

The *Emigration-Development* Nexus: Recent Advances from the Growth Theory Perspective

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Abstract

Using a growth theory perspective, this paper summarizes the recent advances on the bidirectional links between emigration and development. Taken at face value, the stylized facts suggest that (i) helping poor countries to develop can relax credit constraints and lead to massive migration pressures, and (ii) increasing migration can spur the brain drain and increase global inequality. In terms of policy coherence, this means that development policies could reduce the effectiveness of restrictive immigration policies. Recent studies challenge these views. In this paper, I use a *Migration Accounting* model to show that credit constraints, while relevant for the very poorest countries, only have a limited effect on the upward segment of the migration transition curve. I then use a *Development Accounting* model to show that emigration, albeit skill-biased, is likely to generate positive effects on income per capita in most low-income and middle-income countries. Hence, should there be an inconsistency between policy actions, it is of a different nature: for most developing countries, migration barriers jeopardize the effectiveness of development and cooperation policies.

Keywords: Migration; Economic Development; Credit Constraints; Human Capital; Income Inequality.

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1 Introduction

The relationship between emigration and development has been abundantly studied by economists and social scientists for the last 50 years or so. Causality between

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these variables runs in both directions: development affects emigration, and emigration affects development. Nonetheless, these bidirectional links have mostly been studied separately, and the earlier debates on the *Emigration-Development* nexus have been influenced by two major stylized facts. *First*, we observe an inverted-U shaped relationship between emigration rates and economic development in cross-sectional data, usually referred to as the *migration transition curve* (Zelinsky, 1971; de Haas 2007, 2010a, 2010b; Clemens, 2014; Dao et al., 2018). Economic development thus seems to produce additional emigration from origin countries with income per capita levels below \$5,000 to \$6,000. *Second*, well-educated people exhibit much greater propensity to emigrate than the less educated, and tend to agglomerate in countries/regions with high rewards to skill (Grogger and Hanson, 2011; Belot and Hatton, 2012; Docquier and Rapoport, 2012; Kerr et al., 2016). Positive selection is due to migrants' self-selection (high-skilled people being more responsive to economic opportunities and political conditions abroad, having more transferable skills, having greater ability to gather information or finance emigration costs, etc.), and to the skill-selective immigration policies conducted in the major destination countries. Positive selection decreases with economic development. In low-income countries, the ratio of emigration rates between college graduates and the less educated is around 20 (in high-income countries, this ratio is around 1.2). Emigration thus seems to reduce human capital accumulation and the growth potential of poor countries

Taken at face value, these two stylized facts suggest that development and migration policies should be conducted in an integrated manner. As far as development policies are concerned, the fear is that helping poor countries to develop can generate massive migration pressures (In 2010, approximately two thirds of the world population lived in countries where income per capita was smaller than \$6,000), something considered as undesirable by the host-country citizens/voters, if one believes the opinion poll surveys. As for immigration policies, increasing migration may spur the brain drain and slow down the accumulation of human capital in poor countries, with harmful implications for development, global inequality and extreme poverty.

Using a growth theory perspective, this paper summarizes the recent advances on the interplay between emigration, development, and human capital accumulation. Recent studies challenge the views that development policies generate large migration pressures, or that increasing emigration is harmful for economic development. Regarding the effect of development on emigration, I propose a *Migration Accounting* method to disentangle the main drivers of the migration transition curve. The most common explanation of the increasing segment of this curve is the existence of credit constraints preventing potential migrants in poorer countries from realizing their aspirations. Building on a recent companion paper (Dao et al., 2018), I provide evidence that credit constraints, while highly relevant for the very poorest countries, only have a limited effect on the upward segment of the migration transition curve. As far as policy implications are concerned, the results suggest that in the short run (i.e., for a given skill structure and for a given set of macroeconomic determinants),

a rise in income induces small effects on low-skilled (and average) emigration rates. In the long-run, a rise in income increases the proportion of more mobile high-skilled workers but reduces population growth. Hence, economic development has uncertain long-run effect on the emigration stock: the increasing mobility of workers can be offset by smaller population levels.

As for the effect of emigration on development, I use a *Development Accounting* model à la Jones (2014) to identify the causal effect of emigration on the level of income per capita in the origin country. I start from the traditional view, which highlights the detrimental effect of (skill-biased) emigration on labor productivity and economic growth. Then, I account for three feedback mechanisms investigated in the recent literature: (i) migrants' remittances, (ii) the effect of emigration prospects on the expected return to human capital and on ex-ante education decisions (i.e., before deciding whether to emigrate or stay put), and (iii) the potential for migrants to reduce international transaction costs and facilitate the flows of goods, factors, and knowledge between host and home countries (Docquier and Rapoport, 2012). Overall, accounting for these feedback effects, the quantitative analysis reveals that emigration, albeit skill-biased, is likely to generate positive effects on income per capita in most low-income and middle-income countries.

In short, the existence of bidirectional links between emigration and economic development potentially jeopardizes the effectiveness and coherence of separate policy actions. In particular, most high-income countries spend a fraction of their GDP to promote economic growth in the developing world and, at the same time, conduct increasingly restrictive (or selective) immigration policies to reduce migration inflows. In this context, the fear is that development policies can reduce the effectiveness of immigration barriers. Recent studies support a different view. Should there be an inconsistency between policy actions, it is of a different nature: for most developing countries, migration barriers are likely to reduce the effectiveness of development and cooperation policies.

The rest of this paper is organized as following. Section 2 combines recent databases to describe migration trends by education level over the period 1990-2010. Section 3 summarizes the competing theories that are hypothesized to explain the observed inverted-U relationship between development and emigration, and to assess the role of financial constraints. Section 4 discusses the causal impact of the size and skill structure of emigration on development. Section 5 concludes.

