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The link between economic growth and emigration from developing countries: Does migrants' skill composition matter?

Mauro Lanati [1,2] | Rainer Thiele [3]

[1]Department of Economics, Management and Statistics (DEMS), University of Milano-Bicocca, Milan, Italy

[2]European University Institute, Florence, Italy

[3]Kiel Institute for the World Economy, Kiel University, Kiel, Germany

Correspondence
Mauro Lanati, Department of Economics, Management and Statistics (DEMS), University of Milano-Bicocca, Milan, Italy, and European University Institute, Florence, Italy.
Email: mauro.lanati@unimib.it

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Abstract

Tackling the root causes of migration from developing countries through development cooperation has been suggested as an essential part of the policy mix in OECD migrant destinations. This is even though the evidence on whether economic development leads to more or less people emigrating is so far inconclusive. We investigate the relationship between income per capita and emigration to OECD countries separately for three different skill groups—low-skilled, medium-skilled and high-skilled emigrants—being the first to employ panel regression approaches that account for cross-country heterogeneity and cover a policy-relevant time frame of about 5 years. Our findings reveal a universal negative association between income per capita and emigration for all three skill groups and for different income thresholds. This implies that policy makers should not be too concerned about potential trade-offs between (successful) development cooperation and immigration management, at least in the short to medium run that our analysis covers. At the same time, the scope for using development cooperation as a migration policy instrument can be considered to be limited given the modest size of the estimated income effect: Taking our point estimates at face value, a 10% rise in GDP per capita would on average lead to about 3600 fewer immigrants per destination.

1 | INTRODUCTION

Research on how local economic development affects the individual decision to emigrate can be traced back to the seminal papers by Sjaastadt (1962) and Harris and Todaro (1970). Yet, it has for decades played a minor role in the development discourse where the focus has rather been on the opposite question of whether or not emigration fosters local development. Only recently, due to large numbers of arrivals of irregular migrants from developing countries, the topic has gained political prominence. Specifically, policy makers in potential OECD destination countries have stressed the importance of tackling the root causes of migration and have pointed to low levels of economic development as one major driver of emigration. This view is in accordance with the neoclassical prediction of the early papers that (expected) income differentials between destinations and origins are the key determinants of migration decisions.

However, policy makers' presumption that migration can be reduced by supporting economic development has been challenged in the academic literature that accompanied the recent policy debate. The predominant view is that a hump-shaped relationship exists between home-country incomes and emigration pressure (e.g. Clemens, 2014). This would imply that higher incomes in developing countries, which tend to be located on the rising part of the inverted U-curve, lead to more emigration. However, the evidence backing the migration hump is predominantly based on cross-country studies, which capture the long-run link between income and migration and thus have limited direct implications for development policy. By contrast, panel regressions that exploit the time dimension of the income–migration relationship come closer to policy questions such as whether supporting a specific country is associated with more or less emigration from that same country in the subsequent years. So far, they have produced mixed results (e.g. Benček & Schneiderheinze, 2020; Clemens, 2020).

The inconclusive evidence obtained by recent panel data studies constitutes the point of departure of our analysis. We aim to contribute to the literature in two main dimensions. First, following Djajic et al. (2016), who focus on the cross-country dimension, we are the first to investigate the relationship between changes in income per capita over time and emigration to OECD countries separately for three skill groups—low-skilled, medium-skilled and high-skilled workers. In doing so, we combine information on GDP per capita and Gini coefficients to generate income percentiles corresponding to skill groups (Grogger & Hanson, 2011). The key hypothesis is that a variation of per-capita income in countries of origin is likely to impact migration decisions differently depending on skill levels. Liquidity constraints are expected to play an important role in restricting the migration flows of low-skilled workers; at the same time, this skill group's low incomes relative to potential destinations provide strong migration incentives. For high-skilled workers, both liquidity constraints and incentive effects figure less prominently but still point in opposite directions. Whether the net effect for each skill group is positive or negative is then ultimately an empirical question. By employing a panel data approach, we capture the impacts of income changes on migration in the short to medium run, which is arguably of particular relevance for policymakers interested in managing migrant flows.

Second, previous studies have varied considerably in their methodological approach, which might be one reason why their results differ. For instance, several authors have used standard gravity approaches, thereby accounting for the dyadic links between countries of destination and countries of origin (e.g. Adovor et al., 2021; Ortega & Peri, 2013), while others (e.g. Benček & Schneiderheinze, 2020; Clemens, 2020) have focused on the country-of-origin perspective in a purely monadic setting. We shed new light on the robustness of the estimated relationship between per-capita income and emigration from developing countries by applying a broad range of specifications in accordance with the approaches employed in the previous literature. Our preferred specification is a two-step gravity model (e.g. Head & Mayer, 2014), which estimates bilateral migration flows in the first step and enables us to regress emigration at the country level on skill-specific income percentiles in the second step.

