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Migration and development: Dissecting the anatomy of the mobility transition☆

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ABSTRACT

Emigration first increases and then decreases as a country experiences economic development. This inverted U-shaped, cross-sectional relationship between emigration and development was first hypothesized by Zelinsky's theory of the *mobility transition*. Although several mechanisms have been proposed to explain the upward segment of the curve (the most common being the existence of financial constraints), they have not been examined in a systematic way. In this paper, we propose two decomposition methods to disentangle the main drivers of the mobility transition curve to OECD destination countries. Our simple decompositions shed light on the role of both *microeconomic* drivers (i.e., financial incentives and constraints) and *macroeconomic* drivers, as well as the skill composition of the population. Our double decomposition further distinguishes between migration aspirations and realization rates by education level. Overall, we provide consistent evidence that the role of financial constraints, while relevant for the poorest countries, is limited. Rather, a large fraction of the increasing segment is explained by the skill composition and by *macroeconomic* drivers (i.e., by factors that do not change in the short-run).

1. Introduction

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. Since the seminal work of Zelinsky (1971), this is most commonly referred to as the *mobility transition* curve. Contrary to the neoclassical predictions therefore, economic development seems to produce additional emigration from origin countries in early stages of development (see de Haas, 2007, 2010a, 2010b) as shown in Fig. 1a.[1] Adults' emigration rates to the OECD destination countries increase with economic development up to a level of income per capita around $6000 and decrease thereafter. Fig. 1b shows the density of the world population according to income per capita. Approximately two thirds of the world population reside in countries with income per capita levels below $6000. Taken at face value therefore, the *mobility transition curve* suggests that further global economic development will result in higher volumes of international migration from the poorest regions of the world. It is no surprise that co-development policies, those founded on neoclassical principles, have largely proven unsuccessful (see Clemens, 2014; Parsons and Winters, 2014).

While 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 — they have not been examined in a

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[1] Net emigration rates are proxied by changes in emigrant stocks between 2000 and 2010 as a percentage of the resident population in 2000.

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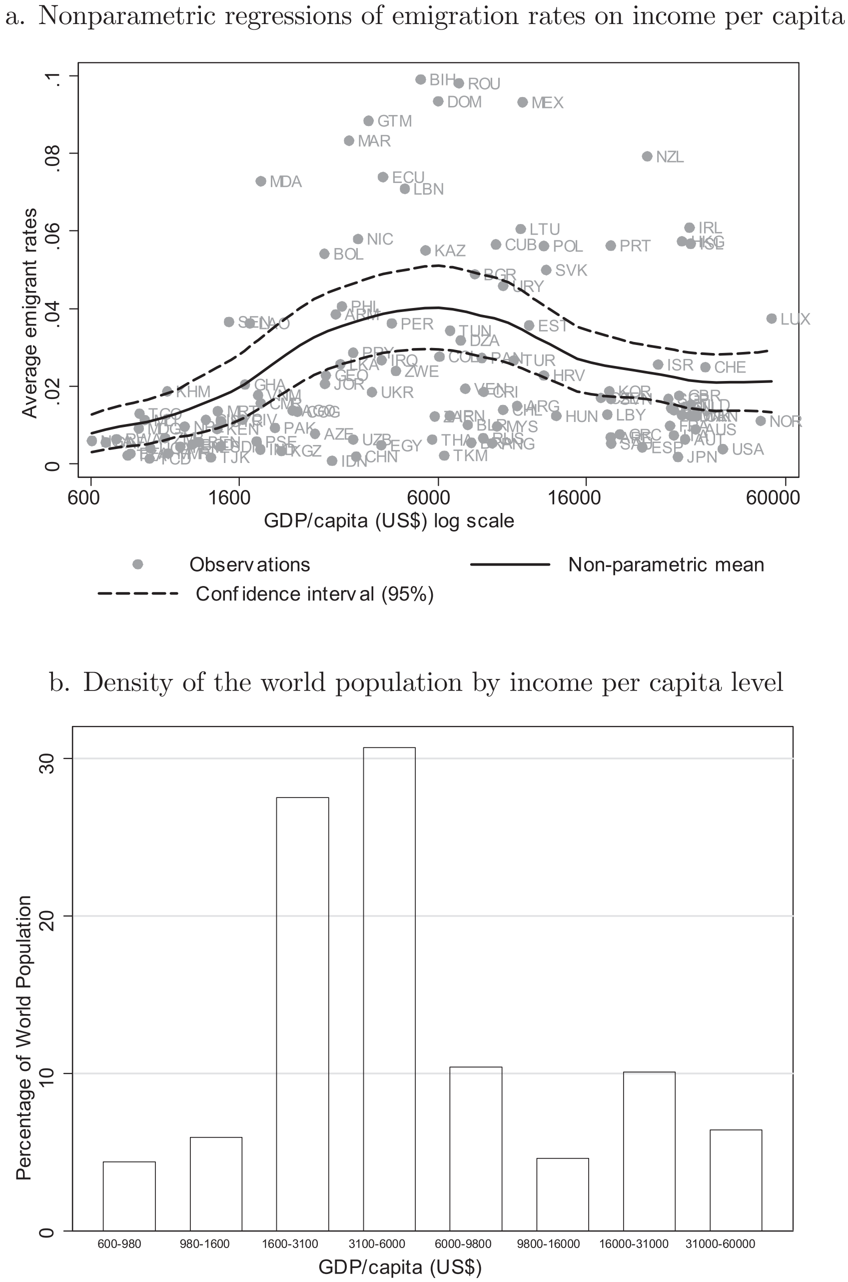

Fig. 1. Emigration rates and development. Notes: Non-parametric regressions using Epanechnikov kernel (see Epanechnikov, 1969), local-mean smoothing, bandwidth 0.5. Our sample includes 123 countries with populations above 2.5 million. We omit small states that typically exhibit unusually large emigration rates, countries in conflict, country pairs with negative net flows, and country pairs with realization rates equal to 0 or 1 (see Section 2.3). Average migration rates are calculated as the difference between migrant stocks in 2000 and 2010, normalized by the population at origin. The migration data derive from the *OECD-DIOC database*. Data on GDP per capita at PPP in 2000 are taken from the *Penn World Tables 7.0*. Population data in 2000 are provided by the *UN-DESA World Population Prospects 2012.*

systematic way. Our understanding of the underlying mechanisms at play therefore, in addition to the potential consequences of changes in policies or in the distribution of world income on international migration remains limited. As argued by Clemens (2014), *"We do not know enough about the mechanisms that create this observed pattern. Theories of the transition are well-developed, though they could benefit from more formalization and unification in a single framework that can explain patterns observed at both the macro- and micro-levels."*

This paper focuses on migration flows to OECD countries, which host about 50% of the worldwide adult migrant stock (Artuc et al., 2015); the destination countries for which the dyadic and skill structures of migration are measured with the greatest precision.[2] We propose a simple methodology to evaluate the competing theories that are hypothesized to underpin the upward segment of the observed inverted-U relationship, which consists of three steps. *In the first step*, we decompose average emigration rates into several additive components and investigate the correlations between them and income per capita. We begin with a simple decomposition that identifies the role of education, to shed light on the correlation between income per capita, the skill structure of the population and skill-specific emigration rates. We subsequently propose a double decomposition that instead distinguishes between bilateral migration aspirations and realization rates by education level. *In the second step*, we estimate regressions to disentangle the effects of both *microeconomic and macroeconomic* drivers of each additive component. Our microeconomic determinants capture the private incentives to migrate, as well as financial constraints that curb migration decisions. Our macroeconomic determinants comprise origin-specific and dyadic migration determinants as identified in the existing literature (i.e., socio-demographic and gravity variables as well as migrant networks). Controlling for *macroeconomic* drivers, we consider the residual effect of income to reasonably provide an upper-bound of

[2] In Appendix A, Fig. A1 shows that the inverted-U mobility transition curve also holds when considering 70 destination countries (33 OECD member states and 37 non-OECD destination countries) for which data by education level are available in the years 2000 and 2010.

the roles of financial incentives and constraints. *In the third step*, we bring together our previous findings and quantify the role of each driver in explaining the changing slope of the mobility transition curve at differing levels of income.

Our paper contributes to a 45 year-old literature on the link between migration and development. Wilbur Zelinsky in his seminal paper (Zelinsky, 1971), developed the theory of the *mobility transition*. This descriptive theory, combining insights from modernization theory and demographic transition analysis, hypothesizes that societies pass through five distinct phases of development, from pre-modern traditional societies to future super-advanced societies, which are accompanied by various forms of internal and international migration. The theory predicts an inverted U-shaped relationship between average emigrate rates and levels of income per capita. This relationship, which we term the *mobility transition curve*, has since been established empirically in differing contexts and variously referred to as: *migration curve* (Akerman, 1976), *migration transition* (Gould, 1979), *migration hump* (Martin, 1993), and *emigration life cycle* (Hatton and Williamson, 1994). The mobility transition curve has most recently been identified in panel data. Using *aggregate* stock data for the years 1960–2000, Clemens (2014) shows that emigration increases with economic development at origin until a level of development commensurate with a per capita income of around $5000 in PPP terms, while falling thereafter.[3]

The inverted U-shaped relationship between emigration and development as identified in the data, is not predicted by neoclassical models of migration. Building upon Sjaastad (1962), this class of models places wage or income differentials at the heart of rational agents' decision as to whether to remain at home or migrate elsewhere. Neoclassical models of migration therefore unambiguously predict that narrowing income differentials between origins and destinations will (monotonically) reduce the intensity of international migration. In the neoclassical *tradition* however, the interplay between incentives to emigrate and financial constraints, which we term *microeconomic* drivers henceforth, can give rise to the mobility transition curve. Increases in personal income make migration more affordable, while simultaneously reducing individual's willingness to migrate. Credit constraints have therefore been proposed as an explanation to the paradox wherein emigration from low-income regions, those in which many citizens would benefit the most from emigrating to higher-income regions, is limited.[4] There is ample historical evidence of the role of financial constraints in the 18th and 19th centuries (Hatton and Williamson, 1994, 1998; Faini and Venturini, 2010; Covarrubias et al., 2015). More recently, Bazzi (2013) provides evidence that financial constraints limit international labor mobility, such that positive agricultural income shocks result in significant increases in international migration, particularly among villages with higher numbers of small landholders. Both mechanisms, emigration incentives and constraints (or aspirations and capabilities), are correlated with income however and are therefore difficult to disentangle from each other.