2 Emigration, development... and education

Although many aspects of migration have been analyzed by demographers, economists, sociologists and other social scientists, data constraints have long impeded some important research avenues. Fortunately, several databases have been recently constructed to document dyadic migration stocks and their skill structure (Docquier et al., 2009; Artuç et al., 2015; Arslan et al., 2014; Bruecker et al., 2013). I combine

these databases to characterize the evolution of emigration rates between 1990 and 2010. I focus on emigration to all OECD countries, which is the best documented and growing component of international migration. Migration to non-OECD countries is ignored. I restrict my sample to emigrants aged 25 and over, who emigrate to one of 35 OECD member states. Data on emigration for the year 1990 are taken from Artuç et al. (2015). For the years 2000 and 2010, I extract data on dyadic migration stocks from the *DIOC* database described in Arslan et al. (2014).

In order to obtain the emigration rates, I have to proxy the size and structure of the native population. For this purpose, I combine data on the population aged 25 years and above, with data on the share of college-educated individuals from different data sources. The skill-specific emigration rates (m_i^s) are proxied as the ratio of emigrants to OECD destination countries (M_i^s) to the sum of the emigrant and resident populations (L_i^s). This gives:

$$m_i^s = \frac{M_i^s}{M_i^s + L_i^s}.$$

Table 1 provides aggregate emigration stocks and skill-specific emigration rates for the years 1990, 2000, 2010 by income group, by country size and by region. It shows that high-skilled emigration rates strongly decrease with economic development and population size. On the contrary, low-skilled emigration rates increase with economic development. In low-income countries and by the year 2010, college-educated individuals were 18 times more migratory than the less educated. The skilled emigration rates were 20 and 30 times greater than the low-skilled emigration rates in the previous decades (i.e., in the years 2000 and 1990, respectively). In high-income countries, college graduates only migrate 1.2 times more than the less educated. This means that international migrants from poor countries strongly self-select along the skill dimension.

As far as country size is concerned, emigration rates are about five times larger in small countries (less than 2.5 million inhabitants) compared with large countries (more than 25 million inhabitants) in all skill groups. Hence, regions with the greatest skilled emigration rates include small and poor countries (e.g., Caribbean and Pacific islands). Overall, skilled emigration rates decreased between 1990 and 2010 in all groups. Exceptions are Eastern Europe, Eastern Asia and South-Central Asia. The worldwide average emigration rate has been pretty stable for the last 20 years, which is due to the increasing demographic share of low-income countries (the group exhibiting the greatest emigration rates). On the contrary, low-skilled emigration rates increased in virtually all groups.

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

Year	Total stock (x 1,000)			Rate low-skill (As %)			Rate high-skill (As %)		
	1990	2000	2010	1990	2000	2010	1990	2000	2010
World	40,717	58,585	81,449	1.3	1.5	1.7	5.2	4.7	5.1
<i>By income group</i>									
High-income	19,570	22,369	26,286	2.7	3.0	3.0	3.9	3.3	3.7
Upper-middle	11,708	20,238	30,229	0.9	1.3	1.6	6.4	5.5	5.1
Lower-middle	8,791	14,739	22,679	0.9	1.1	1.3	8.5	8.4	8.1
Low-income	649	1,240	2,255	0.5	0.8	1.1	16.4	16.2	18.0
<i>By country size</i>									
High-pop	25,603	37,997	52,565	0.9	1.1	1.2	4.0	3.8	4.2
Upper-middle	6,919	9,714	14,204	2.9	3.6	4.3	10.2	8.8	9.4
Lower-middle	6,683	8,880	12,064	4.7	5.5	6.2	12.1	10.5	10.4
Low-pop	1,511	1,994	2,617	8.0	9.3	9.9	28.2	24.5	22.1
<i>By region</i>									
Africa									
Northern	2,016	3,274	4,687	3.1	3.6	4.0	10.8	10.7	9.2
Sub-Saharan	1,375	2,414	4,250	0.5	0.7	0.9	14.1	13.0	11.9
Americas									
Caribbean	1,951	3,055	3,926	9.3	13.2	13.8	43.6	34.6	32.7
Central	3,484	8,166	12,221	6.8	12.2	13.8	13.6	9.4	10.2
South	1,628	3,100	5,214	0.8	1.4	1.9	4.8	4.0	4.5
USA & Can	1,428	1,660	1,905	0.6	0.9	0.7	1.0	0.8	0.9
Asia									
Eastern	1,288	2,248	3,399	0.1	0.1	0.2	2.0	2.4	2.3
South-Cent	1,726	3,302	6,353	0.2	0.3	0.4	3.2	4.4	5.2
South-East	2,583	4,207	5,979	0.8	1.1	1.2	10.8	7.4	6.2
Middle East	2,760	3,840	5,230	2.6	2.8	2.7	10.4	7.4	6.4
Europe									
Eastern	6,644	8,558	12,488	4.3	5.4	7.4	9.5	9.5	11.6
Western	13,304	13,972	14,742	4.5	4.4	4.1	8.4	7.4	7.1
Oceania									
Australia & NZ	397	565	753	2.6	3.4	3.4	4.3	4.3	5.2
Pacific islands	133	223	303	4.1	5.5	5.6	47.2	39.7	27.5

Note. Tab. 1 focuses on emigration to OECD destination countries only. For income groups and regions, I use the World Bank classification. For country size, I distinguish between countries with population above 25 millions (High-pop), between 10 and 25 millions (Upper-middle), between 2.5 and 10 millions (Lower-middle), and below 2.5 millions (Low-pop).

3 How does development affect emigration?

Starting with Zelinsky (1971), a first strand of literature focuses on the effect of development on emigration. Traditional neoclassical models of migration posit that narrowing wage gaps between country pairs monotonically reduce migration along specific corridors. In reality, we instead observe an inverted-U shaped relationship between migration and development in cross-sectional data, most commonly referred to as the *migration transition* curve. Hence, economic development seems to produce additional emigration from origin countries in early stages of development (see de Haas 2007, 2010a, 2010b).

