
Ln(Dist)	0.00631**	0.00578**	0.000837***	0.000775***
	(2.45)	(2.41)	(3.10)	(3.00)
Common language	-0.0194***	-0.0190***	-0.00109***	-0.00103***
	(-5.13)	(-5.19)	(-4.09)	(-4.02)
Colonial links	-0.0256**	-0.0250**	-0.00221**	-0.00212**
	(-2.14)	(-2.10)	(-2.31)	(-2.23)
Ln(diaspora_1990)	-0.00236***	-0.00224***	-0.000190***	-0.000176***
	(-4.38)	(-4.35)	(-4.03)	(-3.99)
Visa requirements	-0.00439		-0.000679**	
	(-1.35)		(-2.27)	
Guestwork prog. 90s		-0.00572		-0.000587
		(-0.72)		(-0.99)
Constant	0.961***	0.960***	0.994***	0.993***
	(39.68)	(41.60)	(391.98)	(402.29)
Observations	5,827	5,848	5,827	5,848

Note: All regressions include country of origin and country of destination fixed effects. t statistics in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

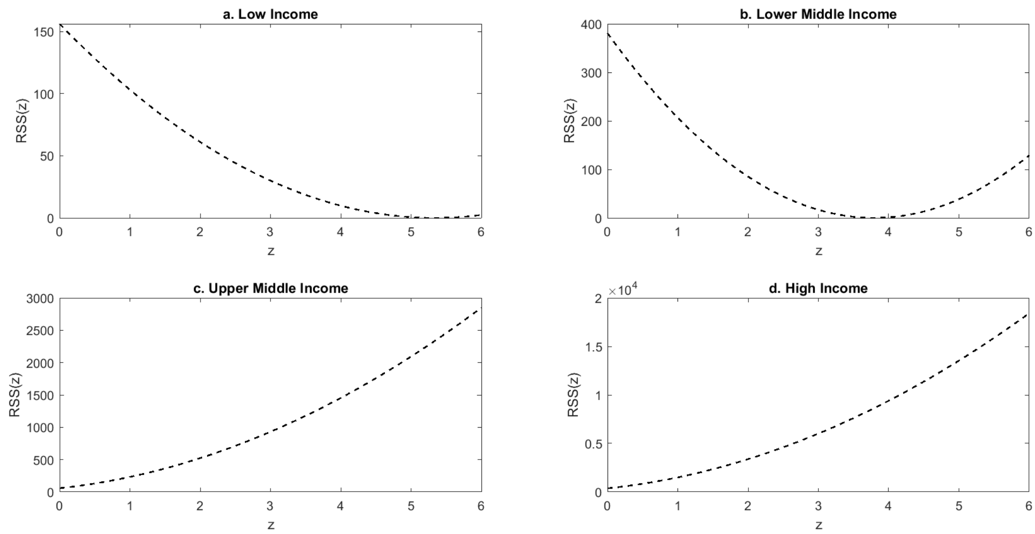
B.1.3 Training technology

Turning to the parameterization of the human capital technology, we use the skill-specific wage proxies and levels of dyadic migration costs to calibrate Λ_i from Eq. (3). Then, Eq. (4) shows that the ex-ante proportion of college graduates (H_i) depends on two unknown parameters, namely z which governs the sensitivity of education decisions to the expected return on higher education, and G_i which governs access to education in the origin country. We calibrate these two parameters iteratively, assuming that z depends on the level of development (in line with our empirical results of Appendix A), and that G_i is country-specific.

We arbitrarily allocate alternative values to z (e.g. 0, 0.1, 0.2, 0.3, etc.) and, for each z, we calibrate the scale variable G_i to the level that exactly matches H_i as a residual from Eq. (4). Let us denote by $G_i(z)$ the scale factor that corresponds to the arbitrary level of z. To identify a level of z that generates realistic human capital responses to migration shocks, we simulate several skill-specific migration shocks and identify the change in H_i. These shocks consist in reducing and increasing migration costs (i.e. $1 - c_{ij,s}$) by 10, 20 and 30 percentage points. For each of these shocks and for each pair of z and $G_i(z)$, we compute the changes in emigration rates ($\Delta m_{i,s}$), and the human capital responses expressed in log variations ($\Delta \ln H_i$). In line with our empirical model depicted in Eq. (17), we then regress $\Delta \ln H_i$ on the corresponding changes in emigration rates differential, $\delta_{i,t} \equiv m_{i,h} - m_{i,l}$, using the same sample of countries as in the empirical section (see Appendix A). Finally, we choose the level of z that minimizes the residual sum of squares (RSS) obtained as the sum of the quadratic differences between the estimated $\gamma^k_{2,v}(z)$ at each potential value of z and the long term semi-elasticity obtained in Appendix A (i.e. γ^k_2), and hence $RSS_k = 1/n \sum_{v=1}^{V} (\gamma^k_{2,v} - \gamma^k_{2,LR})^2$.

As shown on Figure B.1, we find that $z^*_{LOW} = 5.3$, $z^*_{LMI} = 3.8$ and $z^*_{UMI} = z^*_{HIC} = 0$ are the most relevant values respectively for low-income (LOW), lower-middle (LMI), upper-middle (UMI), and high-income countries (HIC). These levels of z^* are compatible with the long-term semi-elasticities of human capital to the emigration differential estimated in our empirical model, and exactly match the observed share of college graduates in the native population of 2010. As z is a proxy for the scarcity of talent or low access to education, it is reassuring that it decreases with the level of development.

Figure B.1: Calibration of z by income group



Note: Each panel depicts, for a specific country income group, the residual sum of squares (RSS) on the vertical axis for a given value of z on the horizontal axis. For each country income group, we chose the level z^* that minimizes the RSS.

B.1.4 Calibration of Training Technology: Validation

The selection of z^* governs the calibration of the proxy for education policy, $G_i(z^*)$. The mean and standard errors of $G_i(z^*)$ equal 0.710 and 0.528, respectively. To validate the calibration strategy, we regress $G_i(z^*)$ (in logs) on empirical counterparts governing access to education in the origin country. We use the level of public education expenditure as a percentage of GDP, the log of the urbanization rate, the log of GDP per capita as well as interactions between education expenditure and country income-group dummies. The first column of Table B.2 shows that $G_i(z^*)$ is positively correlated with the log of public education expenditure and urbanization, and negatively correlated with GDP per capita. When adding interaction terms in Col. (2), the correlations with public education expenditure and urbanization increase and become more significant. The highest correlation with public expenditure in education is obtained in high-income countries, where the average distance to schools is low. In developing countries, access to education is also determined by geographic factors and hence the urbanization rate is a key determinant of access to education.

Table B.2: Calibration of $\ln G_i$ (access to education) – Validation

	(1) $\ln G_i$	(2) $\ln G_i$
log Public expenditure (as % of GDP)	0.279*	0.240**
	(0.15)	(0.09)
log Urbanization rate (as % of population)	0.271**	0.445***
	(0.12)	(0.08)
log GDP per capita	-0.133**	–
	(0.06)	–
Lower-middle × Public exp. (as % of GDP)	–	-0.231*
	–	(0.13)
Upper-middle × Public exp. (as % of GDP)	–	-0.451*
	–	(0.25)
High-income × Public exp. (as % of GDP)	–	1.041***
	–	(0.37)
Constant	1.688*	1.091***
	(0.87)	(0.37)
Obs	162	162
Income-group dummies	No	Yes
R^2	0.049	0.558

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, and * p<0.1.

B.2 Economic Block

We calibrate the general equilibrium model to exactly match the world income distribution, and the estimated elasticities from the existing empirical literature. Calibrating the technological externalities requires calibrating three common elasticities $(\sigma, \epsilon, \kappa)$ and two country-specific parameters $(\overline{\Gamma}_i, \overline{A}_i)$. Common elasticities are taken from the empirical literature, whereas country-specific parameters are calibrated to match two moments for the year 2010, namely the observed level of GDP per worker and the wage ratio between college graduates and the less-educated.

We first calibrate (Γ_i, A_i) to match two country-specific moments, the ratio of wage rates $(w_{i,h}/w_{i,l})$ and nominal income per worker (y_i). An analytical expression for the ratio of wage rates can be obtained by assuming that firms maximize profits and the labor market is competitive. The equilibrium wage rate for type-s workers in country i is equal to their marginal productivity of labor. The nominal wage rates of college graduates and less-educated workers are given by:

$$w_{i,h} = A_i \frac{\Gamma_i}{1+\Gamma_i} \left(\frac{Q(\Gamma_i, h_i)}{L_{i,h}} \right)^{1/\sigma}, \tag{23}$$

$$w_{i,l} = A_i \frac{1}{1+\Gamma_i} \left(\frac{Q(\Gamma_i, h_i)}{L_{i,l}} \right)^{1/\sigma}. \tag{24}$$

This implies that the ratio of wage rates is given by:

$$\frac{w_{i,h}}{w_{i,l}} = \Gamma_i \left(\frac{L_{i,h}}{L_{i,l}}\right)^{-1/\sigma} = \Gamma_i \left(\frac{h_i}{1-h_i}\right)^{-1/\sigma}. \tag{25}$$

Data on the wage ratios are obtained from Hendricks (2004). Data on income per worker are obtained by dividing nominal income per capita in PPP (values from Bolt et al., 2018) by the share of the working-age population in the total population, obtained from the World Development Indicators. In the labor market literature (e.g., Angrist, 1995, Ottaviano and Peri, 2012), the elasticity of substitution between skill groups varies between 1.3 and 3. We assume $\sigma = 2$ and we use the share of college graduates in the labor force (h_i) as defined in the previous section.[30] Assuming a competitive labor market, the ratio of wage rates is given by the ratio of marginal productivities. Practically, we use Eq. (25) and calibrate Γ_i to match the average wage ratio. When Γ_i is known, we compute $Q(\Gamma_i, h_i)$.