Aside from *microeconomic* drivers, economists and geographers have, for almost half a century, proposed a number of complementary theories aimed at explaining the observed relationship between emigration and economic development. A recent survey (Clemens, 2014), lists five alternative classes of theory. (i) Demographic transitions may result in more youthful and economically-active populations, which might result in more emigration should they fail to be absorbed locally into the labor force (see Lee, 2003). (ii) Immigration barriers abroad, for example visas, are typically lower for citizens of wealthier nations and for high-skilled workers, meaning that they are more migratory than their lower-skilled compatriots. Education may stimulate migration aspirations of potential migrants, while selective immigration policies at destination favor educated migrants. The impact of development on the skill composition of migration remains ambiguous however. At early stages of development, improvements in education likely increase the success rate of potential migrants. Since education quality is endogenous with economic development however, further educational improvements likely reduce potential migrants' willingness to move, an effect that is likely compounded by the narrowing educational gaps between origins and potential destinations. (iii) Within-country income inequality, since during initial stages of development that are characterized by rising inequality, worse-off individuals feel relatively deprived and seek alternative 'reference' frames. (iv) Structural transformation due to for example trade linkages that emerge in parallel with the formation of transportation and communication networks that may facilitate mobility (see Massey et al., 1993; Martin and Taylor, 1996; Faini and Venturini, 2010). (v) Information asymmetry whereby migrants for example, having settled, may provide information and send remittances to potential migrants thereby reducing migration costs (see Beine et al., 2010, 2011).

Another plausible theoretical underpinning for the mobility transition curve arises from 'gravity' or geographic variables that may capture both economic development and migration costs. Such a mechanism has been understudied in the literature in this context. Distance from the equator is correlated both with levels of development (lowest for countries near the equator) and with the ease of migrating to rich countries (mostly located at the higher latitudes of each hemisphere). Thus gravity may explain why emigration rates and economic development are positively correlated, without implying a causal effect of development on emigration. Importantly therefore, the roles of both geography and culture, which jointly affect both migration costs and economic development need to be accounted for (see Gallup et al., 1999).

This paper is the first to quantify the competing mechanisms that underpin the mobility transition. We dissect the anatomy of the mobility transition by simultaneously incorporating all relevant *macroeconomic* and *microeconomic* mechanisms into our empirical model. Distinguishing between skill groups proves key, since emigration rates differ enormously between skill groups and many of the underlying mechanisms affect individuals of various educational attainments differently.[5] Our simple and double decomposition exercises reveal consistent results. In particular, we find that *microeconomic* drivers, while relevant for the poorest countries, have only limited power in explaining the upward sloping part of the transition curve. In countries with income per capita levels below $1500, financial constraints are the major mechanism preventing low-skilled workers from realizing their migration aspirations. Nevertheless, these countries exhibit low emigration rates and only account for less than 10% of the world labor force. In countries with income per capita levels between $1500 and $6000 (representing about 60% of the world population), the effect of financial constraints is much smaller. The upward segment of the mobility transition curve is mostly explained by the changing skill composition of working-age populations at origin in addition to *macroeconomic* drivers (i.e., network size and gravity drivers) that are constant or else adjust very slowly. In other words, by factors that do not change in the short-run. This suggests that a rise in income is unlikely to induce large emigration pressures in the short term (i.e., for a given size and skill structure of the population, and for a given socio-demographic environment). In the long-run however, a permanent rise in income,

[3] Clemens (2014) investigates emigration to all destinations, including non-OECD countries. Comparisons between decades reveal that the $5000 turning point has only slightly increased over time. In Appendix A, Fig. A1 shows that the turning point corresponds to a greater level of income when restricting the set of destinations to the OECD member states.

[4] Similarly, de Haas (2010b), proposes to incorporate the notions of agency and individual aspirations into transition theory, by conceptualizing migration at the microeconomic level as a function of aspirations (as characterized by an inverted U-shaped relationship) and capabilities (that increase monotonically with development).

[5] For example, greater inequality in less developed nations, strongly affects the incentives and financial capabilities of less educated individuals. Alternatively, the effect of migrant networks on migration costs has been shown to be greater for the low-skilled (as shown in Beine et al., 2010, 2011).

relaxes other financial constraints and affects other behaviors. In particular, it increases the share of college graduates and reduces population growth. Hence, an increase in permanent income induces uncertain effects with regards the magnitude of emigration stocks, but unambiguously increases the education level of future migrants.

The remainder of the paper is organized as follows. Section 2 describes our data and provides aggregate stylized facts on various components of the mobility transition. In Section 3, we describe our simple decomposition method and highlight the roles of skill-specific emigration rates and of the skill composition of the working-age population. In Section 4, we use a double decomposition method, relying on proxies for migration aspirations and realization rates by education level. Finally, Section 5 concludes.

2. Data and stylized facts

To disentangle the various potential drivers of the mobility transition curve (as detailed in the previous section), we construct measures of migration intensity to OECD member states, by education level, from 123 origin countries, over the 2000–2010 period. We further distinguish between actual and potential migration intensities. Actual migrants are those who have left their country of origin. Potential migrants include those who have left (i.e., actual migrants) in addition to those who have not yet migrated but express a desire to do so. We consider potential migration intensity as a proxy for migration aspirations. The ratio of actual to potential migration, which we term the realization rate, is used as proxy for the capacity of potential migrants to realize their aspirations. In this section we describe the data sources used to compute our migration intensity measures, provide some aggregate stylized facts and discuss some limitations of the data.

2.1. Migration by education level

Data on actual migration flows over the 2000–2010 period are derived from the Database on Immigrants in OECD Countries (*DIOC*), for the 2000 and 2010 census rounds. The *DIOC* database documents bilateral migration stocks by education level from all countries of origin ($i = 1, \dots, I$) to OECD destinations ($j = 1, \dots, J$). Data from the 2010 census round are described in Arslan et al. (2014), while the corresponding data for 2000 are presented in OECD (2008).[6]

We only consider migrants aged 25 and above (as a proxy for the working-age population) and 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). For each country pair, net migration flows are proxied as the difference between the bilateral migrant stocks in 2000 and 2010. We denote the net flow of migrants from country i to country j of education level $s = (h, l)$ as M_{ij}^s. Aggregating these numbers across OECD destinations allows us to characterize the size and structure of net emigration flows to the OECD from all the countries of the world i.e. $\overline{M}_i^s = \sum_j M_{ij}^s$

To compute actual migration *intensities*, we divide our net migration flows by the resident population at origin in 2000. This requires data on the number and average education levels of working-age residents (proxied by the resident population aged 25 and above, which corresponds with our migration data) in each sending country in our sample. This variable, denoted by N_i^s, is taken from Artuc et al. (2015), which proxies the size of the native population in country i from which we can extract the proportion of college graduates (σ_i^l) and less educated natives (σ_i^l). By definition, we have $\sigma_i^l + \sigma_i^h = 1$. Actual migration intensities can be measured as $m_{ij}^s \equiv M_{ij}^s / N_i^s$ at the bilateral level, and as $\overline{m}_i^s \equiv \overline{M}_i^s / N_i^s$ on the aggregate. It follows that the average emigration rate of each sending country is defined as:

$$\overline{m}_i \equiv \sigma_i^h \overline{m}_i^h + \sigma_i^l \overline{m}_i^l. \tag{1}$$

Existing studies of the mobility transition curve have identified the cross-sectional relationship between $\overline{m}_i$ and the level of development at origin, proxied by the log of income per capita (y_i). Fig. 2a and b show the relationships between each component of Eq. (1) and the log level of GDP per capita in US dollars (y). We consider a sample of 123 countries, excluding small states with populations below 2.5 million inhabitants, as well as those experiencing episodes of conflict. The results are obtained using the non-parametric Epanechnikov kernel density estimation (see Epanechnikov, 1969).

The skill composition of the population (σ^s) varies with economic development, possibly reflecting the existence of credit constraints that go beyond the capacity of individuals to finance migration costs. As shown in Fig. 2a, the share of college graduates in the native population σ^h rises constantly with development. This share is 20 times larger in the richest relative to the poorest countries. In addition, migration rates are always greater among college graduates ($\overline{m}^h$) than among the less educated ($\overline{m}^l$), as depicted in Fig. 2b. At low levels of income per capita, positive selection is strong ($\overline{m}^h \simeq 30\overline{m}^l$). In the richest countries, positive selection is much weaker ($\overline{m}^h \simeq 3\overline{m}^l$). Hence, education levels, taken in isolation, likely prove crucial in understanding the foundations of the mobility transition curve, since the hypothesized drivers likely affect the mobility of low-skilled and high-skilled individuals differently. Overall, the college-educated emigration rates ($\overline{m}^h$) decrease with development, while those of the less-educated ($\overline{m}^l$) follow an inverted U-shape.