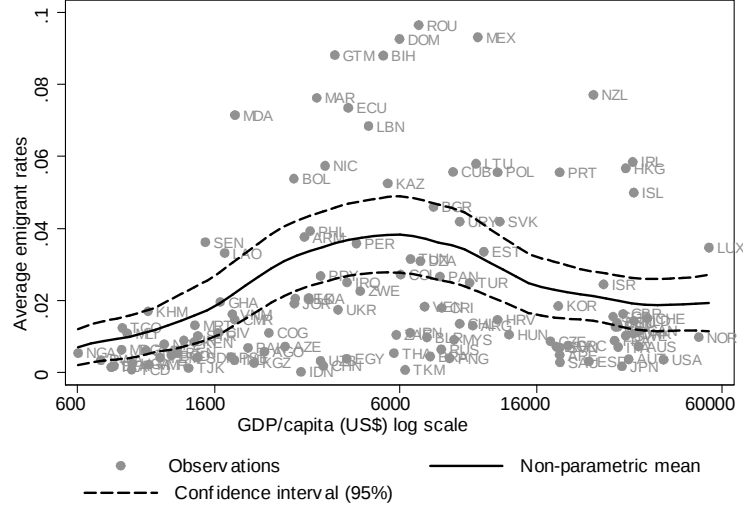
To illustrate this, Figure 1 shows the relationship between average emigration rates ($\bar{m}_i$) and the level of income per capita (y_i) in the origin country. The results are obtained using the non-parametric Epanechnikov kernel density estimation (see Epanechnikov, 1969). I consider a sample of 123 countries, excluding small states with populations below 2.5 million inhabitants, as well as those experiencing episodes of conflict. Using the database described in Section 2, I construct measures of migration flow intensity to OECD member states – which host about 50% of the worldwide adult migrant stock (Artuç et al. 2015) – over the 2000-2010 period. I only consider migrants aged 25 and above (as a proxy for the working-age population). For each origin country, the net emigration flow is proxied as the difference between the emigrant stocks in 2010 and 2000; it is then divided by the size of the native population in 2000. In line with Clemens (2014), Figure 1 shows that increase with economic development up to a level of income per capita (y) around \$6,000 and decrease thereafter. As income per capita increases from \$600 to \$6,000, the average emigration rate increases from 1% to 4%. As income per capita increases from \$6,000 to \$60,000, the average emigration rate decreases from 4% to 2%.

Various explanations of the observed relationship have been conjectured in specific contexts, the most common being the existence of credit constraints preventing potential migrants in poorer countries from realizing their aspirations. Taken at face value therefore, the *migration transition curve* suggests that further global economic development will result in massive volumes of international migration from the poorest regions of the world. Indeed, by the year 2010, approximately two thirds of the world population lived in countries with income per capita levels below \$6,000. If the average emigration rate of these countries increased by 1 percentage point, an additional migrant flow of 0.66% of the world population would move from developing to OECD countries (representing 1/6 of the world population). Consequently, the average immigration rates of the OECD member states would increase by more than 4 percentage points. *Is this an inevitable consequence of development policies?*

To address this question, I propose a *Migration Accounting* method to evaluate the competing theories that are hypothesized to underpin the upward segment of the observed inverted-U relationship. In particular, the goal is to assess whether financial constraints are instrumental to explaining the upward segment the *migration*

transition curve. I proceed in three steps, as described in Dao et al. (2018)

Figure 1. Emigration rates on income per capita
(Non-parametric Epanechnikov regressions)



First, I use the same data sources as above to construct skill-specific measures of migration intensity for the 2000-2010 period. I distinguish between migrants with college education (denoted by h and referred to as the highly skilled) and those with lower levels of education (denoted by l and referred to as the low-skilled). By construction, the average emigration rate of a sending country i is defined as:

$$\bar{m}_i \equiv h_i^N m_i^h + (1 - h_i^N) m_i^l, \quad (1)$$

where m_i^s denotes the average emigration rate of group s , and h_i^N denotes the proportion of college graduates in the native population aged 25 and over.

It follows that:

$$\frac{d\bar{m}_i}{dy_i} \equiv \frac{dh_i^N}{dy_i} (m_i^h - m_i^l) + h_i^N \frac{dm_i^h}{dy_i} + (1 - h_i^N) \frac{dm_i^l}{dy_i}.$$

The skill composition of the native population varies with economic development, possibly reflecting the existence of credit constraints that go beyond the capacity of individuals to finance migration costs. The share of college graduates in the native population h^N rises constantly with development (see Figure 3.a below). It is 20 times larger in the richest relative to the poorest countries. In addition, migration rates are always greater among college graduates (m^h) than among the less educated (m^l). At low levels of income per capita, positive selection is strong ($m^h \simeq 30m^l$) in the very poorest countries. In the richest countries, positive selection is much

weaker. Hence, education levels, taken in isolation (i.e., looking at the first term of the derivative), likely prove crucial in understanding the foundations of the *migration transition curve*. In addition, the other hypothesized drivers are likely to affect the mobility of low-skilled and high-skilled individuals differently (i.e. looking at the second and third terms of the derivative). Overall, the college-educated emigration rates (m^h) decrease with development, while those of the less-educated (m^l) follow an inverted U-shaped and flatter relationship (see Figure 3.e below).

Second, I use regressions to identify the fractions of $\frac{dm^s}{dy}$ that are due to *microeconomic* drivers (i.e., financial incentives and constraints) and to *macroeconomic* drivers. Regressions are conducted at the dyadic level. The set of *macroeconomic drivers* is a vector X_{ij} that includes socio-demographic variables, gravity determinants and existing migrant networks from any origin country i to any destination country j . Having controlled for *macroeconomic* drivers (i.e., all the relevant, origin-specific mechanisms identified in the existing literature), I assume the residual effect of income to reasonably provide an upper-bound for the effect of *microeconomic* drivers. Using a quadratic function of income per capita (in logs), *microeconomic drivers* can induce non-monotonic effects on skill-specific emigration rates. The regression model can be written as:

$$m_{ij}^s = \underbrace{\gamma_m^s X_{ij}}_{\text{Macro}} + \underbrace{a_m^s y_i + b_m^s y_i^2}_{\text{Micro}} + \underbrace{\varepsilon_{ij}^s}_{\text{Residual}},$$

implying that:

$$\begin{aligned} m_i^s &\equiv \sum_{j=1}^{J^s} m_{ij}^s = \gamma_m^s \sum_{j=1}^{J^s} X_{ij} + J^s a_m^s y_i + J^s b_m^s y_i^2 \\ \frac{\partial m_i^s}{\partial y_i} &\equiv J^s a_m^s + 2J^s b_m^s y_i \neq \frac{dm_i^s}{dy_i} \equiv \frac{\partial m_i^s}{\partial y_i} + \gamma_m^s \sum_{j=1}^{J^s} \frac{dX_{ij}}{dy_i} \end{aligned}$$

where J^s stands for the average number of destinations with positive migrant flows from each origin.