We then focus on technological and diaspora externalities. We assume the elasticity of directed technical change to the ratio of skilled workers, $\kappa = 0.10$, in line with Burzyński et al. (2020). The scale parameter $\overline{\Gamma}_i$ is such that the skill bias in the current state of the world matches the observed ratio of wages in 2010. To calibrate the elasticity of TFP with respect to the skill-ratio in the resident labor force, ϵ, Caselli and Ciccone (2013) argue that for an average poor country, increasing college attainment to the level of the US (a share of college graduates equal to 0.31 in 2010) would induce an increase of TFP by 30%. The average human capital of low income countries in 2010 was equal to 0.075. This implies that $\epsilon = 0.10$.

With regard to diaspora externalities, we assume that the TFP is influenced by the average proportion of migrants abroad. To calibrate the size of the diaspora externality, we combine two strands of literature. The first one has identified a causal impact of migration on trade and FDI, with respective elasticities of 0.1 and 0.2 (e.g., Felbermayr et al., 2010, Iranzo and Peri, 2009, Javorcik et al., 2011, Kugler and Rapoport, 2007, Parsons and Vezina, 2018). The other strand of literature has identified a causal effect of trade and FDI on TFP, with respective elasticities of 0.3 and 0.01 (see Feyrer, 2019, Larch et al., 2017). Combining these findings gives a conservative elasticity of total factor productivity to emigration of approximately 0.032. In Eq. (13), we also assume that $\overline{m} = 0.10$ as a benchmark. The scale parameter $\overline{A}_i$ is calibrated as a residual from Eq. (13) and is such that the TFP level in the current state of the world allows us to match the observed level of income per worker in 2010.

As far as the market size externality is concerned, we assume $\lambda = 8.0$ as a benchmark value, which implies that the model predicts conservative market size effects (Feenstra, 1994). The scale parameter $\overline{P}_i$ is such that the price index in the current state of the world equals unity. Under the conservative scenario, the market size externality is halved ($\lambda = 4.0$), implying that an emigration-driven decrease in market size has a greater impact on the ideal price index.

Regarding the elasticity of government consumption to population size, we assume that $\eta = 0.056$, in line with Alesina and Wacziarg (1998) who suggest that a 10% decrease in the population leads to a 0.56% increase in public consumption per capita. In addition, public consumption (x_i) is country-specific and proxied by the ratio of government consumption to the GDP from the World Development Indicators. Furthermore, the average education

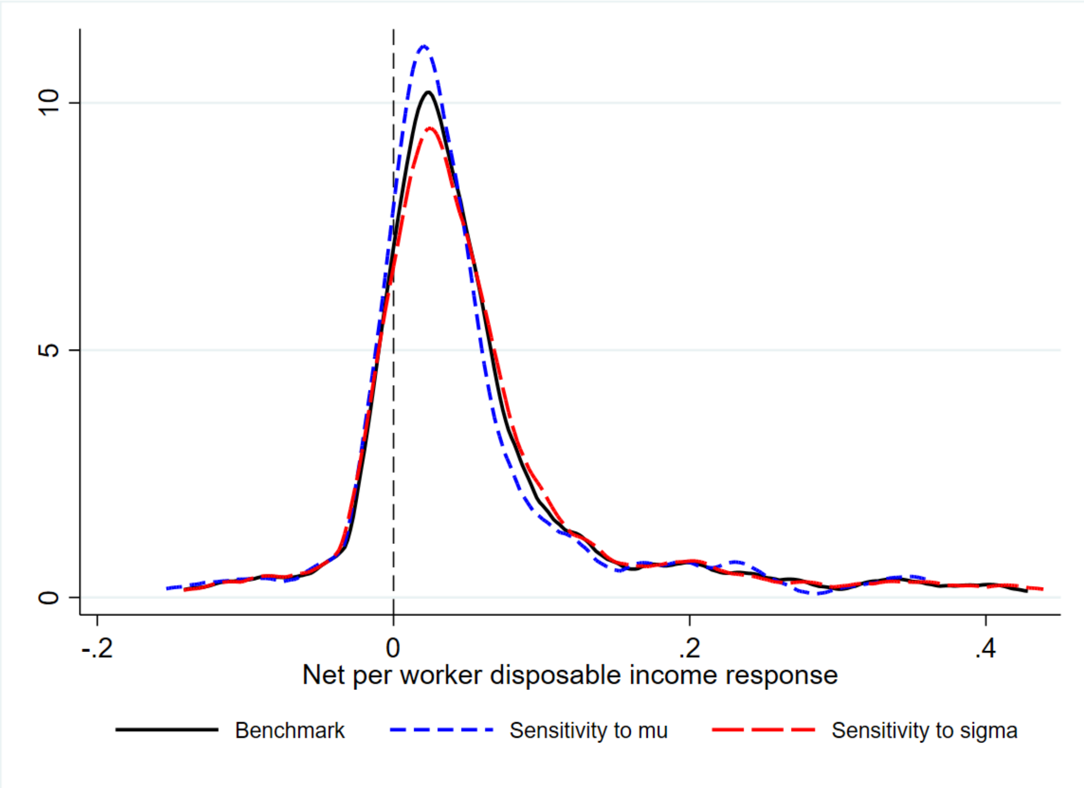
[30] In a robustness check, we show that $\sigma = 1.5$ does not affect our results; see Figure C.1.

cost per worker (c_i) is calibrated to match skill-specific education cost per student from the UNESCO Institute of Statistics and education expenditure in percentage of GDP from the World Development Indicators. Assuming a balanced budget, the baseline income tax rate (τ_i) is obtained, as a sum of the two components: government consumption (x_i) and education expenditure (v_i). Under the conservative scenario, the market size externality is doubled ($\eta = 0.112$), implying that a 10% decrease in population leads to a 1.12% increase in public consumption per capita.

C Robustness of results to different parameter values

Figure C.1 shows that our benchmark results are robust to re-calibrating the model after changing the elasticity of bilateral migration to the wage ratio (using μ=0.8), or the elasticity of substitution between skill groups (using σ=1.5).

Figure C.1: Sensitivity to μ and σ



D Effect of Selection on Economic Development

In Figure D.1, we isolate the effect of positive selection. We consider a new counterfactual scenario (labeled as NS) with the same migration intensity, but without positive selection. Assuming constant wage rates, migration costs are re-calibrated so as to have $m_{ij,h} = m_{ij,l} = \overline{m}_{ij}$ over all corridors j, where $\overline{m}_{ij}$ is the average emigration rate from country i to country j. Keeping total bilateral migration levels constant, the NS counterfactual scenario allows us to isolate the impact of positive selection in migration on the average net income per worker.

The effect of selection is positive in a large majority of countries. Its distribution, shown in Panel D.1a, is right skewed which implies that a majority of individuals benefit somewhat from the selection in emigration. The peak of the density is around 0.7% and below the one observed in Figure 3 which shows the joint effect of the size and skill-composition of emigration. The lower positive effects of selection are driven by market size and fiscal externalities. The skill bias in emigration reduces market size and decreases the tax base, thus increasing the ideal price index and tax rates. Schooling externalities only depend on human capital differentials between emigrants and non-leavers and hence this channel generates similar effects in the NS and NM scenarios. In contrast, diaspora externalities are not affected in the no-selection scenario because they are insensitive to the selection of migrants and only depend on the size of emigrant flows (which remain constant in the NS counterfactual). By assumption, selection alone does not impact remittances either, as we assume that college-educated and less-educated migrants send the same amount of remittances, in line with Bollard et al. (2011). Hence, in comparison to the no-migration scenario, selection by itself generate similar "brain gain" responses but does not affect diaspora externalities nor remittances.

Panel D.1b compares the income response of the observed selection with the counterfactual no-selection income level (in logs), in a setting where only the origin country wages are assumed to be endogenous. The fitted line is decreasing and intersects with zero at an income level around USD 8,000. With some exceptions, this implies that emigrants' selection increases the level of income per worker at low levels of development, and is detrimental in richer countries. The average gain for poor countries is smaller than the gain from migration (around one third of the total effect of migration), and can only be due to the greater incentive to acquire human capital. The income loss at higher levels of development is governed by the human capital flight and the negative fiscal and market size externalities. There is more variability in the response to selection on disposable income per worker. By contrast, the isolated effect of migrant selection on income per natural is similar to that of the no-migration scenario, as shown in Panel D.1d.