2.2. Aspirations and realization rates

Our simple decomposition by education level allows us to examine how the skill composition of the native population affects the mobility transition curve. In a complementary double-decomposition analysis, we further distinguish between actual and potential migrants, which enables us to identify the effect of economic development on migration aspirations and realization rates. We rely upon the *Gallup World Poll surveys*, which identify the proportion of non-migrants expressing a desire to emigrate to another country. The Gallup survey has been canvassing opinions annually in more than 150 countries over the last ten years. As well as documenting various individual characteristics (such as age, gender and education), these surveys also include two relevant questions on emigration intentions. These questions, posed in 142 countries that represent about 97% of the world population, were: (i) *Ideally, if you had the opportunity, would you like to move to another country, or would you prefer to continue living in this country?* (ii) *To which country would you like to move?*

In line with our migration and population data, we only consider Gallup respondents aged 25 and above and distinguish between individuals with college education or otherwise. We aggregate four waves of the Gallup survey (i.e., the years 2007–2010) and consider that these four waves represent a single observation period. Using (year-specific) sample weights, we compute the weighted number of respondents to question (i) and the weighted number of respondents who answered positively to the same question. We then compute the stock of aspiring migrants by multiplying the 2010 population aged 25 and over, in origin countries, by the average proportion of individuals answering in the affirmative to question (i). These aspiring migrants would have increased the 2000–2010 net flow of actual migrants should they had been given the opportunity to emigrate therefore (as in

[6] It is not possible to conduct our analysis using panel data due to the lack of an education dimension in the available migration data. Using data on population by skill level would result in difficulties separating out compositional effects (whereby more educated individuals are more able to migrate) from incentive effects (in which potential migrants' desire to move are a function of the prevailing level of development at origin). Furthermore, any panel study would need to account for the endogeneity between acquiring education and the prospect of migration, what is known as the *brain gain* effect.

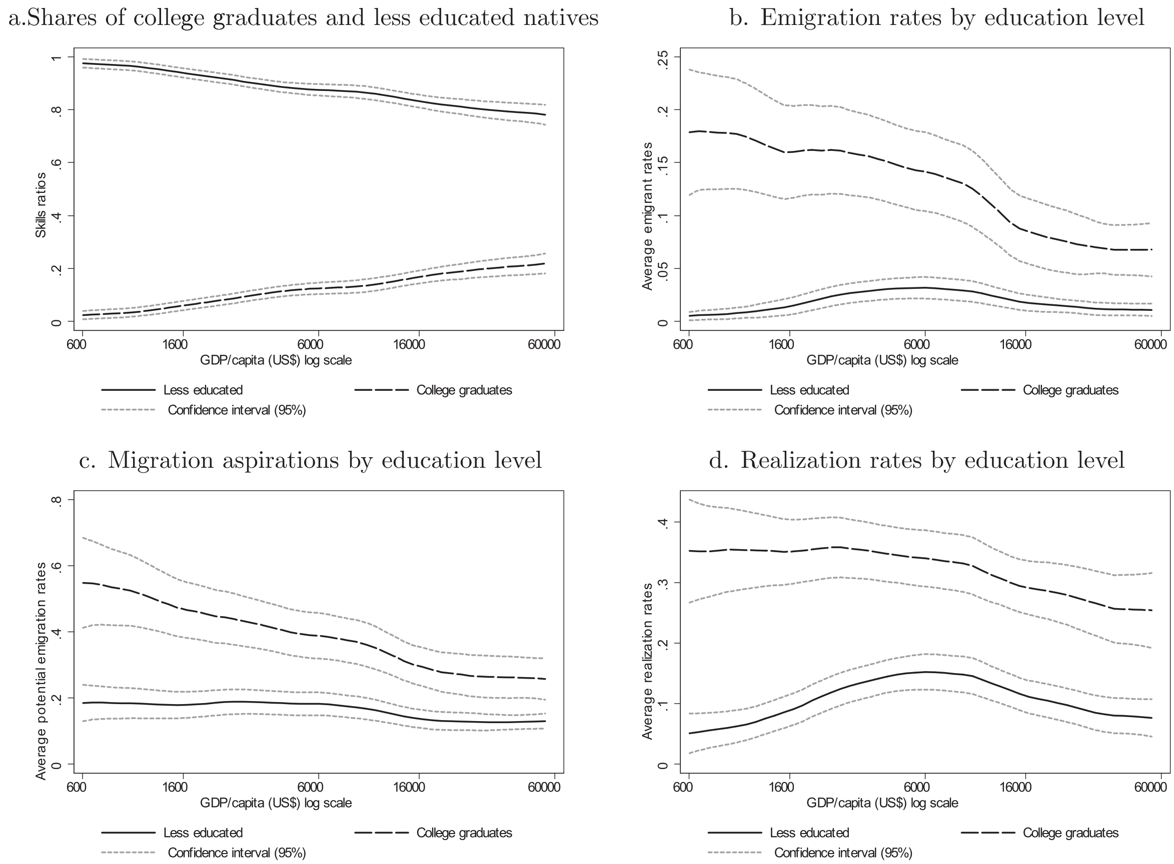

Fig. 2. Nonparametric regressions of the aggregate components of emigration on income per capita. Notes: Non-parametric regression using Epanechnikov kernel, local-mean smoothing, bandwidth 0.5. The migration rates delineated by skill levels are the differences between migrant stocks in 2000 and 2010, normalized by the skill population of the origin countries. Migration aspirations rates are calculated as the sum of the number of non-migrants expressing a willingness to emigrate and the actual migration flows between 2000–2010, normalized by the origin country populations. Realization rates are obtained by dividing the 2000–2010 migration flows by the total number of potential migrants. The sample consists of 123 countries. We omit small states that typically exhibit unusually large emigration rates, countries in conflict, country pairs with negative net flows, and country pairs with realization rates equal to 0 or 1 (see Section 2.3). Data on GDP per capita at PPP in 2000 are taken from the *Penn World Tables 7.0*.

Docquier et al., 2014, 2015). We then use responses to question (ii) to disaggregate the number of desiring migrants by country of destination. About 10 percent of desiring migrants failed to mention a desired destination however and these are ignored then we compute our dyadic shares.

Adding aspiring migrants to actual migration flows, we define the concept of potential migration flows P_{ij}^s, i.e. the total migration flows that would have been observed between 2000 and 2010 if all aspiring migrants had been able or allowed to emigrate. Aggregating bilateral stocks give $\overline{P}_i^s = \sum_j P_{ij}^s$. Thus, potential migration intensities, which captures emigration aspirations, can be measured as $p_{ij}^s \equiv P_{ij}^s/N_i^s$ at the bilateral level and as $\overline{p}_i^s \equiv \overline{P}_i^s/N_i^s$ on the aggregate. For reasons that will be explored later, aspiring migrants can fail to realize their aspirations, such that we define bilateral and aggregate realization rates as $r_{ij}^s \equiv m_{ij}^s/p_{ij}^s$ and $\overline{r}_i^s \equiv \overline{m}_i^s/\overline{p}_i^s$. Our decomposition of emigration rates by skill level, allows us to investigate whether the effect of economic development on emigration is skill specific and whether it is driven by migration aspirations or else by realization rates.

The databases described above allow us to differentiate emigration rates by skill level and to further distinguish between migration aspirations and realization rates. The average emigration rate of country i ($i = 1, \ldots, I$) can be decomposed as:

$$\overline{m}_i = \sigma_i^h \overline{p}_i^h \overline{r}_i^h + \sigma_i^l \overline{p}_i^l \overline{r}_i^l \tag{2}$$

where $\overline{p}_i^s$ is the proportion of potential migrants in the skill-s population and $\overline{r}_i^s$ is the average realization rate. The product of these two variables gives the proportion of natives who have realized their migration aspirations (i.e., $\overline{m}_i^s$). This corresponds to the observed migration rates by skill groups in Eq. (1).

Fig. 2c and 2d show the relationships between $\overline{p}^s$, $\overline{r}^s$, and the log of GDP per capita in US dollars (y); when considering the same sample of 123 countries and implementing non-parametric Epanechnikov kernel density estimations (see Epanechnikov, 1969). Fig. 2c shows that migration aspirations decrease with development for both college-educated and less educated individuals.[7] We observe a positive selection in migration aspirations, but this selection is much weaker when compared to actual migration. At low levels of development, the average willingness to migrate among the highly-educated is greater by a factor of four, when compared to the lower-skilled ($\overline{p}^h \simeq 4\overline{p}^l$). In the richest countries, the ratio falls to one and a half ($\overline{p}^h \simeq 1.5\overline{p}^l$). Fig. 2d describes the relationship between income per capita and the realization rates of college graduates ($\overline{r}_i^h$) and the less-educated ($\overline{r}_i^l$). Overall, the realization rate of the high-skilled slightly decreases with development. Its slope is not as sharp as that of the $\overline{p}^h$ curve. The realization rate of the less educated however, is the only inverted-U shaped component of the decomposition equation (1). At low levels of income per capita, the high-skilled are eight times more likely to realize their migration aspirations compared to the low-skilled ($\overline{r}^h \simeq 8\overline{r}^l$). This ratio falls to

[7] Total potential migration, is equal to the sum of those potential migrants expressing a willingness to migrate (from the Gallup data) and the actual migrants who effectively migrated between 2000 and 2010.