Regression results for actual migration rates are presented in Table 1. The standard errors are clustered by country of origin. Columns (L1) and (H1) include the full set of controls and the log of income per capita (linear specification). Columns (L2) and (H2) add the squared level of the log of income per capita (quadratic specification). Finally, columns (L3) and (H3) represent my parsimonious specifications comprising significant controls only, in addition to the log level of income. I run a horse race between several competing theories underpinning the migration transition curve.

Table 1. Determinants of migration rates by dyad

	Less educated			College Graduates		
	(L1)	(L2)	(L3)	(H1)	(H2)	(H3)
Network (% pop.)	0.4535*** (0.07)	0.4511*** (0.07)	0.4504*** (0.07)	0.8648*** (0.18)	0.8616*** (0.18)	0.8806*** (0.18)
Geog. Dist. (log)	-0.0005* (0.00)	-0.0005* (0.00)		-0.0037*** (0.00)	-0.0036*** (0.00)	-0.0036*** (0.00)
Contiguity	-0.0018 (0.00)	-0.0014 (0.00)		-0.0123*** (0.00)	-0.0119*** (0.00)	-0.0136*** (0.00)
Com. Language	0.0003 (0.00)	0.0005 (0.00)		0.0122*** (0.00)	0.0126*** (0.00)	0.0127*** (0.00)
Colonial Link	-0.0023** (0.00)	-0.0020** (0.00)		0.0486*** (0.01)	0.0490*** (0.01)	0.0484*** (0.01)
Genetic Distance	-0.0001 (0.00)	0.0001 (0.00)		0.0081*** (0.00)	0.0083*** (0.00)	0.0075*** (0.00)
Population (log)	-0.0000 (0.00)	-0.0000 (0.00)		-0.0013* (0.00)	-0.0013* (0.00)	
Pop 15-24 (% pop.)	0.0000 (0.00)	-0.0000 (0.00)		-0.0000 (0.00)	-0.0002 (0.00)	
Import Tariff	-0.0000 (0.00)	-0.0000 (0.00)		0.0005* (0.00)	0.0005* (0.00)	
Educ. Quality	-0.0000 (0.00)	-0.0000* (0.00)		-0.0001 (0.00)	-0.0001 (0.00)	
Pol. restr.	-0.0004 (0.00)	-0.0003 (0.00)		0.0017 (0.00)	0.0018 (0.00)	
GDP/cap	-0.0003 (0.00)	0.0063*** (0.00)	0.0058*** (0.00)	-0.0007 (0.00)	0.0129 (0.02)	-0.0025** (0.00)
GDP/cap Sq.		-0.0004*** (0.00)	-0.0004*** (0.00)		-0.0008 (0.00)	
Constant	0.0095 (0.01)	-0.0166** (0.01)	-0.0256*** (0.01)	0.0492 (0.04)	-0.0039 (0.10)	0.0258 (0.02)
Dest. FE	Yes	Yes	Yes	Yes	Yes	Yes
MRM	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.6072	0.6105	0.6050	0.4571	0.4576	0.4516
N. of obs	1409	1409	1409	1067	1067	1067
Partial R-squared	0.8725	0.8725	0.8828	0.8854	0.8859	0.8864
F-stat	377.4963	376.6303	396.9139	163.1120	166.1433	160.3231

Notes: Standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. OLS regressions estimated on the restricted sample of dyads with realization rates of strictly between 0 and 1 (see Section 2.3). The sample consists of 1,409 observations for low-skilled migration rates and 1,067 observations for high-skilled migration rates. All regressions include destination fixed effects and variables to control for multilateral resistance to migration. Our network variable is instrumented using its 10-year lag. Standard errors are clustered by country of origin. We control for multilateral resistance to migration (MRM) with the inclusion of an additional term capturing the average distance and contiguity of country i and j with respect to all other migration partners (Baier and Bergstrand, 2009; Gröschl, 2012).

Hence, my parsimonious specifications are obtained after running backward step-wise regressions starting from the most complete model. The parsimonious model is used to minimize concerns of collinearity. It explains 60.5% of the overall variation in low-skilled migration rates. The only significant variables are network size, the log of income per capita and its square. A rise in income increases the low-skilled emigration rate when income per capita is below \$1,400. Above this level, low-skilled emigration decreases with development. This confirms that financial constraints are likely to limit the capacity of less educated people to emigrate in low-income countries. The parsimonious model rather explains 45.2% of the overall variability in high-skilled emigration rates. On the one hand, the high-skilled emigration rate increases with network size, linguistic proximity, colonial links and genetic distance. On the other hand, it decreases with contiguity and with income per capita. The results are robust to alternative specifications and regression techniques (see Dao et al., 2018).

Third, to illustrate the role of *microeconomic* drivers and compare it with that of the *Skill Composition* component and that of *macroeconomic* drivers, the derivative of the migration transition can be rewritten as:

$$\frac{d\bar{m}_i}{dy_i} = \underbrace{\frac{dh_i^N}{dy_i}(m_i^h - m_i^l)}_{\text{Skill Composition}} + \underbrace{h_i^N \frac{\partial m_i^h}{\partial y_i}}_{\text{HS Micro}} + \underbrace{(1 - h_i^N) \frac{\partial m_i^l}{\partial y_i}}_{\text{LS Micro}} + \underbrace{\frac{dO_i}{dy_i}}_{\text{Macro}}, \quad (2)$$