Overall, the average effect of selection is positive, but smaller than the effect of migration intensity (see panel D.1c). This result is highly robust to the parameter set of the conservative variant of our model. Panel D.1c shows that selection alone generates more than one-third (0.8%) of the total effects of migration (1.9%). Contrary to the NM scenario, the changes in income generated in our NS scenario are only governed by the reallocation of college graduates and less-educated workers, given that population sizes do not change. The pure income effects are smaller given that population sizes remain constant and the NS scenario only affects part of the channels that drive the total effect of the NM scenario. In particular, remittances and diaspora externalities are not affected by selection per se. Market size and fiscal externalities vary between the NM and NS scenarios whereas schooling externalities are identical. Our results differ somewhat from those in Biavaschi et al. (2020). They use a different modelling framework with lower human capital responses and find that selection increases average welfare of never-migrants by 0.63%, which represents roughly 1/6 of their average total migration effect. The fact that they focus on never-migrants, which is a constant reference population, also disregards population composition effects that our *per worker* measure takes into account. The NS counterfactual gives a rough proxy of the share of the total effect that is generated by the human capital mechanism. This share is low in the short-term, and larger in the long-term (between one fourth and one half depending on the income group). The residual share of the long-term gains from migration is governed by the diaspora and remittance mechanisms, which are independent of the skill selection of emigrants. Panel D.1d details the average effects of the NM and NS scenarios on income per worker and income per natural by country income group.

Figure D.1: Impact of selection per se (NS)

(a) Benchmark

(b) Convergence: $(y_i - y_i^{NS})/y_i^{NS} vs. y_i^{NS}$

(c) Average response NM vs. NS

(d) Selection vs. total migration

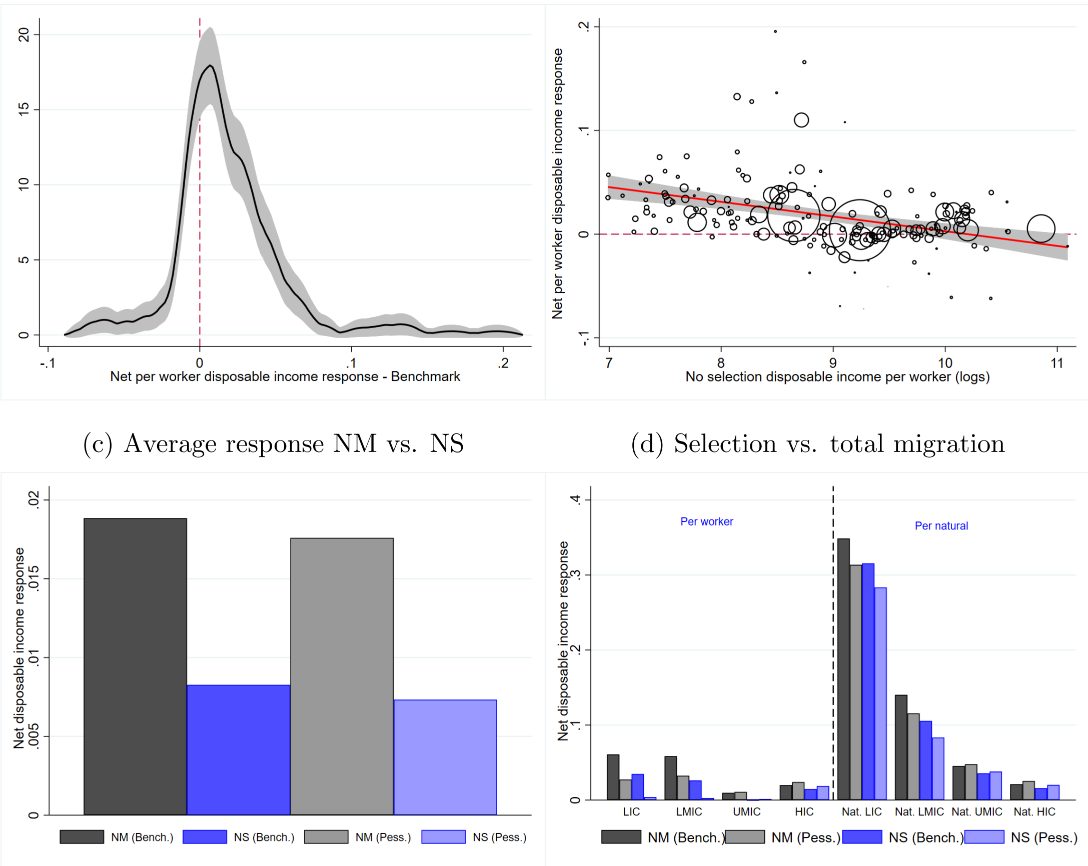
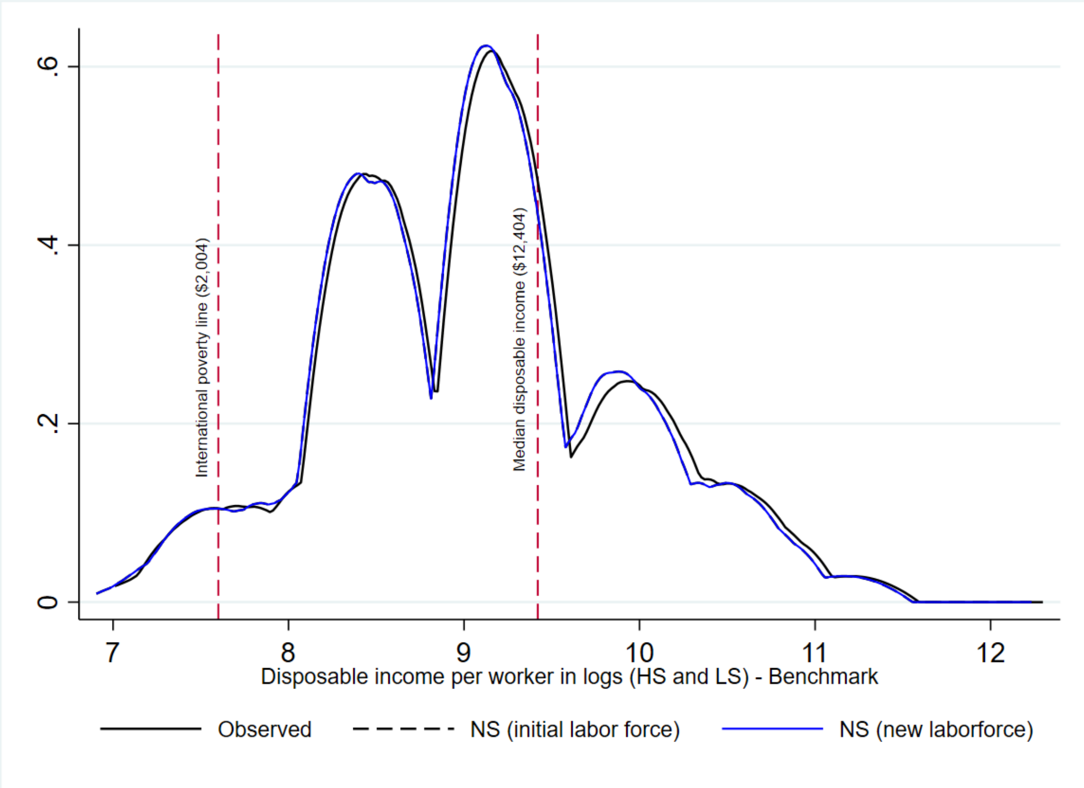


Figure D.2 compares the observed world distribution of income to the one obtained under the counterfactual no-selection (NS) scenario. Selection by itself shifts the density to the right, both at low income levels and at levels above the median.

Figure D.2: Selection and world distribution of income



E Quantitative Results by Country

Tables E.1, E.2 and E.3 provide country-level human capital responses to selective emigration for the no-migration simulations obtained with the empirical estimations and the micro-founded model respectively. Results are shown for the benchmark and conservative scenarios. Tables E.4, E.5 and E.6 detail the welfare implications at the country-level. They show the country-level change in net income for the benchmark and conservative scenarios. In addition, they disentangle the relative impact of each externality for the simulations under the benchmark scenario.

Table E.1: Human capital response to skill biased emigration (1/3)