2 at intermediate income levels (around US $5000) and reaches 3 in the richest countries. Economic development therefore has a greater impact on realization rates than on migration aspirations.

2.3. Data compatibility and sample selection

The Gallup database is a unique and relevant source of information about migration aspirations. First, it is the only comprehensive source of data on migration aspirations worldwide or at the global scale. Secondly, empirical studies reveal that the reported aspirations are correlated with the traditional drivers of migration.[8] Thirdly, there is a high correlation between migration aspirations at year t and actual migration flows at year $t+1$ (Bertoli and Ruyssen, 2017), although actual flows are smaller. Nevertheless, the interpretation of the Gallup questions as well as the combination of data on actual net flows of migrants and on desired migration raise a number of concerns. This section discusses five problems associated with the double decomposition and their implications in terms of sample selection for our analyses in Sections 3 and 4.

- First, actual migration data capture the net dyadic *flow* of migrants between 2000 and 2010, while aspiring migration data are meant to represent the dyadic *stock* of individuals who would like to migrate if they had the opportunity around the year 2010. We consider that the latter stock also represents the additional flow of migrants that would have been observed if the opportunity to migrate had been given to each individual. Hence, the flow of potential migrants P_{ij}^s corresponds to the total migration flows that would have been observed between 2000 and 2010 if all aspiring migrants had been able or allowed to emigrate during that decade (as in Docquier et al., 2014, 2015)
- Secondly, aspiring migrants are asked to provide their first-best destination. Actual migrants however, may have instead migrated to a second-best location (think about refugees and forcibly displaced persons), something we ignore by aggregating the two numbers. In particular, the database includes 3600 values of realization rates that are equal to one (2040 for the high-skilled and 1560 for the low-skilled). This is equivalent to realizing migration aspirations with certainty, due to the total absence of sedentary individuals expressing a desire to emigrate in the Gallup World Polls; while concurrently some migrants actually moved to that destination. These dyadic observations can be considered atypical or inconsistent and their reliability is highly questionable. This is because the absence of aspiring migrants to these countries can arise due to the small sample sizes used in the Gallup World Polls. Moreover, these dyads may also comprise small numbers of actual migrants that are inaccurately measured in the *DIOC* database. Due to statistical disclosure rules, small corridors are usually aggregated in regions of origin that are split out using simple rules. The influence of these atypical observations on the mobility transition curve is limited. These dyads only represent 3.9% and 9.5% of the low-skilled and high-skilled migrant stocks, respectively.
- Thirdly, our database includes a smaller number of realization rates equal to zero (73 and 106 dyads for college graduates and the less educated, respectively). These result from the total absence of actual migrants recorded in the desired destination countries. Most of these cases concern Germany, a destination country for which there is an important lack of information about the country of origin of immigrants in the *DIOC* database. Again, the reliability of these dyadic observations remains questionable.
- Fourthly, the database includes a number of corridors with zero potential migrants (i.e., zero values for p_{ij}^s). In particular, the potential bilateral rate variables p_{ij}^s contain 7.25% of zero values for college graduates and 8.8% for the less educated. The presence of these zeroes may lead to biased and inconsistent OLS results.[9] In addition, realization rates cannot be computed when $p_{ij}^s = 0$, as they basically boil down to 0/0.
- Fifthly, the use of contingent valuation surveys to assess migration preferences is open to criticism (see Clemens and Pritchett, 2016). One might indeed argue that some respondents do not express a desire to emigrate because they interpret “opportunity” in light of the possibilities currently available to them. These might be limited to a life-threatening trip with the prospect of a life in the shadow economy at destination.

In the decomposition and empirical analyses below, we limit our sample to dyads with positive potential migration flows and realization rates strictly comprises between 0 and 1 (in line with Docquier et al., 2014, or Grogger and Hanson, 2011) Although we eliminate a large number of inconsistent observations,[10] the influence of these dyads on the mobility transition curve is negligible. Fig. 3 shows that the mobility transition curve is almost completely explained by those dyads included in our sample, i.e. 1409 dyads for low-skilled migration, and 1067 dyads for high-skilled migration. In addition, restricting our sample allows us to use OLS explorative regressions. For comparability reasons, we will use the same reduced sample throughout the rest of the paper. As developed in Appendix F, the alternative option to keep atypical/inconsistent observations requires using other estimation techniques (due to the large concentration of zeroes and ones) and

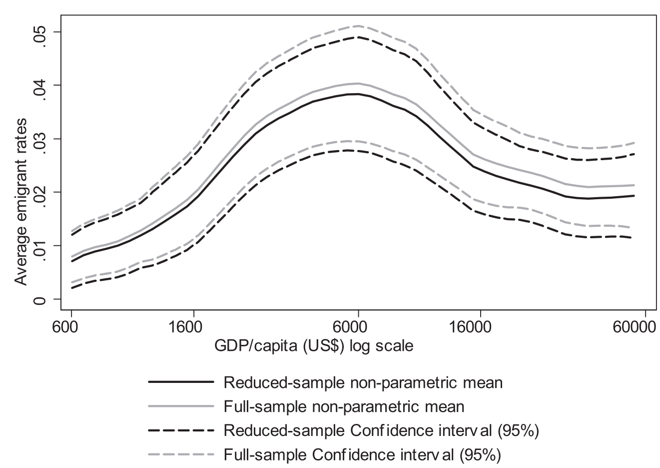

Fig. 3. Mobility transition curve under the full and restricted samples. Notes: The full sample consists of 3359 corridors of positive total migration flows between 123 origin and 33 destination countries. The restricted sample consists of 1409 corridors with realization rates strictly between 0 and 1. Data on GDP per capita at PPP in 2000 are taken from the Penn World Tables 7.0.

[8] Dustmann and Okatenko (2014) show that internal migration intentions depend on individual wealth as well as contentment with local amenities. The role of local amenities is confirmed in Manchin et al. (2014), who also find large effects of social networks on the desire to migrate internationally and locally. Docquier et al. (2014) find that the size of the network of previous migrants and the average income per person at destination are crucial determinants of potential migration and that college graduates exhibit greater actual emigration rates mainly because of better chances in realizing their immigration potentials, rather than because of a higher willingness to migrate.

[9] An alternative is to estimate potential bilateral emigration rates with the Poisson pseudo-maximum likelihood estimator (PPML) described in Santos Silva and Tenreyro (2006, 2011). PPML corrects for the fact that the variance of the error in gravity equations, which is non-linear, varies across country-pairs (heteroskedasticity); it is consistent in the presence of fixed effects; it does not exclude these zeroes and thus eliminates sample selection bias. However, PPML does not apply to realization rates, which exhibit a number of 0/0 and a concentration of ones.

[10] Fig. A2 in Appendix B compares the distribution of realization rates in the full sample with that of the reduced sample.

leads to many counterintuitive results.[11]

3. Simple decomposition: education levels

Starting from the simple decomposition by education level provided in Eq. (1), we compute the total derivative with respect to income per capita. Given $\sigma_i^l = 1 - \sigma_i^h$, this gives:

$$\frac{d\overline{m}_i}{dy_i} \equiv \underbrace{\frac{d\sigma_i^h}{dy_i}(\overline{m}_i^h - \overline{m}_i^l)}_{\text{Skill Composition}} + \underbrace{\sigma_i^h \frac{d\overline{m}_i^h}{dy_i}}_{\text{HS Migration}} + \underbrace{\sigma_i^l \frac{d\overline{m}_i^l}{dy_i}}_{\text{LS Migration}} . \tag{3}$$

The total derivative can be expressed as the sum of three additive components, labeled as *Skill Composition*, *HS Migration*, and *LS Migration*. In line with the stylized facts of the previous section, the magnitude of each of these components is strongly correlated with the level of economic development at origin (see Fig. 2). Each positive component can result in the upward segment of the mobility transition curve, while each negative component is in line with the neoclassical theory. In particular, the *Skill Composition* component is always positive. As income per capita increases, the share of college graduates increases and this mechanically increases the average emigration rate.[12] Remember $\overline{m}^h \simeq 30\overline{m}^l$ in the bottom countries, and $\overline{m}^h \simeq 3\overline{m}^l$ in industrialized countries. An upward segment of the mobility transition curve could be observed when the effect of the first term dominates, even if the emigration rates of each skill group decreased with development (i.e., $d\overline{m}^s/dy$ are jointly negative). Given Fig. 2b, we expect the *HS Migration* component to be zero 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 σ^h is small. It becomes non negligible in countries where income per capita exceeds \$6000. Conversely, the *LS Migration* component has an ambiguous sign since $\overline{m}^l$ is an inverted U-shaped function of income per capita.

The size of the three components of Eq. (3) is illustrated in Fig. 4a, which provides the results of non-parametric Epanechnikov kernel regressions of all three components with respect to the log of income per capita (y). It typically shows that the *Skill Composition* and *LS Migration* components explain approximately half of the positive slope of the mobility transition curve at levels of income per capita below \$1000 or else between \$4000 and \$6000. At higher income levels however (i.e., between \$2500 and \$3000), those income levels corresponding to the highest values of the slope of the mobility transition curve, the *LS Migration* component accounts for around 3/4 of the gradient, while the *Skill Composition* component accounts for only 1/4. Fig. A3. a in the Appendix shows that estimating the derivatives of σ^h, $\overline{m}^h$ and $\overline{m}^l$ with respect to y separately and aggregating the three components as in (1) almost perfectly fits the (one-step) non-parametric Epanechnikov kernel regression of $\overline{m}$ on y.