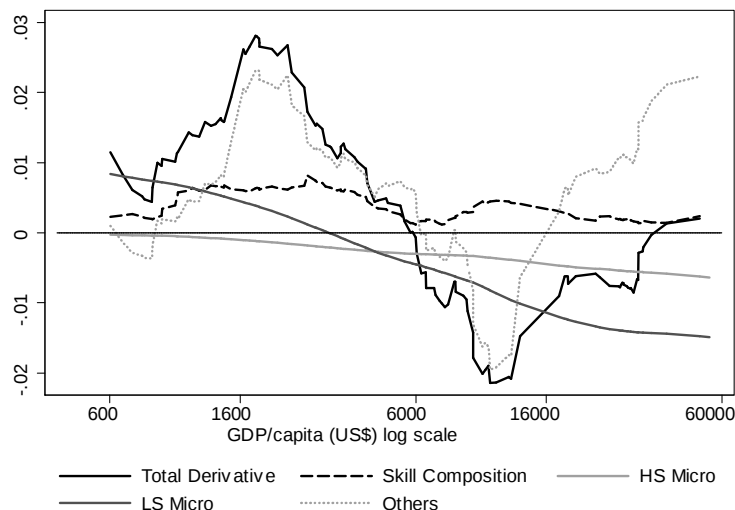
which allows identifying four components of the migration transition curve: the skill composition one, the effect of financial incentives and constraints for high-skilled and low-skilled individuals, and the role of *macroeconomic* drivers.

Figures 2 describes the results of the decomposition of the total slope (the bold curve). It typically shows that the *Skill Composition* explains approximately one fourth of the positive slope of the migration transition curve at levels of income per capita below \$1,000 or else between \$4,000 and \$6,000. In addition, a large portion of the curve can be explained by the *macroeconomic drivers* (in particular, the gravity and network effects). The *HS Micro* component is always nil or negative, since the high-skilled emigration rate always decreases with development. The size of this component is limited at low levels of development however since h_i^N is small. As far as financial constraints are concerned, the *LS Micro* component effect is larger than that of the *Skill Composition* for origin countries below \$1,000 (note that countries below \$1,000 accounted for less than 5% of the world population in the year 2010). For origin countries between \$1,000 and \$6,000 however (i.e., in countries accounting for more than 60% of the world population in the year 2010), the *Skill Composition* effect exceeds that of the *LS Micro*.

This implies that financial constraints, while relevant for the very poorest countries, only have a limited effect on the upward segment of the migration transition curve. As far as policy implications are concerned, our results suggest that in the short run (i.e., for a given skill structure and for a given set of macroeconomic determinants, O), a rise in income induces small effects on low-skilled and average

emigration rates. In the long-run, a rise in income increases h^N (i.e., increasing the number of more mobile high-skilled workers) and affects O (e.g., lower population growth), which increases the share of college graduates among emigrants as well as the average emigration rate. Nevertheless, economic growth has an uncertain effect on the emigration stock, since increasing the mobility of workers can be offset by smaller populations. Overall, this implies that the risk of a massive emigration response to economic development is limited, both in the short-run and in the long-run.

Figure 2. Dissecting the migration transition curve
(Decomposition of the slope using Eq. (2))



4 How does emigration affect development?

Another strand of literature focuses on the development implications of emigration. Starting with Bhagwati and Hamada (1974), a series of models were developed in the 1970s to explore the welfare consequences of skill-biased emigration in various institutional settings. Domestic labor markets rigidities, informational imperfections, as well as fiscal and other types of externalities (Bhagwati and Hamada 1974; McCulloch and Yellen 1977) were introduced to emphasize the negative consequences of the brain drain for those left behind. Emigration was viewed as contributing to increased inequality at the international level, with rich countries becoming richer at the expense of poor countries. The first papers to analyze the development effects of emigration in an endogenous growth framework rested on similar arguments and reached similar conclusions (e.g., Miyagiwa 1991, Haque and Kim 1995). *Are these human capital losses large and inevitable? Can their economic implications be attenuated or reversed in a globalized context?*

The macroeconometric literature failed identifying large causal effects of human capital on economic growth. However, these studies suffer from inextricable identification problems. Greater effects are identified when using parameterized *Development Accounting* models, even in the absence of technological externalities (Jones, 2014). In this paper, I follow this approach and construct a *Development Accounting* model to estimate the effect of (skill-biased) emigration on income per capita under the traditional and recent views. My model is calibrated using the average country characteristics observed at each level of economic development (as proxied by the observed level of income per capita). These characteristics are depicted in Figure 3 for the year 2010.