	Observation				NM (Econometric approach)				NM (Micro-founded approach)				
					Long run		Short run			Long run		Short run	
ISO	Λ	H	h	$m_h - m_l$	h	Δh	h	Δh	Λ	h	Δh	h	Δh
AFG	3.141	0.083	0.078	0.057	0.069	0.009	0.077	0.002	2.960	0.069	0.009	0.077	0.002
AGO	3.338	0.036	0.030	0.187	0.020	0.010	0.029	0.001	2.699	0.022	0.008	0.030	0.000
ALB	2.601	0.091	0.078	0.108	0.091	-0.012	0.091	-0.012	2.212	0.081	-0.003	0.081	-0.003
ARE	2.085	0.157	0.157	0.002	0.157	0.000	0.157	0.000	2.081	0.157	0.000	0.157	0.000
ARG	1.923	0.121	0.114	0.066	0.121	-0.007	0.121	-0.007	1.795	0.112	0.002	0.112	0.002
ARM	2.443	0.207	0.191	0.094	0.207	-0.016	0.207	-0.016	2.205	0.192	-0.001	0.192	-0.001
AUS	1.213	0.301	0.296	0.026	0.301	-0.006	0.301	-0.006	1.181	0.263	0.033	0.263	0.033
AUT	1.243	0.229	0.223	0.031	0.229	-0.006	0.229	-0.006	1.203	0.197	0.026	0.197	0.026
AZE	2.349	0.136	0.132	0.035	0.136	-0.004	0.136	-0.004	2.266	0.133	0.000	0.133	0.000
BDI	3.736	0.015	0.011	0.218	0.007	0.004	0.011	0.000	2.917	0.007	0.004	0.011	0.001
BEL	1.238	0.312	0.307	0.022	0.312	-0.005	0.312	-0.005	1.209	0.280	0.026	0.280	0.026
BEN	3.581	0.017	0.014	0.181	0.009	0.004	0.013	0.001	2.931	0.011	0.003	0.014	0.000
BFA	3.266	0.010	0.009	0.085	0.008	0.002	0.009	0.000	2.988	0.008	0.001	0.010	0.000
BGD	2.887	0.076	0.074	0.030	0.069	0.005	0.073	0.001	2.801	0.070	0.004	0.074	0.000
BGR	1.271	0.199	0.199	-0.004	0.199	0.001	0.199	0.001	1.278	0.202	-0.003	0.202	-0.003
BHR	2.105	0.183	0.180	0.019	0.183	-0.003	0.183	-0.003	2.065	0.180	0.000	0.180	0.000
BHS	2.919	0.147	0.110	0.256	0.147	-0.036	0.147	-0.036	2.106	0.117	-0.007	0.117	-0.007
BIH	2.586	0.096	0.085	0.102	0.096	-0.011	0.096	-0.011	2.266	0.087	-0.002	0.087	-0.002
BLR	1.632	0.179	0.173	0.041	0.179	-0.006	0.179	-0.006	1.563	0.167	0.006	0.167	0.006
BLZ	3.713	0.145	0.097	0.297	0.145	-0.049	0.145	-0.049	2.337	0.114	-0.017	0.114	-0.017
BOL	1.607	0.142	0.143	-0.008	0.145	-0.003	0.143	0.000	1.621	0.151	-0.009	0.145	-0.003
BRA	3.567	0.095	0.094	0.021	0.095	-0.002	0.095	-0.002	3.493	0.095	-0.001	0.095	-0.001
BRB	3.812	0.191	0.115	0.339	0.191	-0.076	0.191	-0.076	2.106	0.136	-0.021	0.136	-0.021
BRN	2.021	0.137	0.129	0.069	0.137	-0.008	0.137	-0.008	1.879	0.127	0.002	0.127	0.002
BTN	3.077	0.055	0.052	0.052	0.046	0.006	0.051	0.001	2.915	0.048	0.004	0.052	0.000
BWA	3.086	0.044	0.043	0.032	0.044	-0.001	0.044	-0.001	2.988	0.044	-0.001	0.044	-0.001
CAF	3.891	0.013	0.010	0.246	0.006	0.004	0.009	0.000	2.931	0.006	0.004	0.009	0.000
CAN	1.172	0.498	0.497	0.003	0.498	-0.001	0.498	-0.001	1.168	0.489	0.008	0.489	0.008
CHE	1.552	0.217	0.209	0.045	0.217	-0.008	0.217	-0.008	1.478	0.197	0.012	0.197	0.012
CHL	2.033	0.137	0.133	0.032	0.137	-0.004	0.137	-0.004	1.967	0.133	0.001	0.133	0.001
CHN	1.360	0.082	0.081	0.018	0.082	-0.001	0.082	-0.001	1.336	0.078	0.003	0.078	0.003
CIV	3.339	0.042	0.038	0.104	0.030	0.008	0.037	0.001	2.988	0.033	0.005	0.038	0.000
CMR	3.779	0.038	0.030	0.207	0.019	0.011	0.029	0.001	2.988	0.023	0.007	0.031	-0.001
COG	3.147	0.051	0.049	0.050	0.044	0.005	0.048	0.001	2.988	0.046	0.003	0.049	0.000
COL	2.974	0.171	0.168	0.022	0.171	-0.003	0.171	-0.003	2.908	0.169	-0.001	0.169	-0.001
COM	3.838	0.049	0.038	0.202	0.025	0.013	0.037	0.001	2.988	0.025	0.013	0.037	0.002
CPV	4.569	0.049	0.028	0.291	0.019	0.009	0.033	-0.005	2.567	0.015	0.013	0.031	-0.003
CRI	2.048	0.159	0.155	0.030	0.159	-0.004	0.159	-0.004	1.985	0.154	0.001	0.154	0.001
CUB	2.808	0.121	0.096	0.210	0.061	0.034	0.092	0.004	2.152	0.050	0.046	0.085	0.010
CYP	1.825	0.309	0.300	0.036	0.309	-0.009	0.309	-0.009	1.748	0.292	0.007	0.292	0.007
CZE	1.139	0.148	0.143	0.044	0.148	-0.006	0.148	-0.006	1.087	0.097	0.045	0.097	0.045
DEU	1.222	0.277	0.271	0.027	0.277	-0.006	0.277	-0.006	1.188	0.241	0.030	0.241	0.030
DJI	3.432	0.029	0.022	0.231	0.014	0.009	0.021	0.001	2.633	0.015	0.007	0.022	0.000
DNK	1.387	0.228	0.219	0.053	0.228	-0.010	0.228	-0.010	1.311	0.194	0.025	0.194	0.025
DOM	1.823	0.146	0.139	0.049	0.146	-0.007	0.146	-0.007	1.720	0.136	0.004	0.136	0.004
DZA	2.757	0.112	0.104	0.073	0.088	0.016	0.101	0.002	2.544	0.088	0.016	0.102	0.002
ECU	1.916	0.173	0.172	0.006	0.170	0.002	0.172	0.000	1.904	0.167	0.005	0.171	0.001
EGY	2.290	0.130	0.126	0.037	0.116	0.010	0.124	0.002	2.205	0.113	0.013	0.123	0.003
ERI	4.072	0.031	0.022	0.276	0.013	0.010	0.021	0.001	2.916	0.013	0.009	0.021	0.001
ESP	1.379	0.186	0.184	0.014	0.186	-0.002	0.186	-0.002	1.359	0.179	0.005	0.179	0.005
EST	1.547	0.312	0.309	0.014	0.312	-0.003	0.312	-0.003	1.524	0.303	0.005	0.303	0.005
ETH	3.270	0.027	0.025	0.086	0.021	0.004	0.024	0.001	2.988	0.021	0.004	0.024	0.001
FIN	1.520	0.385	0.391	-0.022	0.385	0.005	0.385	0.005	1.555	0.402	-0.011	0.402	-0.011
FJI	4.133	0.191	0.124	0.317	0.068	0.056	0.126	-0.002	2.480	0.060	0.063	0.121	0.003
FRA	1.407	0.233	0.226	0.036	0.233	-0.007	0.233	-0.007	1.355	0.211	0.015	0.211	0.015
FSM	2.698	0.148	0.138	0.058	0.148	-0.010	0.148	-0.010	2.484	0.141	-0.003	0.141	-0.003
GAB	2.795	0.054	0.044	0.187	0.030	0.015	0.042	0.002	2.266	0.028	0.017	0.042	0.003
GBR	1.529	0.256	0.243	0.064	0.256	-0.013	0.256	-0.013	1.426	0.221	0.022	0.221	0.022

Table E.2: Human capital response to skill biased emigration (2/3)