3.1. Macroeconomic versus microeconomic drivers

As an additional step in dissecting the anatomy of the mobility transition curve, we now identify the fractions of $\frac{d\overline{m}^s}{dy}$ that are due to *microeconomic* drivers (i.e. financial incentives and constraints) and *macroeconomic* drivers (denoted by a vector X_{ij} that includes socio-demographic variables, gravity determinants and existing migrant networks). We implement simple OLS regressions to estimate (and subsequently quantify) the relative contributions of all factors that the literature has highlighted as being potential explanations of the mobility transition. Importantly, we separately evaluate the impact of all these variables on both high-skilled and low-skilled emigration rates. Identifying the influence of gravity drivers and network effects requires our analysis to be conducted at the dyadic level, as well as controlling for absolute geography, culture and other exogenous determinants of migration flows. Using a quadratic function of income per capita (in logs), we allow the *microeconomic drivers* to induce non-monotonic effects on skill-specific emigration rates. Our regression model can be written as:

$$m_{ij}^s = \gamma_m^s X_{ij} + a_m^s y_i + b_m^s y_i^2 + \epsilon_{ij}^s \tag{4}$$

which implicitly assumes that income per capita is a good proxy for the financial incentives and constraints of both types of workers. This is in line with Clemens et al. (2008) who demonstrate that the income/productivity of all types of workers is mostly determined by the locality in which they are employed. Nevertheless, we also recognize that within-country inequality depends upon levels of development. In Appendix E, we use within-country inequality data from Hendricks (2004) to construct proxies for low-skilled and high-skilled income levels (y_i^s) and re-estimate Eq. (4). The results are presented in Table A1.

Once estimated, the model implies that:

$$\overline{m}_i^s \equiv \sum_{j=1}^{J^s} m_{ij}^s = \gamma_m^s \sum_{j=1}^{J^s} X_{ij} + J^s a_m^s y_i + J^s b_m^s y_i^2 \tag{5}$$

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

We can therefore compute the partial derivatives of skill-specific emigration rates with respect to income, $\frac{\partial \overline{m}_i^s}{\partial y_i}$, which clearly differ from the total derivatives that appeared in Eq. (1) since most *macroeconomic* drivers (X_{ij}) are correlated with income:

$$\frac{\partial \overline{m}_i^s}{\partial y_i} \equiv J^s a_m^s + 2J^s b_m^s y_i \qquad \neq \qquad \frac{d\overline{m}_i^s}{dy_i} \equiv \frac{\partial \overline{m}_i^s}{\partial y_i} + \gamma_m^s \sum_{j=1}^{J^s} \frac{dX_{ij}}{dy_i}$$

Having controlled for *macroeconomic* drivers (i.e., all the relevant, origin-specific mechanisms identified in the existing literature), we consider the residual effect of income to reasonably provide an upper-bound for the effect of *microeconomic* drivers (i.e. an upper-bound for financial incentives and constraints).

Finally, to illustrate the role of *microeconomic* drivers and compare it with that of the *Skill Composition* component, the derivative of the mobility transition curve in Eq. (3) can be rewritten as:

$$\frac{d\overline{m}_i}{dy_i} = \underbrace{\frac{d\sigma_i^h}{dy_i}(\overline{m}_i^h - \overline{m}_i^l)}_{\text{Skill Composition}} + \underbrace{\sigma_i^h \frac{\partial \overline{m}_i^h}{\partial y_i}}_{\text{HS Micro}} + \underbrace{\sigma_i^l \frac{\partial \overline{m}_i^l}{\partial y_i}}_{\text{LS Micro}} + \underbrace{\frac{dO_i}{dy_i}}_{\text{Others}} , \tag{6}$$

where $\frac{\partial \overline{m}_i^s}{\partial y_i}$ is computed as the partial derivative of Eq. (5) with respect to y_i.

The total derivative can now be expressed as the sum of four additive components. The skill-specific partial derivatives (referred to as *HS Micro* and *LS Micro*) proxy financial incentives and constraints for high-skilled and low-skilled natives, respectively. The last term $\frac{dO_i^s}{dy_i} = \sigma_i^h \gamma_m^h \sum_{j=1}^{J^h} \frac{dX_{ij}}{dy_i} + \sigma_i^l \gamma_m^l \sum_{j=1}^{J^l} \frac{dX_{ij}}{dy_i}$ captures the residual effect of macroeconomic and gravity drivers (referred to as *Others*).

3.2. Empirical results

We proceed by estimating Eq. (4) using GDP per capita data (PPP in 2005) international USD (Chain series) in 2000 (y_i) from the *Penn World*

[11] In Appendix F, PPML regression results are provided. We include observations with realization rates of 1 and potential migration rates of 0 in Table A4 and A5.

[12] Note that the literature on migration and development has also identified an effect of emigration prospects on human capital formation (Mountford, 1997). This implies that $\left(\overline{m}_i^h - \overline{m}_i^l\right)$ may influence σ_i^h. Beine et al. (2008) empirically demonstrate that this effect is positive and significant in developing countries, whatever the level of income per capita at origin. Hence, we assume that this *brain gain* mechanism does not distort the size of $d\sigma_i^h/dy_i$.

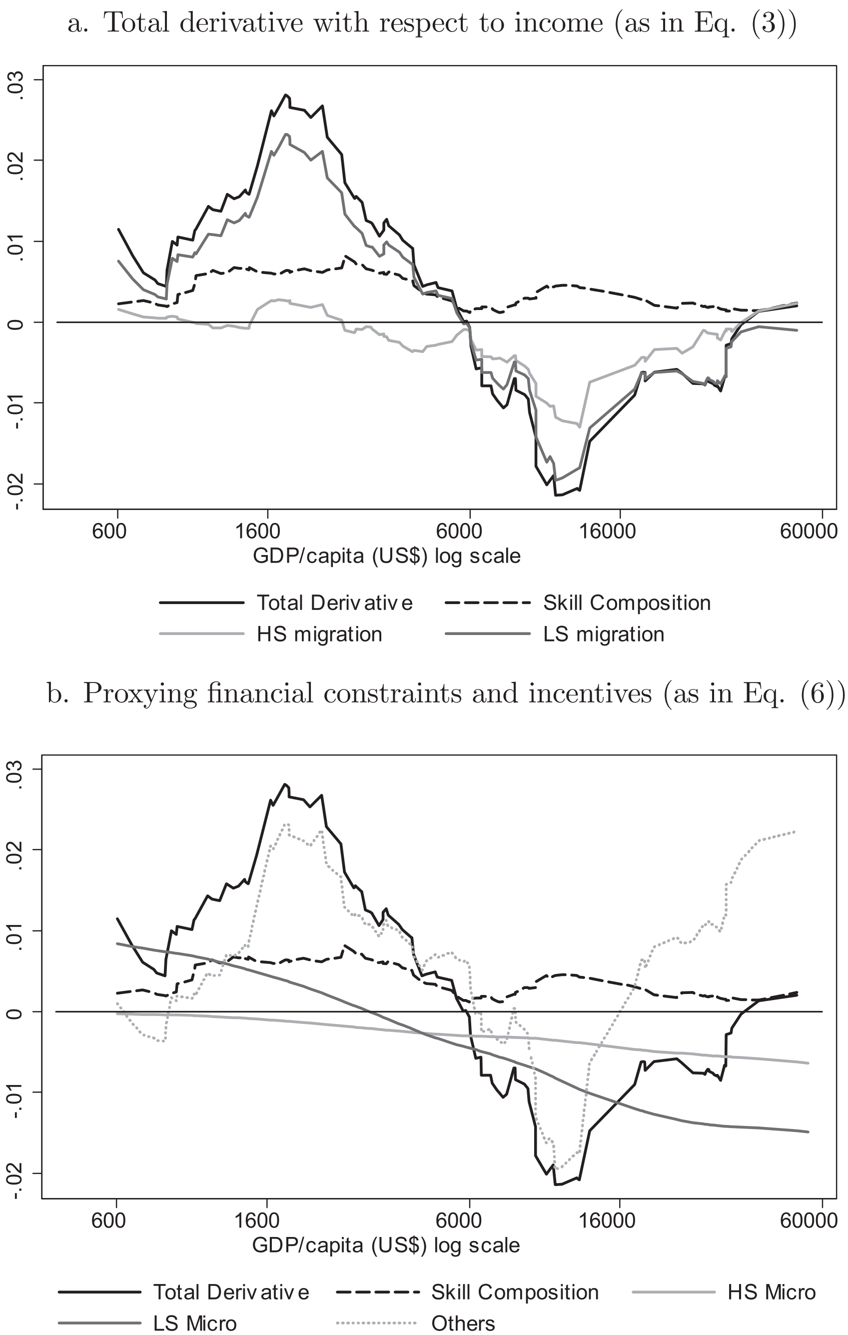

Fig. 4. Simple decomposition: education levels.

Tables 7.0. The set of explanatory variables (X_{ij}) includes the following variables: [13]

- Gravity drivers includes the log of geographic distance between sending and receiving countries and a set of dummy variables that equal one should the sending and receiving countries by contiguous, speak a common language or share a colonial heritage after 1945. These variables are obtained from the *CEPII Dyadic Distance Database* described in Mayer and Zignago (2011). We also include a measure of genetic diversity provided in Spolaore and Wacziarg (2015) as a proxy for cultural distance.[14] In addition, we also include a dyadic variable that captures the changes in the restrictiveness of the migration policy of a destination country j towards an origin country i between 2000 and 2010. The restrictiveness index is taken from the *Demig* database (DEMIG, 2015).
- To account for pre-existing migrant networks, we use the total stock of bilateral migrants from i to j in the year 2000, divided by the native population of country i in the same year. This variable captures the probability that a native from country i has a friend or

[13] Fig. A4 in Appendix C depicts the cross-sectional relationships between the main potential drivers of emigration rates and the log-level of income per capita in the origin country. Descriptive statistics are provided in Appendix G (see Table A6).