Figure 3. Average country characteristics by level of development

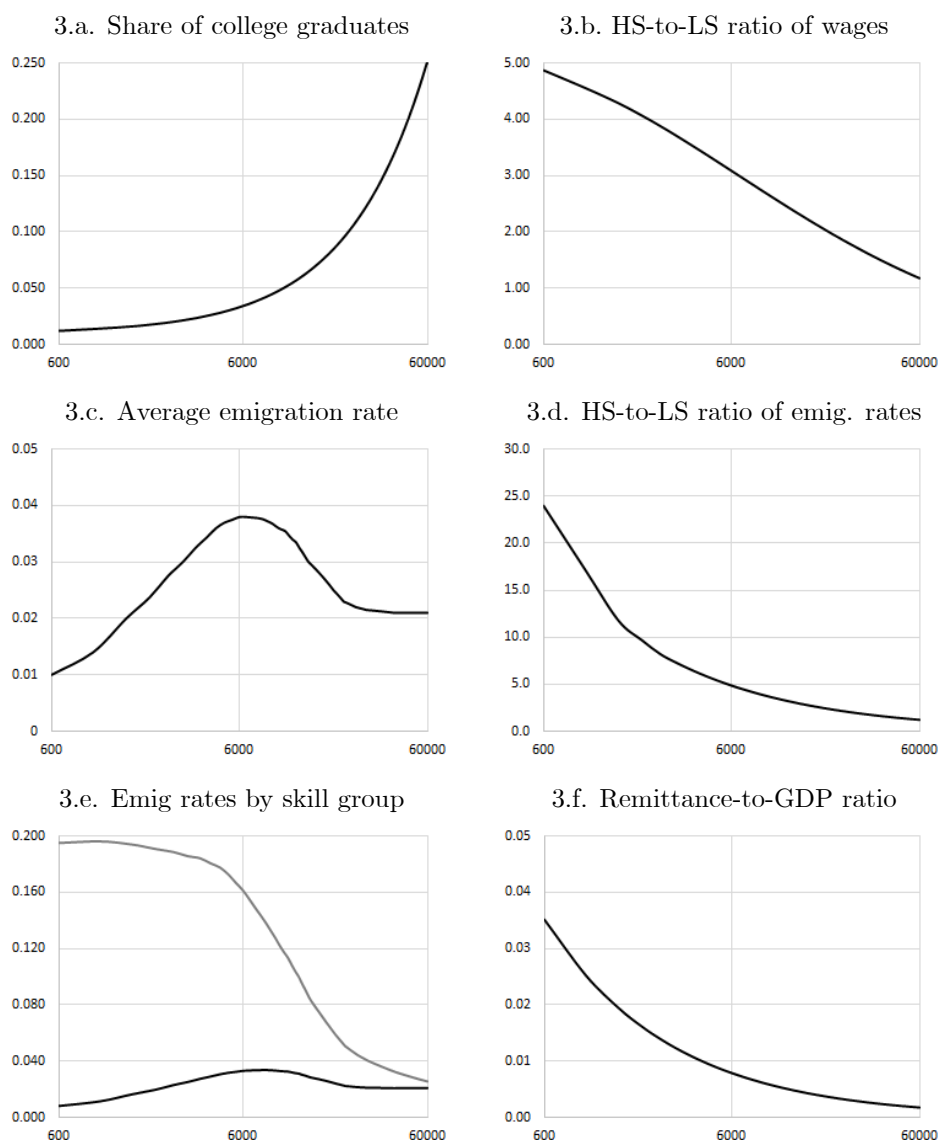


Figure 3.a shows the increasing relationship between income per capita (in logs) and the share of college graduates in the labor force; the education data are described in Section 2. Figure 3.b shows the decreasing relationship between income per capita and the ratio of earnings between college graduates and the less educated; data on returns to skills are taken from Hendriks (2004). Figure 3.c shows the inverted-U shaped relationship between income per capita and the average emigration rate, as depicted on Figure 1. Figure 3.d shows the decreasing relationship between income per capita and the ratio of emigration rates between college graduates and the less educated; the migration data are described in Section 2. Figure 3.e shows the relationship between income per capita and skill-specific emigration rates, as extracted from Eq. (1). Figure 3.f shows the decreasing relationship between income per capita and the ratio of remittance inflows to GDP; data are taken from the World Development Indicators (World Bank, 2017).

4.1 Insights from a minimalist model

The labor market and growth literatures have shown that a CES (constant elasticity of substitution) production framework explains well the disparities in macroeconomic performance between countries and the patterns of wage inequality between skill groups. In the CES framework, a rise in human capital mechanically increases the average income because highly educated workers are more productive than the less educated.

The CES technology below determines the average level of income per capita (y_i) and skill-specific wage rates (w_i^s) in country i as a function of the structure of the resident population:

$$y_i = y(h_i^L) = A_i \left[\theta_i (h_i^L)^{\frac{\sigma-1}{\sigma}} + (1 - \theta_i)(1 - h_i^L)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \quad (3)$$

$$\frac{w_i^h}{w_i^l} = \frac{\theta_i}{1 - \theta_i} \left(\frac{h_i^L}{1 - h_i^L} \right)^{-1/\sigma} \quad (4)$$

where h_i^L stands for the proportion of college graduates in the resident labor force, A_i denotes the total factor productivity (TFP), θ_i is relative productivity parameters capturing the skill bias in production.

The production technology can be calibrated to match the patterns of income per capita and wage inequality depicted on Figure 3. In line with the labor market literature (e.g., Ottaviano and Peri, 2012; Angrist, 1995), the elasticity of substitution (σ) between college-educated and less educated workers varies between 1.5 and 3. When σ is fixed, θ can be calibrated to match wage inequality levels (w_i^h/w_i^l), and A_i can then be calibrated to match the level of income per capita. In what follows, I assume $\sigma = 2$ (the results below are highly robust to the choice of σ) and I use the human capital levels (h_i^L) depicted on Figure 3.a. For each level of economic development, I use Eq. (4) and calibrate θ_i to match the average wage ratio depicted

on Figure 3.b. When θ_i is known, I use Eq. (3) and calibrate A_i to exactly match the level of income per capita.

I then simulate the minimalist model to assess the effect of emigration on income per capita. Mechanically, emigration adversely affects human capital accumulation. By definition, the share of college graduates in the resident labor force depends on the share of college graduates in the native population (h_i^N) and on skill-specific emigration rates (m_i^s):

$$h_i^L = \frac{h_i^N(1 - m_i^h)}{h_i^N(1 - m_i^h) + (1 - h_i^N)(1 - m_i^l)},$$

from which we can extract h_i^N (as h_i^L and m_i^s are observed):

$$h_i^N = \frac{h_i^L(1 - m_i^l)}{1 - m_i^h + h_i^L(m_i^h - m_i^l)}.$$

It is straightforward to show that $h_i^L < h_i^N$ when $m_i^h > m_i^l$: other things being equal, positive selection in emigration reduces the level of human capital in the origin country. The patterns in Figure 3 allow quantifying the magnitude of this effect. On average, emigration reduces the proportion of college graduates by 0.2 percentage points at a level of income per capita around \$1,000 (from 1.2 to 1.0%), by 0.3 percentage points at a level of income around \$2,000 (from 1.8 to 1.5%), and by 0.4 percentage points at a level of income around \$6,000 (from 3.4 to 3.0%). In absolute terms, skill-biased emigration has limited effects on the share of college graduates in the labor force. As positive selection decreases with economic development, the effect gets smaller for higher level of income.