Our findings reveal a universal negative association between income per capita and emigration for all three skill groups and across various specifications. This suggests that, on average, even for low-skilled workers in low-income countries, opportunity cost considerations along the lines of the traditional neoclassical models tend to dominate liquidity constraints in shaping migration decisions in the short to medium run.

The remainder of the paper is structured as follows. Section 2 contains a brief review of the literature that is related to our analysis. In Section 3, we introduce our econometric approach and provide a brief discussion of the migration data by skill level that are employed in the empirical analysis. Section 4 presents the estimation results, starting with a baseline specification and then adding a series of robustness checks. Section 5 closes the paper with some concluding remarks.

2 | RELATED LITERATURE

The arguably most influential strand in the literature related to the present analysis posits that the income-emigration nexus forms a hump shape (e.g. Clemens, 2014; Dao et al., 2018). The notion of an inverted u-shaped relationship between development and emigration dates back to Zelinsky (1971), who called it the mobility transition theory. The term 'migration hump', which is often used in the current debate, was coined by Martin and Taylor (1996). On a conceptual level, much of the literature on the migration hump has examined the various factors that may be responsible for its occurrence (see Clemens, 2014, for an excellent overview). Most notably, several authors attribute an important role to liquidity constraints (e.g. Faini & Venturini, 1994; Hatton & Williamson, 1994): At low levels of per capita GDP, additional income facilitates emigration for liquidity-constrained individuals in countries of origin, thus raising the number of people who actually leave. At some point, the liquidity constraint is no longer as binding, so further increases in real incomes cause the emigration rate to fall from its peak as predicted by the neo-classical model that focusses on incentive effects.

Authors from the social sciences (e.g. de Haas 2010a, 2010b) have broadened this income-centred approach by arguing that people's propensity to migrate depends not only on income but more broadly on people's aspirations and capabilities (including income, social and human resources) to do so. In this setting, migration is expected to increase as long as aspirations increase faster than local livelihood opportunities, which is also supposed to give rise to a hump-shaped relationship.

In its income-centred version, the migration hump hypothesis receives empirical support in cross-sectional settings, that is when comparing emigration rates from richer and poorer developing countries (e.g. Clemens, 2014; Dao et al., 2018; Djajic et al., 2016). The majority of developing countries are estimated to be located on the upward-sloping part of the migration hump. Clemens and Postel (2018), for example, estimate the turning point to be at levels of GDP per capita between US $8000 and US$ 10,000. Dao et al. (2018) come up with a somewhat lower value of US $6000.

As highlighted by Borjas (1987) and Dao et al. (2018), among others, the skill composition of the population is an important factor driving emigration decisions. In their cross-country analysis, Djajic et al. (2016) confirm the migration hump hypothesis across skill groups, obtaining a positive and significant income effect for the group of low-skilled emigrants (i.e. liquidity effects dominate), whereas at higher skill levels the effect turns negative even though it loses its statistical significance. These findings therefore suggest a clear policy implication: To the extent that development assistance to countries of origin is successful in fostering local economic development, it is likely to encourage additional emigration, pointing to a trade-off between development and immigration policy objectives.

Yet, the conclusions derived from cross-country studies have their limitations as inputs for policy making. First, cross-country heterogeneity renders causal interpretation difficult. Benček and Schneiderheinze (2020), for example, show that countries located at the upward-sloping part of the migration hump, on average, differ markedly from richer countries with respect to crucial exogenous factors such as distance to OECD countries, size and past colonial ties. These factors, in turn, tend to be negatively related to both development and emigration. Second, the cross-country estimates are best interpreted as capturing the long-term association between economic development and emigration. Development policy makers, in contrast, are arguably more interested in how their support of specific countries shapes emigration from these countries in the subsequent years. By estimating variations within countries over relatively short time periods, panel data studies address exactly this kind of question. They also come closer to a causal interpretation of the estimates through the inclusion of a set of fixed effects that account for unobserved, time-invariant country heterogeneity.