[14] We use the probability that two alleles (a particular form taken by a gene) at a given locus selected at random from two populations are different (as a proxy for time since isolation) from Spolaore and Wacziarg (2009). Genetic distance is based on blood samples and proxies the time since the two populations shared common ancestors. Spolaore and Wacziarg (2015) find a pattern of positive and significant relationships between genetic distance and various measures of cultural distance, including language, religion, values, and norms.

relative in country j at the beginning of the period. Given the endogeneity of this variable, we instrument it with its 10-year lag.

- Socio-demographic drivers include: the log of the population size, the share of the population in country i aged between 15 and 24 in 2000, as a proxy for the adult population in the age of migration between 2000 and 2010, average weighted import tariffs, as proxies for the degree of openness of country i and an index of education quality. The shares of the population aged 15–24 are obtained from the *UN-DESA World Population Prospects 2012*. Information on weighted import tariffs derive from the *World Integrated Trade Solution (WITS)* as of the year 2000. This variable is constructed using the average of all effectively applied import tariffs, weighted by their corresponding trade value.[15] The lower the import tariffs, the more open a country. Data on education quality are proxied by the test score results of high school students in maths, science and reading skills, which are taken from Angrist et al. (2013).
- Each regression includes a full set of destination fixed effects. These capture the relative attractiveness of all destinations as well as accounting for immigration policies that do not discriminate between origins. Finally, the gravity regressions that we estimate, although not formally derived from an underlying random utility model, nevertheless manifest similarly. One particular concern in this regard is the potential role of multilateral resistance to migration (MRM) (see Bertoli and Fernández-Huertas Moraga, 2013), which is the observation that the attractiveness of a particular destination country for potential migrants at origin will likely also depend upon the relative attractiveness of alternative destinations. To account for any potential bias that might arise from the existence of MRM, we follow the approach of Baier and Bergstrand (2009), once adapted to the case of migration as in Gröschl (2012) and control for 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.

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 our parsimonious specifications comprising significant controls only, in addition to the log level of income. We run a horse race between several competing theories underpinning the mobility transition curve. Hence, our parsimonious specifications are obtained after running backward stepwise regressions starting from the most complete model. Our decision as to whether include a variable or not, is based on its p-value (i.e., the variable should be significantly different from zero at the 5% threshold) and on the global fit of the model before and after eliminating that variable. The correlations between the log of income per capita, its square, gravity and socio-demographic determinants prove important. In our subsequent counterfactual simulations, we use the estimates of the parsimonious regressions to minimize concerns of collinearity.[16]

Our parsimonious model 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 \$1400. Above this level, low-skilled emigration decreases with development. Our 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.[17] As further robustness checks, we run similar regressions in the Appendix (i) with proxies of skill-specific wages instead of aggregate income per capita (see Table A1), (ii) when using the full sample and the PPML regression technique (see Tables A4 and A5). The effect of income per capita becomes insignificant when using a proxy for high-skilled income levels. Using alternative regression techniques yields qualitatively similar results, confirming the robustness of our benchmark estimates.

3.3. *Simple decomposition: a synthesis*

Fig. 4b describes the results of our simple decomposition as in Eq. (6). The magnitudes of the *Skill Composition* (by construction) and *HS Micro* (due to the low level of σ^h at low income levels) effects are very much in line with those of Fig. 3a. Conversely, dissecting the *macroeconomic* and *microeconomic* drivers of the *LS Migration* curve reveals that a large portion of the curve can be explained by gravity and network effects. In addition, for origin countries below \$1000, the *LS Micro* component effect is larger than that of the *Skill Composition*. Remember countries below \$1000 account for less than 5% of the world population. For origin countries between \$1000 and \$6000 however (i.e., in countries accounting for more than 60% of the world population), the *Skill Composition* effect exceeds that of the *LS Micro*. Overall, this means that financial constraints, while relevant for the very poorest countries, only have a limited effect on the upward segment of the mobility transition curve. As far as policy implications are concerned, our results suggest that in the short run (i.e., for a given skill structure, σ^s and for a given set of macroeconomic determinants, O), a rise in income induces only small effects on low-skilled and average emigration rates. In the long-run, a rise in income increases σ^s (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 O has an uncertain effect on the emigration stock, since increasing the mobility of workers can be offset by smaller populations.

4. Double decomposition: aspirations and realization

In this section, we check whether the limited effect of financial constraints is confirmed when using the Gallup proxies for migration aspirations and realization rates. We hypothesize that the role of financial constraints is reflected by the effect of income per capita on the capacity to realize migration aspirations. We proceed as in the previous section, but now exploit the double decomposition in Eq. (2) and compute its total derivative with respect to the log of income per capita. This gives:

$$\frac{d\overline{m}_i}{dy_i} = \underbrace{\frac{d\sigma_i^h}{dy_i}(\overline{m}_i^h - \overline{m}_i^l)}_{\text{Skill Composition}} + \underbrace{\sigma_i^h \overline{r}_i^h \frac{d\overline{p}_i^h}{dy_i}}_{\text{HS Aspiration}} + \underbrace{\sigma_i^h \overline{p}_i^h \frac{d\overline{r}_i^h}{dy_i}}_{\text{HS Realization}} + \underbrace{\sigma_i^l \overline{r}_i^l \frac{d\overline{p}_i^l}{dy_i}}_{\text{LS Aspiration}} + \underbrace{\sigma_i^l \overline{p}_i^l \frac{d\overline{r}_i^l}{dy_i}}_{\text{LS Realization}}. \tag{7}$$

[15] Data for 12 European countries (Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain and the United Kingdom) are unavailable. Under the common trade policy, the EU15 (plus Austria, Finland, Sweden) apply the same tariff rates to all their imports. The weighted tariffs are therefore not equivalent due to the differences in import volumes. For the sake of simplicity and given the difficulty of working with 6-digit commodity lines in order to calculate the exact weighted tariffs for each country however, we decided to use the average value of the European Union, which is available, for those 12 countries.

[16] In each regression, we instrument the network variable in 2000 by its 10-year lag. Partial R-squared and F-statistics of the first stage IV regressions show a high correlation between the migration stocks of these two periods.

[17] The counterintuitive sign of the effect of being contiguous may be due to the fact that our set of destination countries only includes OECD member states and contiguity captures low income differentials between origin and destination countries. Alternatively, this result could be interpreted as a border effect when geographic distance is small.

Table 1
Determinants of migration rates by dyad.

	Less educated			College Graduates		
	(L1)	(L2)	(L3)	(H1)	(H2)	(H3)
Network (% pop.)	0.4535***	0.4511***	0.4504***	0.8648***	0.8616***	0.8806***
	(0.07)	(0.07)	(0.07)	(0.18)	(0.18)	(0.18)
Geo. Dist. (log)	−0.0005*	−0.0005*		−0.0037***	−0.0036***	−0.0036***
	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)
Contiguity	−0.0018	−0.0014		−0.0123***	−0.0119***	−0.0136***
	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)
Com. Lang.	0.0003	0.0005		0.0122***	0.0126***	0.0127***
	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)
Colonial Link	−0.0023**	−0.0020**		0.0486***	0.0490***	0.0484***
	(0.00)	(0.00)		(0.01)	(0.01)	(0.01)
Genetic Dist.	−0.0001	0.0001		0.0081***	0.0083***	0.0075***
	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)
Population (log)	−0.0000	−0.0000		−0.0013*	−0.0013*	
	(0.00)	(0.00)		(0.00)	(0.00)	
Pop 15–24 (% pop.)	0.0000	−0.0000		−0.0000	−0.0002	
	(0.00)	(0.00)		(0.00)	(0.00)	
Import Tariff	−0.0000	−0.0000		0.0005*	0.0005*	
	(0.00)	(0.00)		(0.00)	(0.00)	
Educ. Quality	−0.0000	−0.0000*		−0.0001	−0.0001	
	(0.00)	(0.00)		(0.00)	(0.00)	
Pol. restr.	−0.0004	−0.0003		0.0017	0.0018	
	(0.00)	(0.00)		(0.00)	(0.00)	
GDP/cap	−0.0003	0.0063***	0.0058***	−0.0007	0.0129	−0.0025**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)
GDP/cap Sq.		−0.0004***	−0.0004***		−0.0008	
		(0.00)	(0.00)		(0.00)	
Constant	0.0095	−0.0166**	−0.0256***	0.0492	−0.0039	0.0258
	(0.01)	(0.01)	(0.01)	(0.04)	(0.10)	(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 estimted on the restricted sample of dyads with realization rates of strictly between 0 and 1 (see Section 2.3). The sample consists of 1409 observations for low-skilled migration rates and 1067 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.

The total derivative can be expressed as the sum of five additive components, labeled as *Skill Composition*, *HS Aspiration*, *HS Realization, LS Aspiration* and *LS Realization*. Using non-parametric Epanechnikov kernel regressions, we estimate the relationship between the log of income per capita and the size of each of these five components. The results are depicted in Fig. 5a. In line with our intuition and with Fig. 5a, it shows that the *Skill Composition* and *LS Realization* components explain approximately half of the positive slope of the mobility transition curve at levels of income per capita below \$6000, although the *LS Realization* component slightly dominates between \$2000 and \$3500. As far as migration aspirations of low-skilled and high-skilled workers are concerned, they have negligible effects on the slope of the mobility transition curve at lower levels of development (i.e. below \$6000).