	Observation				NM (Econometric approach)				NM (Micro-founded approach)				
					Long run		Short run			Long run		Short run	
ISO	Λ	H	h	$m_h - m_l$	h	Δh	h	Δh	Λ	h	Δ h	h	Δ h
GEO	1.716	0.483	0.490	-0.024	0.483	0.006	0.483	0.006	1.760	0.500	-0.011	0.500	-0.011
GHA	2.916	0.058	0.048	0.171	0.033	0.015	0.046	0.002	2.408	0.033	0.015	0.046	0.002
GIN	3.344	0.028	0.025	0.105	0.020	0.005	0.024	0.001	2.988	0.020	0.005	0.024	0.001
GMB	3.769	0.050	0.039	0.221	0.024	0.014	0.037	0.001	2.898	0.029	0.010	0.040	-0.001
GNB	4.968	0.018	0.011	0.381	0.005	0.006	0.011	0.000	2.988	0.006	0.005	0.011	0.000
GNQ	3.045	0.056	0.047	0.215	0.058	-0.012	0.058	-0.012	2.489	0.050	-0.004	0.050	-0.004
GRC	1.294	0.185	0.183	0.009	0.185	-0.002	0.185	-0.002	1.281	0.179	0.005	0.179	0.005
GRD	4.795	0.202	0.110	0.303	0.202	-0.092	0.202	-0.092	2.348	0.147	-0.036	0.147	-0.036
GTM	3.522	0.053	0.050	0.053	0.053	-0.003	0.053	-0.003	3.316	0.052	-0.002	0.052	-0.002
GUY	7.049	0.210	0.094	0.361	0.065	0.029	0.131	-0.037	2.744	0.050	0.044	0.119	-0.025
HND	4.231	0.062	0.053	0.138	0.040	0.013	0.052	0.001	3.574	0.047	0.006	0.056	-0.003
HRV	2.285	0.139	0.137	0.016	0.139	-0.002	0.139	-0.002	2.243	0.137	0.000	0.137	0.000
HTI	6.158	0.059	0.029	0.466	0.013	0.016	0.032	-0.003	2.978	0.014	0.016	0.031	-0.002
HUN	1.469	0.139	0.129	0.084	0.139	-0.010	0.139	-0.010	1.342	0.111	0.018	0.111	0.018
IDN	2.694	0.067	0.066	0.015	0.067	-0.001	0.067	-0.001	2.653	0.066	0.000	0.066	0.000
IND	2.787	0.084	0.081	0.039	0.074	0.007	0.080	0.001	2.677	0.075	0.006	0.081	0.001
IRL	1.480	0.394	0.401	-0.022	0.394	0.007	0.394	0.007	1.521	0.416	-0.016	0.416	-0.016
IRN	2.698	0.126	0.119	0.068	0.126	-0.008	0.126	-0.008	2.513	0.121	-0.002	0.121	-0.002
IRQ	2.491	0.154	0.147	0.051	0.130	0.017	0.144	0.003	2.360	0.128	0.019	0.143	0.004
ISL	1.904	0.326	0.304	0.088	0.326	-0.022	0.326	-0.022	1.722	0.287	0.016	0.287	0.016
ISR	1.341	0.323	0.313	0.042	0.323	-0.010	0.323	-0.010	1.282	0.280	0.034	0.280	0.034
ITA	1.458	0.111	0.108	0.037	0.111	-0.004	0.111	-0.004	1.402	0.102	0.006	0.102	0.006
JAM	4.207	0.219	0.154	0.239	0.101	0.053	0.160	-0.006	2.733	0.091	0.064	0.155	0.000
JOR	2.045	0.225	0.217	0.043	0.225	-0.008	0.225	-0.008	1.956	0.215	0.002	0.215	0.002
JPN	1.408	0.333	0.331	0.007	0.333	-0.002	0.333	-0.002	1.398	0.327	0.004	0.327	0.004
KAZ	1.864	0.227	0.233	-0.028	0.227	0.005	0.227	0.005	1.921	0.235	-0.002	0.235	-0.002
KEN	3.772	0.037	0.030	0.208	0.019	0.011	0.028	0.001	2.983	0.023	0.007	0.031	-0.001
KGZ	1.927	0.111	0.110	0.014	0.106	0.004	0.109	0.001	1.900	0.103	0.007	0.108	0.002
KHM	3.859	0.026	0.020	0.248	0.012	0.008	0.019	0.001	2.871	0.014	0.005	0.021	-0.001
KWT	1.995	0.175	0.164	0.074	0.175	-0.011	0.175	-0.011	1.846	0.161	0.003	0.161	0.003
LAO	3.642	0.062	0.049	0.213	0.031	0.017	0.047	0.002	2.801	0.035	0.014	0.050	-0.001
LBN	2.671	0.198	0.170	0.153	0.198	-0.028	0.198	-0.028	2.217	0.174	-0.004	0.174	-0.004
LBR	7.684	0.025	0.010	0.602	0.004	0.006	0.011	-0.002	2.933	0.004	0.005	0.012	-0.002
LBY	2.339	0.105	0.099	0.065	0.085	0.014	0.097	0.002	2.184	0.081	0.018	0.095	0.004
LCA	3.310	0.176	0.148	0.143	0.176	-0.028	0.176	-0.028	2.696	0.158	-0.010	0.158	-0.010
LKA	3.300	0.089	0.078	0.134	0.089	-0.011	0.089	-0.011	2.848	0.083	-0.005	0.083	-0.005
LSO	3.019	0.044	0.043	0.010	0.042	0.001	0.043	0.000	2.988	0.043	0.001	0.043	0.000
LTU	1.673	0.387	0.405	-0.069	0.387	0.018	0.387	0.018	1.806	0.429	-0.024	0.429	-0.024
LUX	1.290	0.232	0.221	0.059	0.232	-0.011	0.232	-0.011	1.209	0.179	0.042	0.179	0.042
LVA	1.718	0.299	0.285	0.062	0.299	-0.014	0.299	-0.014	1.606	0.270	0.015	0.270	0.015
MAR	3.421	0.070	0.055	0.204	0.036	0.019	0.053	0.001	2.640	0.037	0.017	0.054	0.000
MDA	2.205	0.145	0.122	0.173	0.083	0.039	0.116	0.006	1.796	0.053	0.068	0.098	0.024
MDG	3.721	0.023	0.018	0.195	0.012	0.006	0.018	0.001	2.988	0.013	0.006	0.018	0.001
MDV	2.280	0.045	0.042	0.056	0.045	-0.002	0.045	-0.002	2.151	0.043	0.000	0.043	0.000
MEX	2.777	0.116	0.121	-0.040	0.116	0.005	0.116	0.005	2.906	0.119	0.002	0.119	0.002
MKD	1.893	0.106	0.110	-0.033	0.106	0.004	0.106	0.004	1.967	0.111	-0.001	0.111	-0.001
MLI	4.088	0.008	0.006	0.266	0.003	0.003	0.006	0.000	2.988	0.004	0.002	0.006	0.000
MLT	2.224	0.190	0.179	0.055	0.190	-0.011	0.190	-0.011	2.063	0.178	0.001	0.178	0.001
MMR	2.950	0.105	0.104	0.012	0.101	0.003	0.104	0.000	2.915	0.102	0.002	0.104	0.000
MNG	2.987	0.102	0.098	0.039	0.090	0.009	0.097	0.001	2.869	0.092	0.006	0.098	0.000
MOZ	4.961	0.008	0.005	0.395	0.002	0.003	0.005	0.000	2.988	0.004	0.002	0.006	-0.001
MRT	3.044	0.063	0.060	0.040	0.055	0.005	0.060	0.001	2.919	0.057	0.004	0.060	0.000
MUS	6.119	0.072	0.029	0.594	0.074	-0.045	0.074	-0.045	2.352	0.049	-0.020	0.049	-0.020
MWI	3.464	0.012	0.011	0.132	0.008	0.003	0.010	0.000	3.005	0.008	0.002	0.010	0.000
MYS	2.604	0.168	0.159	0.060	0.168	-0.008	0.168	-0.008	2.448	0.161	-0.002	0.161	-0.002
NAM	3.125	0.061	0.059	0.044	0.061	-0.003	0.061	-0.003	2.988	0.060	-0.001	0.060	-0.001
NER	3.316	0.008	0.007	0.099	0.006	0.001	0.007	0.000	2.988	0.006	0.001	0.007	0.000
NGA	3.139	0.092	0.088	0.048	0.079	0.009	0.086	0.002	2.988	0.082	0.006	0.088	0.000
NIC	2.802	0.098	0.082	0.165	0.058	0.025	0.079	0.003	2.304	0.053	0.029	0.077	0.005

Table E.3: Human capital response to skill biased emigration (3/3)