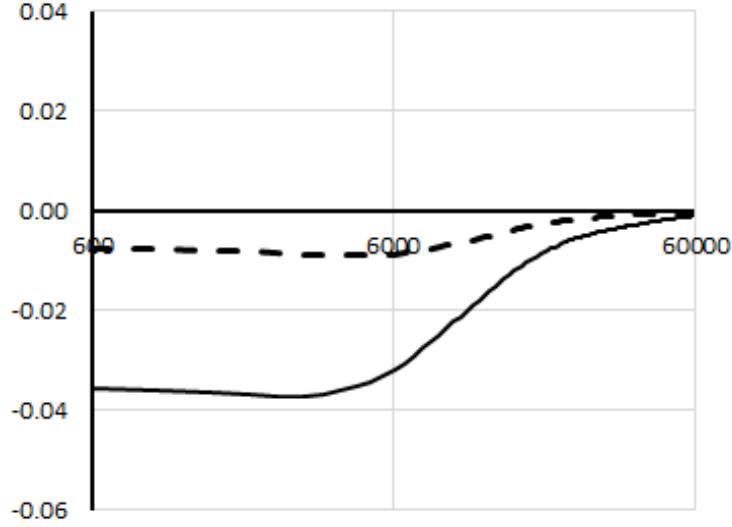
For given θ_i and A_i (i.e., in the absence of technological externality) and for given h_i^N (i.e., disregarding the potential effect of emigration on human capital acquisition), I use Eq. (3) to simulate the counterfactual level of income per capita without emigration, $y(h_i^N)$, and compare it to the observed level, $y(h_i^L)$. In line with Jones (2014), I express the effect of emigration on income as percentage of the no-migration counterfactual level:

$$\Delta_i = \frac{y(h_i^L) - y(h_i^N)}{y(h_i^N)}.$$

A negative results means that emigration reduces the level of income per capita.

The predictions of the minimalist model are depicted in Figure 4. The dotted curve shows how the income effect due to (skill-biased) emigration varies with the observed level of development, y_i . As emigrants are always positively selected, Δ_i is negative for all levels of development. In the poorest countries of the world (i.e., countries with y_i below \$6,000), the income loss amounts to 1% of the potential no-migration income level (the loss is even slightly smaller than 1%). Due to smaller selection, the effect gets smaller at higher level of income. Hence, small development effects are obtained in this minimalist model.

Figure 4. Average effect of emigration on income - Traditional view



4.2 Pessimistic model with schooling externalities

Greater contributions of human capital to productivity can be obtained by assuming technological externalities. In the same CES framework, I now assume two schooling externalities, an aggregate productivity externality and directed technical changes:

$$A_i = A_{0i} \left(\frac{h_i^L}{1 - h_i^L} \right)^\epsilon, \quad (5)$$

$$\frac{\theta_i}{1 - \theta_i} = R_{0i} \left(\frac{h_i^L}{1 - h_i^L} \right)^\kappa. \quad (6)$$

Eq. (5) formalizes a simple Lucas-type, aggregate externality (see Lucas, 1988) and assumes that the scale of the total productivity factor (TFP) is a concave function of the skill-ratio in the resident labor force. This externality captures the fact that college-educated workers facilitate innovation and the adoption of advanced technologies (see Benhabib and Spiegel, 1994; Caselli and Coleman, 2006; Ciccone and Papaioannou, 2009), and are more supportive to reforms improving the quality of institutions (Castello-Climente, 2008; Bobba and Coviello, 2007; Murin and Wacziarg, 2014). Using the average characteristics (in logs) depicted in Figure 3, the correlation between the calibrated TFP level and the skill ratio is equal to 0.89, and the elasticity is close to 0.4. Given the bidirectional causation relationship between productivity/income and education decisions, I consider this elasticity as an upper bound for the aggregate externality. For illustrative purpose, I assume that half the correlation is due to the technological externality (i.e., $\epsilon = 0.2$).

In Eq. (6), the skill-biased technical change affects the relative productivity of high-skilled workers (see Acemoglu, 2002; Restuccia and Vandenbroucke, 2013). For

example, Autor et al. (2003) show that computerization is associated with declining relative industry demand for routine manual and cognitive tasks, and increased relative demand for non-routine cognitive tasks. The observed relative demand shift favors college versus non-college labor. When comparing low-income, middle-income and high-income countries, skill-biased technical changes also capture the transition from agriculture to nonagriculture, or from the traditional to the modern sector (see Ciccone and Papaioannou, 2009; Volrath, 2009; Gollin et al., 2014). In logs, the correlation between the calibrated skill bias and the skill ratio is equal to 0.91, and the elasticity is close to 0.2. Given the bidirectional causation relationship between the skill bias and education decisions, I consider this elasticity as an upper bound for the skill-bias externality. Again, I assume that half the correlation is due to the skill-bias externality (i.e., $\kappa = 0.1$).

The bold curve in Figure 4 shows how the income effect due to emigration varies with the observed level of development when schooling externalities are factored in. In the poorest countries of the world (i.e., countries with y_i below \$6,000), the income loss is around 4% (four times greater than without externalities). The effect gets gradually smaller in countries where income per capita exceed \$6,000. This is the most pessimistic assessment of the economic cost of (skill-biased) emigration.

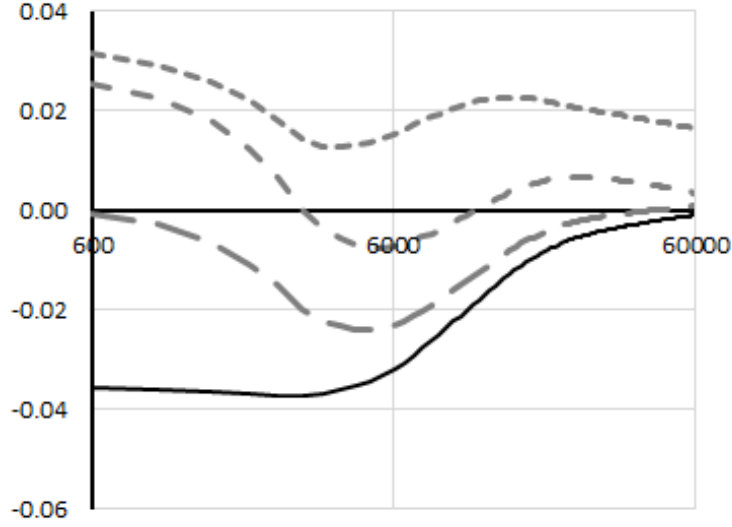
4.3 Optimistic model with compensating mechanisms

Can these income losses be offset by other mechanisms? This is the question which has received the most attention for the last ten years or so. Recent studies dealing with the development impact of emigration account for indirect feedback effects. The most important ones are remittances, endogenous education decisions, and diaspora externalities (Docquier and Rapoport, 2012). Starting from the most pessimistic view (i.e., the model with schooling externalities), I add these compensating mechanisms into the *Development Accounting* framework. The augmented income effects are depicted in Figure 5.