To identify the roles of *microeconomic* and *macroeconomic* drivers, we implement simple OLS regressions of dyadic potential migration rates and realization rates using the same determinants as in the previous section. Our regression models can be written as:

$$p_{ij}^s = \gamma_p^s X_{ij} + a_p^s y_i + b_p^s y_i^2 + \varepsilon_{ij}^s, \tag{8}$$

$$r_{ij}^s = \gamma_r^s X_{ij} + a_r^s y_i + b_r^s y_i^2 + \varepsilon_{ij}^s, \tag{9}$$

assuming that income per capita is a good proxy for the financial incentives and constraints of both types of workers. In Appendix E, we re-estimate the regression models (8) and (9) using separate proxies for low-skilled and high-skilled income levels (y_i^s). The results are provided in Tables A2 and A3.

Once estimated, the model implies that:

$$\overline{p}_i^s \equiv \sum_{j=1}^{J^s} p_{ij}^s = \gamma_p^s \sum_{j=1}^{J^s} X_{ij} + J^s a_p^s y_i + J^s b_p^s y_i^2, \tag{10}$$

$$\overline{r}_i^s = \sum_{j=1}^{J^s} \frac{p_{ij}^s r_{ij}^s}{\overline{p}_i^s} = \gamma_r^s \sum_{j=1}^{J^s} \frac{X_{ij} p_{ij}^s}{\overline{p}_i^s} + a_r^s y_i + b_r^s y_i^2, \tag{11}$$

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

To illustrate the role of *microeconomic* drivers, the derivative of the mobility transition curve in Eq. (7) can now be rewritten as:

$$\frac{d\overline{m}_i}{dy_i} = \underbrace{\frac{d\sigma_i^h}{dy_i}(\overline{m}_i^h - \overline{m}_i^l)}_{\text{Skill composition}} + \underbrace{\sigma_i^h \overline{r}_i^h \frac{\partial \overline{p}_i^h}{\partial y_i}}_{\text{HS Incentive}} + \underbrace{\sigma_i^h \overline{p}_i^h \frac{\partial \overline{r}_i^h}{\partial y_i}}_{\text{HS Constraint}} + \underbrace{\sigma_i^l \overline{r}_i^l \frac{\partial \overline{p}_i^l}{\partial y_i}}_{\text{LS Incentive}} + \underbrace{\sigma_i^l \overline{p}_i^l \frac{\partial \overline{r}_i^l}{\partial y_i}}_{\text{LS Constraint}} + \underbrace{\frac{dO_i^s}{dy_i}}_{\text{Others}}, \tag{12}$$

where $\frac{\partial \overline{p}_i^s}{\partial y_i}$ and $\frac{\partial \overline{r}_i^s}{\partial y_i}$ can be replaced by the analytical expressions of the partial derivatives of Eqs. (10) and (11) with respect to y_i.

The total derivative can now be rewritten as the sum of six additive components. The skill-specific partial derivatives of the potential migration rates (referred to as *HS Incentive* and *LS Incentive*) proxies

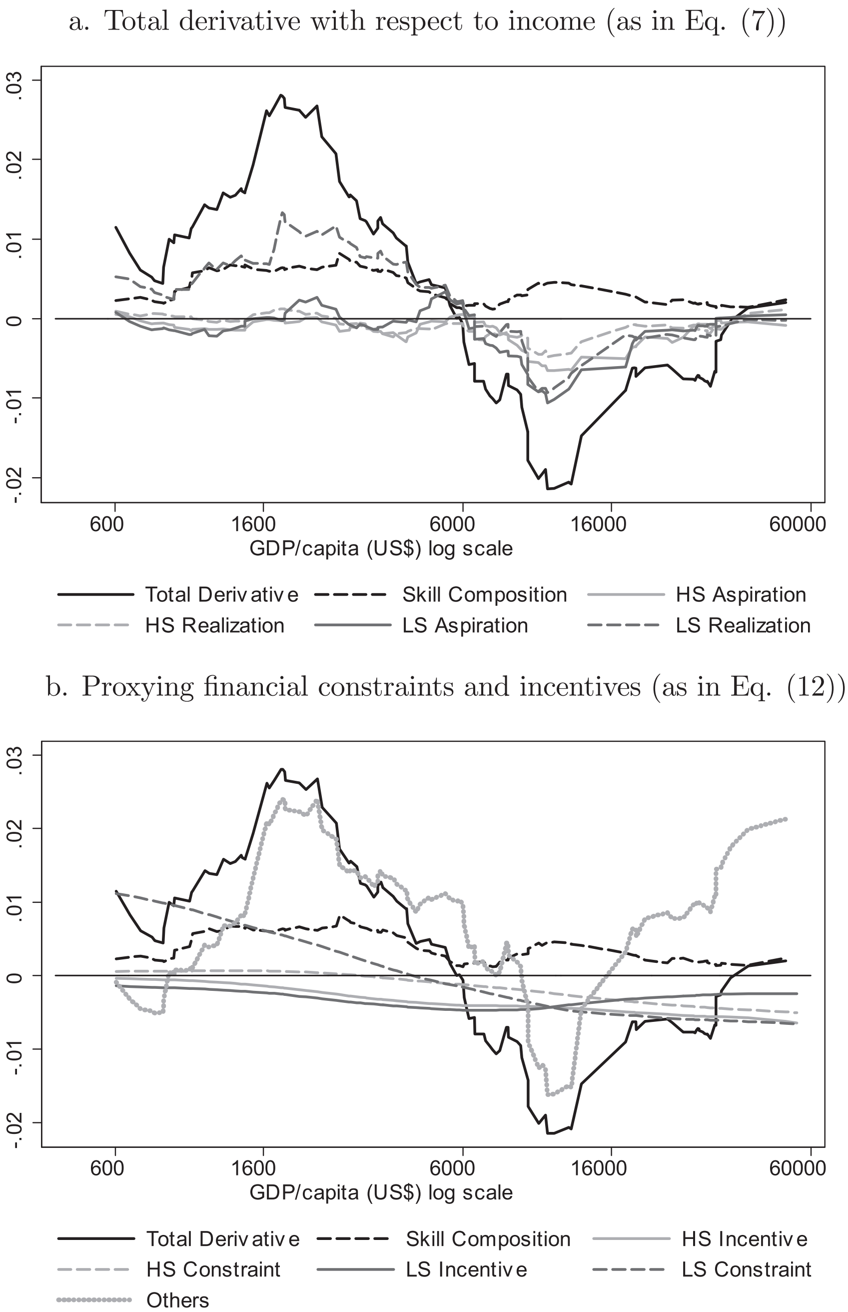

Fig. 5. Double decomposition: aspirations and realization rates.

for the financial incentives to emigrate; the skill-specific partial derivatives of the realization rates (referred to as *HS Constraint* and *LS Constraint*), proxies for the financial constraints for high-skilled and low-skilled natives, respectively. The residual term captures the effect of *macroeconomic drivers* (referred to as *Others*).

4.1. Empirical results

Regression results for migration aspirations and realization rates are presented in Tables 2 and 3. As in Table 1, all estimations include both destination fixed effects and variables controlling for multilateral resistance to migration. The standard errors are clustered by country of origin. Columns (L1) and (H1) include the full set of controls and the linear specification in income. Columns (L2) and (H2) present the results obtained with the quadratic specification. Columns (L3) and (H3) represent our parsimonious specifications comprising significant controls only (in addition to the log level of income) and minimizing collinearity issues.[18]

Focusing first upon migration aspirations, Table 2 reveals that migration aspirations of the low-skilled monotonically decrease with the log of income per capita and the magnitude of the coefficient is small.[19] In addition, $\overline{p}_i^l$ increases with the size of the network and with linguistic proximity and decreases with geographic distance and contiguity (see footnote 17 above). Our parsimonious model explains 56.3% of the overall variability in potential low-skilled migration. As for college graduates, their aspirations to emigrate monotonically decrease with the log of income per capita and this effect is larger than for

[18] In each regression, we instrument the network variable in 2000 by its ten-year lag. Partial R-squared and F-statistics of the first stage IV regressions show a high correlation between the migration stocks of these two periods.

[19] Similar results are obtained when using proxies for the income level of the low-skilled (see Table A2).

Table 2
Determinants of migration aspirations by dyad.