	Observation				NM (Econometric approach)				NM (Micro-founded approach)				
					Long run		Short run			Long run		Short run	
ISO	Λ	H	h	$m_h - m_l$	h	Δh	h	Δh	Λ	h	Δh	h	Δh
NLD	1.352	0.250	0.241	0.043	0.250	-0.009	0.250	-0.009	1.291	0.216	0.025	0.216	0.025
NOR	1.109	0.283	0.277	0.026	0.283	-0.005	0.283	-0.005	1.079	0.211	0.066	0.211	0.066
NPL	3.206	0.039	0.035	0.103	0.028	0.007	0.034	0.001	2.874	0.030	0.005	0.036	0.000
NZL	1.210	0.316	0.307	0.035	0.316	-0.009	0.316	-0.009	1.161	0.252	0.055	0.252	0.055
OMN	2.075	0.156	0.155	0.003	0.156	0.000	0.156	0.000	2.070	0.155	0.000	0.155	0.000
PAK	2.420	0.048	0.043	0.106	0.034	0.009	0.041	0.001	2.161	0.031	0.012	0.040	0.002
PAN	2.378	0.186	0.171	0.095	0.186	-0.015	0.186	-0.015	2.142	0.171	0.000	0.171	0.000
PER	1.919	0.204	0.197	0.039	0.204	-0.007	0.204	-0.007	1.841	0.195	0.003	0.195	0.003
PHL	2.444	0.294	0.276	0.079	0.228	0.049	0.265	0.011	2.245	0.216	0.060	0.260	0.016
PNG	2.892	0.147	0.144	0.022	0.137	0.007	0.143	0.001	2.827	0.139	0.005	0.144	0.001
POL	1.556	0.191	0.177	0.085	0.191	-0.015	0.191	-0.015	1.413	0.156	0.020	0.156	0.020
PRT	1.892	0.114	0.116	-0.011	0.114	0.001	0.114	0.001	1.916	0.116	0.000	0.116	0.000
PRY	2.092	0.112	0.110	0.022	0.104	0.005	0.109	0.001	2.046	0.101	0.008	0.108	0.002
QAT	1.992	0.169	0.168	0.007	0.169	-0.001	0.169	-0.001	1.978	0.168	0.000	0.168	0.000
ROM	2.604	0.139	0.127	0.091	0.139	-0.013	0.139	-0.013	2.336	0.129	-0.003	0.129	-0.003
RWA	4.470	0.010	0.007	0.325	0.003	0.003	0.006	0.000	3.014	0.005	0.002	0.007	-0.001
SAU	2.085	0.220	0.218	0.011	0.220	-0.002	0.220	-0.002	2.062	0.218	0.000	0.218	0.000
SDN	3.147	0.050	0.048	0.050	0.042	0.005	0.047	0.001	2.988	0.044	0.003	0.048	0.000
SEN	3.900	0.036	0.028	0.226	0.017	0.011	0.027	0.001	2.988	0.021	0.007	0.029	-0.001
SGP	2.441	0.463	0.458	0.020	0.463	-0.005	0.463	-0.005	2.391	0.457	0.002	0.457	0.002
SLB	3.032	0.146	0.143	0.023	0.135	0.007	0.141	0.001	2.963	0.138	0.005	0.142	0.000
SLE	4.248	0.036	0.025	0.292	0.014	0.011	0.024	0.001	2.988	0.015	0.010	0.024	0.001
SLV	2.425	0.094	0.087	0.060	0.077	0.010	0.087	0.000	2.228	0.069	0.018	0.083	0.004
SOM	4.158	0.037	0.027	0.267	0.016	0.011	0.026	0.001	2.988	0.016	0.011	0.026	0.001
SRB	2.378	0.129	0.128	0.010	0.125	0.003	0.128	0.000	2.352	0.124	0.004	0.127	0.001
STP	8.706	0.035	0.011	0.624	0.005	0.007	0.015	-0.004	2.988	0.008	0.003	0.019	-0.008
SUR	3.869	0.117	0.070	0.324	0.117	-0.047	0.117	-0.047	2.372	0.085	-0.015	0.085	-0.015
SVK	1.302	0.135	0.123	0.097	0.135	-0.013	0.135	-0.013	1.164	0.082	0.041	0.082	0.041
SVN	1.339	0.160	0.158	0.014	0.160	-0.002	0.160	-0.002	1.320	0.153	0.005	0.153	0.005
SWE	1.217	0.320	0.313	0.030	0.320	-0.007	0.320	-0.007	1.180	0.273	0.040	0.273	0.040
SWZ	2.741	0.077	0.074	0.031	0.069	0.005	0.073	0.001	2.655	0.070	0.004	0.074	0.000
SYR	2.295	0.091	0.087	0.055	0.091	-0.005	0.091	-0.005	2.167	0.087	0.000	0.087	0.000
TCD	2.224	0.011	0.010	0.081	0.009	0.002	0.010	0.000	2.044	0.007	0.003	0.009	0.001
TGO	3.241	0.063	0.059	0.077	0.049	0.009	0.057	0.001	2.988	0.050	0.009	0.057	0.002
THA	2.173	0.119	0.117	0.010	0.119	-0.001	0.119	-0.001	2.151	0.118	0.000	0.118	0.000
TJK	2.349	0.094	0.094	0.005	0.093	0.001	0.094	0.000	2.336	0.093	0.001	0.094	0.000
TKM	2.360	0.105	0.104	0.010	0.105	-0.001	0.105	-0.001	2.336	0.104	0.000	0.104	0.000
TON	4.532	0.133	0.076	0.269	0.133	-0.057	0.133	-0.057	2.483	0.100	-0.024	0.100	-0.024
TTO	4.822	0.152	0.072	0.506	0.152	-0.080	0.152	-0.080	2.266	0.100	-0.028	0.100	-0.028
TUN	2.838	0.105	0.096	0.086	0.105	-0.009	0.105	-0.009	2.577	0.099	-0.003	0.099	-0.003
TUR	2.390	0.088	0.088	0.007	0.088	-0.001	0.088	-0.001	2.372	0.088	0.000	0.088	0.000
TZA	3.803	0.012	0.009	0.214	0.006	0.003	0.009	0.000	2.988	0.006	0.003	0.009	0.000
UGA	3.526	0.029	0.024	0.152	0.018	0.007	0.024	0.001	2.988	0.020	0.004	0.025	-0.001
UKR	1.924	0.175	0.164	0.073	0.175	-0.011	0.175	-0.011	1.779	0.160	0.004	0.160	0.004
URY	1.894	0.121	0.112	0.082	0.121	-0.009	0.121	-0.009	1.731	0.109	0.004	0.109	0.004
USA	1.424	0.316	0.314	0.009	0.316	-0.002	0.316	-0.002	1.411	0.309	0.005	0.309	0.005
UZB	2.492	0.082	0.078	0.053	0.082	-0.004	0.082	-0.004	2.360	0.079	-0.001	0.079	-0.001
VCT	4.497	0.191	0.121	0.280	0.191	-0.071	0.191	-0.071	2.613	0.152	-0.031	0.152	-0.031
VEN	1.955	0.209	0.201	0.047	0.209	-0.008	0.209	-0.008	1.861	0.198	0.003	0.198	0.003
VNM	3.102	0.072	0.065	0.107	0.051	0.014	0.063	0.002	2.761	0.054	0.011	0.064	0.000
VUT	3.189	0.037	0.029	0.219	0.018	0.011	0.028	0.001	2.478	0.019	0.010	0.029	0.001
WSM	4.011	0.124	0.077	0.264	0.053	0.024	0.087	-0.011	2.477	0.039	0.037	0.076	0.000
YEM	2.930	0.136	0.135	0.003	0.134	0.001	0.135	0.000	2.920	0.135	0.001	0.135	0.000
ZAF	3.809	0.052	0.041	0.214	0.052	-0.011	0.052	-0.011	2.988	0.047	-0.006	0.047	-0.006
ZAR	3.895	0.036	0.028	0.232	0.017	0.011	0.027	0.001	2.988	0.018	0.010	0.027	0.001
ZMB	3.375	0.046	0.041	0.114	0.032	0.009	0.040	0.001	2.988	0.033	0.009	0.040	0.001
ZWE	4.398	0.056	0.039	0.316	0.020	0.019	0.037	0.002	2.988	0.022	0.017	0.037	0.001

Table E.4: Welfare implications for those left behind (1/3)

		Net dispo. income response		Channels under benchmark scenario					
ISO	$m_h - m_l$	Bench.	Pess. view	Hum cap.	Tech. ext.	Dias. ext.	Fis. ext.	Mkt. size	Rem.
AFG	5.7%	4.4%	1.6%	2.9%	0.6%	0.7%	-0.1%	-0.5%	0.9%
AGO	18.7%	3.8%	0.0%	2.5%	1.2%	0.9%	-0.1%	-0.7%	0.1%
ALB	10.8%	10.8%	11.5%	-0.5%	-0.2%	4.4%	-1.6%	-6.6%	15.2%
ARE	0.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
ARG	6.6%	0.5%	0.6%	0.3%	0.1%	0.7%	-0.1%	-0.5%	0.2%
ARM	9.4%	5.5%	5.3%	-0.1%	0.0%	1.5%	-0.3%	-1.4%	5.8%
AUS	2.6%	2.8%	4.1%	1.0%	1.3%	0.6%	0.0%	-0.5%	0.5%
AUT	3.1%	3.8%	4.8%	0.9%	1.1%	1.2%	-0.3%	-1.1%	2.0%
AZE	3.5%	2.3%	2.2%	-0.1%	0.0%	0.4%	0.0%	-0.3%	2.4%
BDI	21.8%	4.5%	1.5%	1.6%	1.9%	0.2%	-0.1%	-0.2%	0.9%
BEL	2.2%	7.5%	8.2%	0.8%	1.0%	1.2%	-0.3%	-1.0%	5.8%
BEN	18.1%	3.6%	1.1%	1.1%	1.0%	0.2%	0.0%	-0.1%	1.5%
BFA	8.5%	1.9%	0.9%	0.4%	0.5%	0.1%	0.0%	-0.1%	1.0%
BGD	3.0%	8.3%	7.0%	1.0%	0.2%	0.2%	0.0%	-0.1%	7.1%
BGR	-0.4%	1.9%	1.8%	-0.1%	-0.1%	2.2%	-0.5%	-2.3%	2.7%
BHR	1.9%	0.1%	0.1%	0.0%	0.0%	0.2%	0.0%	-0.2%	0.0%
BHS	25.6%	-2.1%	-2.1%	-1.0%	-0.4%	2.5%	-0.4%	-2.8%	0.0%
BIH	10.2%	6.4%	6.4%	-0.4%	-0.1%	3.4%	-1.4%	-4.4%	9.4%
BLR	4.1%	1.4%	1.7%	0.5%	0.3%	0.8%	-0.2%	-0.7%	0.7%
BLZ	29.7%	-2.3%	-2.2%	-3.0%	-0.9%	3.9%	-2.7%	-5.7%	6.1%
BOL	-0.8%	2.6%	3.2%	-0.7%	-0.4%	1.2%	-0.5%	-1.1%	4.1%
BRA	2.1%	-0.1%	-0.2%	-0.3%	-0.1%	0.2%	-0.1%	-0.2%	0.3%
BRB	33.9%	-6.5%	-5.7%	-2.9%	-1.0%	4.4%	-3.3%	-7.2%	3.5%
BRN	6.9%	0.4%	0.4%	0.2%	0.1%	0.8%	-0.1%	-0.6%	0.0%
BTN	5.2%	2.0%	0.4%	1.2%	0.3%	0.4%	-0.1%	-0.3%	0.4%
BWA	3.2%	0.0%	0.0%	-0.2%	-0.1%	0.1%	0.0%	-0.1%	0.3%
CAF	24.6%	3.8%	0.6%	1.5%	2.2%	0.3%	0.0%	-0.2%	0.0%
CAN	0.3%	0.7%	1.0%	0.2%	0.3%	1.1%	-0.2%	-1.0%	0.2%
CHE	4.5%	2.7%	3.2%	0.8%	0.5%	1.7%	-0.4%	-1.6%	1.7%
CHL	3.2%	0.2%	0.2%	0.1%	0.0%	0.7%	-0.1%	-0.5%	0.0%
CHN	1.8%	1.0%	1.2%	0.1%	0.2%	0.1%	0.0%	-0.1%	0.6%
CIV	10.4%	3.9%	1.4%	1.7%	0.5%	0.5%	-0.1%	-0.3%	1.7%
CMR	20.7%	4.2%	0.1%	2.5%	0.9%	0.5%	-0.1%	-0.4%	0.8%
COG	5.0%	1.9%	0.5%	1.1%	0.3%	0.4%	-0.1%	-0.3%	0.5%
COL	2.2%	1.3%	1.1%	-0.3%	-0.1%	1.0%	-0.2%	-0.8%	1.7%
COM	20.2%	38.4%	29.9%	5.2%	1.4%	2.3%	-0.6%	-2.2%	32.4%
CPV	29.1%	14.8%	6.9%	4.3%	2.5%	5.3%	-4.2%	-8.1%	15.1%
CRI	3.0%	1.7%	1.7%	0.1%	0.0%	0.9%	-0.3%	-0.7%	1.7%
CUB	21.0%	10.2%	0.6%	10.3%	3.0%	3.0%	-3.1%	-2.9%	0.0%
CYP	3.6%	4.1%	4.6%	0.7%	0.3%	3.0%	-1.5%	-3.5%	5.2%
CZE	4.4%	5.1%	8.0%	1.1%	2.8%	1.0%	-0.2%	-0.8%	1.2%
DEU	2.7%	3.0%	4.2%	0.9%	1.2%	1.3%	-0.3%	-1.1%	1.0%
DJI	23.1%	7.6%	3.3%	2.3%	1.6%	0.5%	-0.1%	-0.4%	3.7%
DNK	5.3%	3.0%	4.0%	1.2%	1.0%	1.1%	-0.4%	-0.9%	1.1%
DOM	4.9%	9.6%	9.9%	0.4%	0.2%	2.9%	-0.4%	-3.3%	9.9%
DZA	7.3%	4.4%	0.6%	3.7%	0.8%	1.8%	-0.4%	-1.6%	0.2%
ECU	0.6%	5.4%	4.8%	0.6%	0.2%	2.1%	-0.5%	-2.1%	5.2%
EGY	3.7%	7.6%	5.1%	2.4%	0.7%	0.3%	0.0%	-0.2%	4.5%
ERI	27.6%	5.8%	0.7%	3.8%	2.0%	1.1%	-0.1%	-0.9%	0.0%
ESP	1.4%	1.8%	2.0%	0.3%	0.2%	0.5%	-0.1%	-0.4%	1.3%
EST	1.4%	2.2%	2.4%	0.4%	0.2%	1.4%	-0.4%	-1.3%	1.9%
ETH	8.6%	2.8%	1.1%	1.5%	0.6%	0.3%	0.0%	-0.2%	0.7%
FIN	-2.2%	-0.7%	-1.1%	-0.7%	-0.4%	1.5%	-0.5%	-1.4%	0.8%
FJI	31.7%	27.2%	5.7%	17.9%	3.4%	5.2%	-2.5%	-6.2%	9.5%
FRA	3.6%	3.4%	3.9%	0.8%	0.6%	0.8%	-0.1%	-0.6%	2.0%
FSM	5.8%	-3.9%	-2.5%	-0.5%	-0.1%	4.3%	-6.6%	-6.4%	5.4%
GAB	18.7%	6.6%	1.6%	4.1%	2.0%	0.7%	-0.1%	-0.5%	0.4%
GBR	6.4%	2.4%	3.3%	1.3%	0.9%	1.7%	-0.5%	-1.5%	0.5%