Adding remittances. – The less disputable compensating mechanism is the remittance channel. On average, recorded remittances represent 3% of GDP in low-income countries. This is a rather conservative estimate as official data are likely to underestimate the actual level of remittances. Figure 3.f shows that the ratio of official remittances to GDP rapidly decreases with income per capita. Remittances reallocate income from donors to recipient countries, and may attenuate or fully compensate the income loss due to skill-biased emigration as shown in di Giovanni et al. (2015).

Starting from the pessimistic model with schooling externalities (bold curve), the long-dash curve on Figure 5 shows that remittances almost fully offset the domestic income loss in the poorest countries of the world (where income per capita is below \$1,000). The income loss is roughly divided by two in countries around \$4,000. The effect of remittances decreases as domestic income gets larger. This is because the ratio of remittances to GDP decreases with economic development (see Figure 3.f).

Figure 5. Average effect of emigration on income - Newer literature



Endogenizing education decisions. – Starting with Mountford (1997), Stark et al. (1997), Vidal (1998) and Beine et al. (2001), the link between skill-biased emigration rates and pre-migration human capital formation has been theoretically investigated in the recent literature. Skill-biased emigration prospects are shown to raise the expected return to human capital, thus inducing more people to invest (or people to invest more) in education at home before deciding whether to emigrate or stay put. Macro-level evidence of the same relationship can be found in the literature. Beine et al. (2008) estimate that a doubling of a country’s emigration rate of highly-skilled workers is associated with a 5% increase in the stock of human capital possessed by its nationals (including emigrants) within a decade. Their findings suggest that under certain conditions the stimulus to skill formation may be strong enough to bring the economy’s stock of human capital to a higher level in the post-migration equilibrium. Micro-level evidence of a positive impact of emigration on the *net* stock of human capital in the source country has been provided in many studies. These include Chand and Clemens (2008) on Fiji, Gibson and McKenzie (2011) on Tonga and Papua New Guinea, Batista et al. (2012) on Cape Verde, Shrestha (2017) on Nepal, or Theoharides (2017) on the Philippines. To identify causation, these studies exploit survey data on education choices and migration intentions, micro data on education and exposition to migration by region, or quasi-natural experimental methods.

Starting from the model with schooling externalities and remittances, the middle-dash curve on Figure 5 shows the income response to emigration with endogenous education. I assume that h_i^N depends on skill-biased emigration prospects (m_i^h/m_i^l) and the elasticity of h_i^N to m_i^h/m_i^l equals 0.05 as in Beine et al. (2008). This is a rather conservative estimate as the long-run elasticity is larger, but imprecisely

estimated. The no-migration counterfactual now involves a smaller pre-migration, level of human capital (h_i^N). It comes out that the income response to (skill-biased) emigration becomes positive in virtually all countries. Emigration increases income per capita by 2.2% in the poorest countries. Middle-income countries around \$6,000 experience a small income loss (-0.5%).

Accounting for diaspora externalities. – Finally, empirical studies show that migrant networks stimulate immaterial transfers from destination to origin countries. They generate business links and stimulates trade and FDI. This, in turn, increases the level of total factor productivity. A first strand of literature has identified a causal impact of migration on trade and FDI, with respective elasticities of 0.1 and 0.2 (e.g., Iranzo and Peri, 2009; Felbermayr et al., 2010; Parsons and Vezina, 2017; Kugler and Rapoport, 2007; Javorcik et al., 2010). Another strand has identified a causal effect of trade and FDI on TFP, with respective elasticities of 0.3 and 0.01 (see Anderson et al., 2016; Feyrer, 2009). Combining these findings gives a conservative elasticity of total factor productivity to emigration around 0.03. Starting from Eq. (5), I add a linearized diaspora externality into the *Development Accounting* framework. This gives:

$$A_i = A_{0i} \left(\frac{h_i^L}{1 - h_i^L} \right)^\epsilon (1 + \rho m_i).$$

The choice of this linear specification for the last term ensures that the TFP level remains positive when $m_i = 0$. The elasticity of productivity to the proportion of emigrants is thus given by $\rho m / (1 + \rho m)$. I calibrate in such a way that this elasticity is equal to 0.03 when the proportion of migrants abroad equals 3% (i.e., the world average level); this gives $\rho = 0.62$.

Starting from the model with schooling externalities, remittances and endogenous education decisions, the short-dash curve on Figure 5 represents the income response to emigration with diaspora externalities. The income gain from emigration now reaches 3% in the poorest countries of the world, whereas the effect becomes positive in middle-income countries around \$6,000 (countries with the largest diasporas abroad, relatively to their population). On average, the income gain equals 2% in richer countries.

5 Concluding remarks

This paper summarizes the recent progress of the literature on the links between emigration and development, and quantifies its main findings. Firstly, I develop a *Migration Accounting* model to disentangle the main drivers of the migration transition curve. The model reveals that credit constraints, while relevant for the very poorest countries, only have a limited effect on the upward segment of the migration transition curve. This suggests that the risk of a massive emigration response to economic development is limited. Secondly, I develop a *Development Accounting* model

to quantify the effect of emigration on the level of income per capita in the origin country. The model reveals that emigration, albeit skill-biased, is likely to generate positive effects on income per capita in low-income and middle-income countries. Still, the effect is small in the majority of countries, which is due to the fact that average emigration rates are low. My estimates are likely to be conservative. It is possible that standard growth theory underestimates the size of the development impact of emigration. This is because it disregards potential mechanisms such as transfers of behavioral norms (fertility, education, gender-egalitarian, culture, etc.) or political remittances (influence of diasporas on the number of voters and on political preferences). Accounting for these effects in a quantitative framework is a challenging task.

The complex links between emigration and development might pose a problem of coherence for development and migration policies. However, should there be an inconsistency between policy actions, it is not the one expected from earlier literature (i.e., development policies jeopardizing the effectiveness of restrictive immigration policies). On the contrary, we may fear that migration barriers reduce the effectiveness of development and cooperation policies.

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