	Less educated			College Graduates		
	(L1)	(L2)	(L3)	(H1)	(H2)	(H3)
Network (% pop.)	1.3483***	1.3477***	1.3482***	1.2354***	1.2599***	1.2516***
	(0.17)	(0.17)	(0.16)	(0.37)	(0.38)	(0.37)
Geo. Dist. (log)	−0.0034***	−0.0034***	−0.0027***	−0.0125***	−0.0125***	−0.0112***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Contiguity	−0.0125***	−0.0124***	−0.0119***	−0.0291***	−0.0322***	−0.0296***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Com. Lang.	0.0135***	0.0135***	0.0152***	0.0360***	0.0328***	0.0380***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Colonial Link	0.0050	0.0051		0.0811***	0.0773***	0.0821***
	(0.00)	(0.00)		(0.03)	(0.03)	(0.03)
Genetic Dist.	0.0013	0.0013		0.0180***	0.0165***	0.0175***
	(0.00)	(0.00)		(0.00)	(0.00)	(0.01)
Population (log)	0.0004	0.0004		−0.0004	−0.0001	
	(0.00)	(0.00)		(0.00)	(0.00)	
Pop 15–24 (% pop.)	−0.0003	−0.0003		0.0005	0.0017	
	(0.00)	(0.00)		(0.00)	(0.00)	
Import Tariff	0.0001	0.0001		0.0007	0.0008	
	(0.00)	(0.00)		(0.00)	(0.00)	
Educ. Quality	−0.0003**	−0.0003**		−0.0006	−0.0005	
	(0.00)	(0.00)		(0.00)	(0.00)	
Pol. restr.	−0.0012	−0.0012		0.0006	−0.0006	
	(0.00)	(0.00)		(0.00)	(0.00)	
GDP/cap	−0.0009	0.0007	−0.0028***	−0.0043	−0.1093**	−0.0109***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.05)	(0.00)
GDP/cap Sq.		−0.0001			0.0061**	
		(0.00)			(0.00)	
Constant	0.0360	0.0297	0.0363*	0.1164	0.5260**	0.1358 **
	(0.04)	(0.05)	(0.02)	(0.13)	(0.26)	(0.06)
Dest. FE	Yes	Yes	Yes	Yes	Yes	Yes
MRM	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.5681	0.5680	0.5632	0.4422	0.4504	0.4368
N. of obs	1409	1409	1409	1067	1067	1067
Partial R-squared	0.8725	0.8725	0.8751	0.8854	0.8859	0.8864
F-stat	377.4963	376.6303	382.0562	163.1120	166.1433	160.3231

Notes: Standard errors are in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. OLS regressions estimted on the restricted sample of dyads with realization rates of strictly between 0 and 1 (see Section 2.3). The sample consists of 1409 observations for low-skilled migration rates and 1067 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.

the low-skilled.[20] The aspirations of the high-skilled increase with the size of the network, with linguistic proximity, colonial links and with genetic distance and they decrease with geographic distance and contiguity. The results on population size are negative, which might be indicative of the fact that larger countries usually exhibit lower (international) emigration rates since their citizens have access to better opportunities at home. Our parsimonious model explains 43.7% of the overall variability in the migration aspirations of the highly skilled.

The determinants of realization rates are presented in Table 3. Interestingly, both the linear and squared terms of the log of income per capita are now highly significant for both low-skilled and high-skilled workers. The relationship between realizing migration and financial capacity is non-linear, implying that economic progress is likely to increase the capacity of workers to financially meet the cost of international movement during early stages of development. After computing the turning points of these quadratic relationships, we find that low-skilled realization rates tend to increase with development in countries where income per capita is below \$4640;[21] high-skilled realization rates increase with development when income per capita is below \$3540.[22]

In addition, low-skilled realization rates increase with the network size and decrease with distance and population size. As for the highly skilled, their realization rates respond to the same determinants, as well as to linguistic proximity and colonial links. Overall, the gravity channels play an important role in determining the realization of migration. Migrant networks mitigate these costs related to long-distance movement and have sizable effects on the success of migration. The magnitude of network effects is globally similar across skill groups. Our parsimonious models explain 23.5% and 37.3% of the overall variability in the realization rates of the low-skilled and high-skilled, respectively.

4.2. Double decomposition: a synthesis

Fig. 5b describes the results of our double decomposition Eq. (12). The *HS Incentive* and *HS Constraint* components are always zero or negative and of low amplitude (due to the low level of σ^h at low income levels). Globally, the *LS Incentive* component is also negative, meaning that migration aspirations of the low-skilled are decreasing with income after controlling for the *macroeconomic drivers*. Conversely, the *LS Constraint* component is positive when income per capita is smaller than \$5000. Below \$1500, the *LS Constraint* component effect is the largest positive component. For income levels between \$1500 and \$6000 however, the *LS Constraint* component is smaller than the *Skill Composition* one. These results are very much in line with those of the simple decomposition. As before, a large portion of this curve is explained by the *macroeconomic* drivers (i.e. predominantly by gravity and network effects) and by the skill composition of the population.

[20] When using proxies for the income level of the high-skilled, migration aspirations become independent of income (see Table A2). This is in line with the results of the simple decomposition in Table A1.

[21] When using proxies for the income level of the low-skilled, the turning point equals \$5120 (see Table A3).

[22] When using proxies for the income level of the high-skilled, the realization rate monotonically decreases with income (see Table A3).

Table 3
Determinants of realization rates by dyad.

	Less educated			College Graduates		
	(L1)	(L2)	(L3)	(H1)	(H2)	(H3)
Network (% pop.)	2.5594***	2.4139***	2.4921***	2.8480***	2.7494***	2.7874***
	(0.450)	(0.467)	(0.443)	(0.507)	(0.470)	(0.487)
Geo. Dist. (log)	−0.0152**	−0.0156**	−0.0218***	−0.0287***	−0.0285***	−0.0365***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.009)
Contiguity	−0.0131	0.0076		0.0193	0.0319	
	(0.028)	(0.026)		(0.028)	(0.028)	
Com. Lang.	0.0050	0.0178		0.0807***	0.0937***	0.0866***
	(0.013)	(0.012)		(0.021)	(0.021)	(0.023)
Colonial Link	0.0067	0.0212		0.1390***	0.1543***	0.1459***
	(0.023)	(0.022)		(0.041)	(0.040)	(0.040)
Genetic Dist.	−0.0263**	−0.0146		−0.0065	−0.0004	
	(0.011)	(0.010)		(0.018)	(0.017)	
Population (log)	−0.0142***	−0.0152***	−0.0168***	−0.0311***	−0.0322***	−0.0315***
	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)	(0.008)
Pop 15–24 (% pop.)	0.0028	−0.0030		−0.0049	−0.0098	
	(0.003)	(0.004)		(0.006)	(0.006)	
Import Tariff	−0.0014	−0.0013		0.0033	0.0031	
	(0.001)	(0.001)		(0.002)	(0.002)	
Educ. Quality	0.0017	0.0016		0.0033*	0.0028	
	(0.001)	(0.001)		(0.002)	(0.002)	
Pol. restr.	0.0120	0.0161		0.0048	0.0095	
	(0.012)	(0.012)		(0.016)	(0.016)	
GDP/cap	−0.0186*	0.3826***	0.3529***	−0.0448**	0.3788***	0.3383***
	(0.010)	(0.090)	(0.082)	(0.018)	(0.146)	(0.123)
GDP/cap Sq.		−0.0237***	−0.0209***		−0.0245***	−0.0207***
		(0.005)	(0.005)		(0.008)	(0.007)
Constant	1.0946***	−0.4917	−0.2464	1.5606***	−0.0916	0.3783
	(0.315)	(0.415)	(0.370)	(0.398)	(0.764)	(0.665)
Dest. FE	Yes	Yes	Yes	Yes	Yes	Yes
MRM	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.2167	0.2494	0.2345	0.3715	0.3879	0.3733
N. of obs	1409	1409	1409	1067	1067	1067
Partial R-squared	0.8725	0.8725	0.8778	0.8854	0.8859	0.8886
F-stat	377.4963	376.6303	384.7583	163.1120	166.1433	163.0592

Notes: Standard errors are in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. OLS regressions estimted on the restricted sample of dyads with realization rates of strictly between 0 and 1 (see Section 2.3). The sample consists of 1409 observations for low-skilled migration rates and 1067 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.

5. Conclusion

In his seminal paper, Zelinsky (1971) was the first to hypothesize an inverted U-shaped relationship between emigration and development, a relationship that he termed the *mobility transition*; which has subsequently been observed in a variety of settings. Neo-classical explanations have been unable to explain the upward segment of the curve wherein migration increases with development at origin for countries at low or intermediate levels of income per capita. The existence of this upward sloping segment of the curve has therefore constituted a decades-old puzzle for which several potential explanations have been proposed in numerous geographical and historical contexts. Overall, the most common explanation is the existence of financial constraints that prevents the poorer workers from poor countries to realize their migration aspirations. If the existence of financial constraints is the major explanation, improving the economic situation of the bottom billion is likely to result in large migration pressures towards industrialized countries.

In this paper we analyze rich aggregated micro-data on individual's aspirations and realization rates in a decomposition framework with two skill groups. Having confirmed the existence of the *mobility transition* non-parametrically, we subsequently decompose it into migration rates of more and less skilled and their proportions in the population. We then use regression analyses to run a horse race between several competing theories underpinning the observed relationship for the first time. Having identified statistically significant variables from this analysis, we explore the roles of *microeconomic* drivers (i.e., financial incentives and constraints), skill composition and *macroeconomic* drivers in generating the upward segment of the mobility transition curve.

Our key result is that the contributions of *microeconomic* drivers are limited. With the exception of the poorest countries (representing less than 10% of the world population), a large fraction of the increasing segment is explained by *macroeconomic* drivers and by the skill composition of the population. The latter effect is particularly important in countries where GDP per capita in PPP value is between $1500 and $6000. While our conclusion is somewhat at odds with many pre-existing explanations, it is rather intuitive. Emigration increases with development, because the proportion of college graduates in the native population increases and it is precisely this group that has highest propensity to emigrate abroad. Hence, our results suggest that in the short term, a rise in income induces small effects on low-skilled and average emigration rates. In the long-run, a rise in income may increase the share of college graduates among emigrants and the average emigration rate. Nevertheless, the effect on emigration stocks is uncertain since the increasing mobility of workers can be offset by smaller populations.

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jdeveco.2017.12.003.

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