Table E.5: Welfare implications for those left behind (2/3)

		Net dispo. income response		Channels under benchmark scenario					
ISO	$m_h - m_l$	Bench.	Pess. view	Hum cap.	Tech. ext.	Dias. ext.	Fis. ext.	Mkt. size	Rem.
GEO	-2.4%	5.2%	4.5%	-0.8%	-0.4%	1.3%	-0.2%	-1.2%	6.5%
GHA	17.1%	8.2%	3.2%	4.0%	1.6%	0.8%	-0.2%	-0.6%	2.6%
GIN	10.5%	3.7%	1.5%	1.8%	0.8%	0.4%	0.0%	-0.3%	1.0%
GMB	22.1%	10.2%	4.5%	3.6%	1.0%	1.5%	-0.2%	-1.3%	5.6%
GNB	38.1%	11.1%	5.3%	2.3%	2.9%	1.4%	-0.1%	-1.2%	5.9%
GNQ	21.5%	-1.2%	-1.5%	-0.8%	-0.3%	1.3%	-0.1%	-1.1%	0.0%
GRC	0.9%	1.4%	1.6%	0.2%	0.2%	1.6%	-0.3%	-1.5%	1.2%
GRD	30.3%	-11.2%	-9.6%	-5.9%	-1.7%	5.3%	-3.5%	-10.9%	5.5%
GTM	5.3%	6.4%	6.2%	-0.6%	-0.1%	2.3%	-0.4%	-2.4%	7.6%
GUY	36.1%	33.3%	4.4%	14.6%	2.6%	6.8%	-5.8%	-11.3%	26.4%
HND	13.8%	19.1%	13.3%	2.6%	0.4%	2.6%	-1.0%	-2.7%	17.3%
HRV	1.6%	6.0%	6.0%	0.0%	0.0%	2.7%	-0.8%	-3.0%	7.2%
HTI	46.6%	34.6%	21.0%	6.9%	2.4%	2.9%	-0.5%	-2.9%	25.9%
HUN	8.4%	4.6%	5.5%	1.0%	1.0%	1.2%	-0.3%	-1.0%	2.7%
IDN	1.5%	0.6%	0.5%	-0.1%	0.0%	0.1%	0.0%	-0.1%	0.7%
IND	3.9%	3.5%	1.8%	1.5%	0.3%	0.2%	0.0%	-0.1%	1.7%
IRL	-2.2%	-3.5%	-3.2%	-0.9%	-0.6%	3.4%	-1.7%	-4.5%	0.7%
IRN	6.8%	-0.3%	-0.4%	-0.4%	-0.1%	0.5%	-0.1%	-0.4%	0.3%
IRQ	5.1%	5.2%	1.6%	3.6%	0.9%	1.1%	-0.2%	-0.9%	0.7%
ISL	8.8%	4.0%	4.7%	1.5%	0.6%	2.4%	-1.1%	-2.6%	3.1%
ISR	4.2%	8.1%	9.1%	1.4%	1.3%	1.2%	-0.2%	-1.0%	5.4%
ITA	3.7%	1.5%	1.9%	0.4%	0.4%	1.2%	-0.2%	-1.0%	0.9%
JAM	23.9%	42.8%	17.0%	18.3%	3.2%	6.2%	-5.8%	-8.6%	29.6%
JOR	4.3%	10.4%	10.0%	0.3%	0.1%	0.8%	-0.2%	-0.6%	10.1%
JPN	0.7%	0.5%	0.6%	0.2%	0.2%	0.2%	0.0%	-0.1%	0.1%
KAZ	-2.8%	-0.5%	-0.5%	-0.3%	-0.1%	1.8%	-0.3%	-1.8%	0.1%
KEN	20.8%	5.4%	1.3%	2.5%	0.9%	0.5%	-0.1%	-0.4%	2.1%
KGZ	1.4%	12.2%	10.8%	0.9%	0.4%	0.1%	0.0%	-0.1%	10.9%
KHM	24.8%	4.8%	0.8%	2.0%	1.3%	1.0%	-0.1%	-0.9%	1.4%
KWT	7.4%	0.5%	0.7%	0.4%	0.1%	0.7%	-0.1%	-0.6%	0.0%
LAO	21.3%	6.5%	0.3%	4.5%	1.2%	2.2%	-0.2%	-2.1%	0.9%
LBN	15.3%	33.6%	32.2%	-0.6%	-0.2%	2.7%	-0.3%	-3.0%	35.0%
LBR	60.2%	17.1%	7.1%	2.4%	3.7%	1.2%	-0.1%	-1.0%	10.8%
LBY	6.5%	4.5%	1.2%	3.4%	1.0%	0.8%	-0.1%	-0.6%	0.0%
LCA	14.3%	-3.2%	-2.4%	-2.1%	-0.5%	4.0%	-1.4%	-5.9%	2.7%
LKA	13.4%	3.0%	2.5%	-1.3%	-0.3%	1.0%	-0.1%	-0.9%	4.5%
LSO	1.0%	21.9%	18.8%	0.2%	0.1%	0.0%	0.0%	0.0%	21.6%
LTU	-6.9%	1.5%	0.5%	-2.0%	-0.9%	2.2%	-0.7%	-2.3%	5.2%
LUX	5.9%	18.9%	20.2%	1.6%	1.8%	2.0%	-0.3%	-1.9%	15.6%
LVA	6.2%	8.4%	8.7%	1.2%	0.6%	1.7%	-0.4%	-1.6%	6.9%
MAR	20.4%	13.1%	5.9%	5.3%	1.5%	2.7%	-0.9%	-2.8%	7.4%
MDA	17.3%	39.4%	25.8%	11.5%	4.3%	2.4%	-1.1%	-2.1%	24.3%
MDG	19.5%	6.3%	3.0%	2.4%	1.4%	0.4%	0.0%	-0.3%	2.5%
MDV	5.6%	0.1%	0.0%	-0.1%	0.0%	0.1%	0.0%	-0.1%	0.2%
MEX	-4.0%	2.2%	2.6%	0.5%	0.1%	2.8%	-1.0%	-3.2%	2.9%
MKD	-3.3%	3.9%	4.2%	-0.1%	0.0%	3.1%	-0.8%	-3.7%	5.5%
MLI	26.6%	6.2%	2.8%	0.6%	1.6%	0.5%	-0.1%	-0.4%	3.9%
MLT	5.5%	0.7%	1.8%	0.1%	0.0%	4.1%	-2.8%	-5.8%	5.1%
MMR	1.2%	0.7%	0.1%	0.5%	0.1%	0.1%	0.0%	-0.1%	0.1%
MNG	3.9%	12.6%	10.2%	1.6%	0.3%	0.3%	-0.1%	-0.2%	10.6%
MOZ	39.5%	3.0%	-1.7%	0.7%	2.0%	0.3%	-0.1%	-0.2%	0.3%
MRT	4.0%	1.4%	0.1%	1.1%	0.2%	0.5%	-0.1%	-0.4%	0.0%
MUS	59.4%	-6.1%	-8.1%	-3.6%	-2.6%	2.6%	-0.7%	-3.2%	1.4%
MWI	13.2%	2.4%	0.6%	1.0%	1.1%	0.1%	0.0%	-0.1%	0.2%
MYS	6.0%	0.1%	0.0%	-0.3%	-0.1%	0.5%	-0.1%	-0.4%	0.5%
NAM	4.4%	0.3%	0.2%	-0.4%	-0.1%	0.2%	-0.1%	-0.2%	0.8%
NER	9.9%	3.2%	2.0%	0.5%	1.0%	0.1%	0.0%	0.0%	1.7%
NGA	4.8%	11.1%	8.6%	1.7%	0.3%	0.2%	0.0%	-0.2%	9.0%
NIC	16.5%	19.4%	11.2%	6.8%	2.0%	2.2%	-0.6%	-2.1%	11.1%

Table E.6: Welfare implications for those left behind (3/3)

		Net dispo. income response		Channels under benchmark scenario					
ISO	$m_h - m_l$	Bench.	Pess. view	Hum cap.	Tech. ext.	Dias. ext.	Fis. ext.	Mkt. size	Rem.
NLD	4.3%	2.5%	3.5%	1.1%	1.0%	1.3%	-0.3%	-1.2%	0.6%
NOR	2.6%	4.6%	7.3%	1.4%	2.6%	1.0%	-0.2%	-0.8%	0.7%
NPL	10.3%	15.5%	12.5%	1.7%	0.5%	0.3%	0.0%	-0.2%	13.2%
NZL	3.5%	2.7%	5.3%	1.6%	2.1%	3.0%	-1.5%	-3.4%	0.8%
OMN	0.3%	0.2%	0.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.2%
PAK	10.6%	6.8%	3.8%	2.4%	1.5%	0.4%	0.0%	-0.3%	2.9%
PAN	9.5%	1.5%	1.5%	-0.1%	0.0%	1.6%	-0.3%	-1.5%	1.7%
PER	3.9%	2.2%	2.3%	0.3%	0.1%	1.3%	-0.2%	-1.1%	1.8%
PHL	7.9%	21.7%	12.1%	9.6%	2.5%	1.7%	-0.2%	-1.4%	9.5%
PNG	2.2%	1.7%	0.3%	1.3%	0.3%	0.3%	0.0%	-0.2%	0.1%
POL	8.5%	4.1%	5.2%	1.3%	0.9%	2.2%	-0.7%	-2.3%	2.6%
PRT	-1.1%	1.7%	2.0%	0.0%	0.0%	2.9%	-1.1%	-3.3%	3.3%
PRY	2.2%	4.3%	3.0%	1.3%	0.5%	0.7%	-0.1%	-0.6%	2.5%
QAT	0.7%	1.0%	1.0%	0.0%	0.0%	0.1%	0.0%	-0.1%	1.0%
ROM	9.1%	-0.5%	-0.3%	-0.5%	-0.1%	2.6%	-0.6%	-2.9%	1.0%
RWA	32.5%	3.5%	-0.4%	0.8%	1.7%	0.2%	0.0%	-0.2%	1.0%
SAU	1.1%	0.2%	0.2%	0.0%	0.0%	0.1%	0.0%	-0.1%	0.1%
SDN	5.0%	3.8%	2.3%	1.1%	0.3%	0.2%	0.0%	-0.1%	2.4%
SEN	22.6%	12.9%	7.9%	2.6%	0.9%	1.2%	-0.3%	-1.0%	9.6%
SGP	2.0%	0.3%	0.3%	0.2%	0.1%	0.9%	-0.1%	-0.7%	0.0%
SLB	2.3%	3.3%	1.7%	1.2%	0.2%	0.3%	-0.1%	-0.2%	1.9%
SLE	29.2%	7.4%	1.7%	4.4%	1.8%	0.8%	-0.1%	-0.6%	1.2%
SLV	6.0%	25.4%	21.0%	3.6%	1.1%	4.5%	-2.0%	-6.4%	24.5%
SOM	26.7%	6.3%	0.7%	4.5%	1.7%	1.6%	-0.1%	-1.4%	0.0%
SRB	1.0%	18.1%	16.4%	0.7%	0.2%	1.5%	-0.4%	-1.4%	17.5%
STP	62.4%	1.4%	-7.2%	1.3%	1.4%	3.4%	-2.8%	-4.2%	2.3%
SUR	32.4%	-14.2%	-12.0%	-2.9%	-1.0%	5.0%	-6.4%	-9.1%	0.2%
SVK	9.7%	6.9%	10.0%	1.5%	2.8%	2.4%	-0.6%	-2.4%	3.2%
SVN	1.4%	1.2%	1.4%	0.2%	0.2%	1.2%	-0.3%	-1.1%	0.9%
SWE	3.0%	5.3%	6.7%	1.2%	1.5%	0.9%	-0.2%	-0.7%	2.6%
SWZ	3.1%	4.2%	2.8%	1.1%	0.3%	0.2%	0.0%	-0.1%	2.8%
SYR	5.5%	0.8%	0.8%	-0.1%	0.0%	0.5%	-0.1%	-0.4%	0.9%
TCD	8.1%	3.1%	1.7%	0.7%	2.4%	0.1%	0.0%	0.0%	0.0%
TGO	7.7%	13.2%	9.6%	3.0%	0.6%	0.5%	-0.1%	-0.3%	9.5%
THA	1.0%	0.8%	0.8%	0.0%	0.0%	0.2%	0.0%	-0.2%	0.8%
TJK	0.5%	22.7%	21.8%	0.3%	0.1%	0.0%	0.0%	0.0%	22.4%
TKM	1.0%	0.2%	0.1%	0.0%	0.0%	0.1%	0.0%	-0.1%	0.2%
TON	26.9%	1.8%	2.9%	-4.6%	-1.4%	5.5%	-4.8%	-11.5%	18.7%
TTO	50.6%	-9.0%	-9.3%	-4.5%	-1.7%	3.8%	-1.2%	-5.8%	0.4%
TUN	8.6%	2.3%	2.1%	-0.6%	-0.2%	1.8%	-0.6%	-1.8%	3.7%
TUR	0.7%	0.3%	0.3%	0.0%	0.0%	1.4%	-0.2%	-1.3%	0.4%
TZA	21.4%	4.0%	1.3%	1.3%	1.9%	0.2%	0.0%	-0.1%	0.8%
UGA	15.2%	5.0%	2.2%	1.6%	0.7%	0.3%	0.0%	-0.2%	2.6%
UKR	7.3%	4.2%	4.2%	0.5%	0.2%	1.1%	-0.3%	-0.9%	3.6%
URY	8.2%	0.7%	1.0%	0.4%	0.2%	1.6%	-0.4%	-1.5%	0.4%
USA	0.9%	0.6%	0.8%	0.3%	0.2%	0.2%	0.0%	-0.2%	0.1%
UZB	5.3%	2.4%	2.3%	-0.2%	-0.1%	0.3%	-0.1%	-0.2%	2.7%
VCT	28.0%	-9.5%	-8.4%	-5.9%	-1.4%	4.8%	-4.0%	-9.0%	6.0%
VEN	4.7%	0.4%	0.6%	0.3%	0.1%	0.7%	-0.2%	-0.6%	0.1%
VNM	10.7%	7.3%	3.4%	3.2%	0.7%	0.9%	-0.2%	-0.8%	3.4%
VUT	21.9%	7.3%	2.7%	3.0%	1.8%	0.7%	-0.2%	-0.6%	2.6%
WSM	26.4%	29.4%	14.4%	11.0%	2.7%	6.4%	-6.7%	-10.7%	26.8%
YEM	0.3%	3.4%	3.1%	0.2%	0.0%	0.3%	-0.1%	-0.2%	3.2%
ZAF	21.4%	-1.8%	-2.3%	-1.7%	-0.5%	0.5%	-0.1%	-0.4%	0.5%
ZAR	23.2%	8.4%	3.4%	4.0%	1.5%	0.5%	0.0%	-0.3%	2.8%
ZMB	11.4%	4.5%	1.3%	3.1%	0.8%	0.3%	0.0%	-0.2%	0.5%
ZWE	31.6%	24.9%	15.0%	6.9%	1.8%	1.0%	-0.1%	-0.8%	16.0%