Panel data studies of the development-migration nexus have so far come up with mixed results. Employing decadal migrant stocks provided by the World Bank for both OECD and Non-OECD destinations, Clemens (2020) finds that increasing GDP per capita is on average associated with more emigration in poor countries and that the effect reverses only after GDP per capita exceeds about \$10,000. In a similar vein, based on census data from Indonesia, Bazzi (2017) estimates that positive income shocks in poor rural areas increase emigration, whereas the opposite effect occurs for the most developed regions within the country. Two studies addressing the specific case of doctors (Adovor et al., 2021; Moullan, 2013) identify a negative impact of income per capita on emigration. This finding could still be in line with the inverted U-shape hypothesis, given that highly skilled emigrants such as doctors are likely to be located on the descending segment of the migration hump. Another group of papers (Benček & Schneiderheinze, 2020; Böhme et al., 2020; Clist & Restelli, 2021; Ortega & Peri, 2013), however, point to a universal negative income-migration relationship once cross-country heterogeneity is accounted for through the inclusion of an appropriate set of fixed effects. Similarly, using Gallup-World Poll data on migration intentions, Langella and Manning (2021) find a (weakly) significant negative relationship between aggregate per capita GDP and individuals' desire to emigrate to poorer countries. Beine et al. (2021) show in the case of Turkey that higher incomes at origin lead to less internal migration, with a stronger effect for refugees as compared to non-refugees.

Taken together, the panel data evidence so far is not sufficient to guide policy making. In the subsequent analysis, we aim to broaden and enrich the evidence base by looking at skill-specific emigration and by performing a number of robustness checks that reflect the approaches used in the previous literature. In doing so, our main focus is not on the full u-shape of the income-migration relationship (or its absence) but rather on the question of whether there is an upward-sloping part for the poorer segment of the population, which typically is the target group of development policy interventions. We leave aside the debate on the existence of a long-term migration hump.

3 | ECONOMETRIC SPECIFICATION AND DATA

The policy question underlying our empirical analysis is whether (successful) development cooperation leads to more or less emigration from the developing country that received the support. We thus focus on the determinants of bilateral migration flows, for which gravity models have become the standard analytical tool (e.g. Lanati & Thiele, 2018; Ortega & Peri, 2013). Gravity models are able to capture all relevant drivers of migration, including dyadic variables such as the existence of migrant networks as well as the standard push and pull factors. They can be estimated using either a one-step approach or a two-step approach. The one-step approach directly regresses migration on a set of dyadic and country-specific explanatory variables including income per capita at origin (e.g. Beine & Parsons, 2015). In the two-step approach, bilateral migration flows are estimated first, with destination-time and origin-time fixed effects absorbing all country-specific push and pull factors (e.g. Adovor et al., 2021). The origin-time fixed effects from the first-step estimation, which can be interpreted as average emigration from a specific country relative to other countries, are then regressed on income per capita and other time-varying push factors at origin.

In the preferred baseline regression below, we follow Adovor et al. (2021) and estimate the relationship between income per capita and emigration using a two-step strategy based on a structural gravity model of international migration. This is because the two-step estimator has distinctive advantages over the one-step procedure in our setting. Most notably, we do not have to re-scale our dependent variable in the first step to obtain emigration rates differentiated by skill level, as origin-time fixed effects completely absorb the impact of all origin-specific drivers of emigration, including a country's total population which is normally included as a denominator of the dependent variable (e.g. Beine et al., 2011). In the one-step procedure, calculating emigration rates with population differentiated by skill level available from the Barro and Lee (2013) dataset as the denominator would lead to a severe loss of information due to missing data. There are also methodological advantages of the two-step approach. First, when using the one-step approach the error term is likely to be correlated across destinations for a given origin, leading to a downward-biased standard error of our estimated coefficient of interest (Head & Mayer, 2014). Second, by employing a monadic regression in the second step, the two-step approach also renders it possible to perform an instrumental variable estimation along the lines described below, which can hardly be achieved in the dyadic setting of the one-step approach. Despite its disadvantages, we still apply the one-step approach in one of our robustness checks but only for the case of aggregate migration because of the above-mentioned data problems.

In the two-step approach, the econometric specification of the income-emigration link reduces to

$$\widehat{S}_{i(l),t} = \beta_i + \beta_t + ln\left(GDPpc_{i,t-5}\right) * \gamma + X_{i,t-5} * \upsilon + \epsilon_{i(l),t}, \tag{1}$$

where $GDPpc_{i,t-5}$ is GDP per capita at origin i in year t, $X_{i,t-5}$ denotes a set of time-varying push factors, and β_i and β_t are country and year fixed effects, respectively. $\widehat{S}_{i(l),t}$ is the origin-year fixed effect for skill group l obtained from estimating the following equation in the first step:

$$M_{ji(l),t} = exp\left[S_{i(l),t} + S_{j(l),t} + S_{ij(l)} + ln\left(MigStocks_{ji,t-5}\right) * \delta + \tau_{ji(l),t}\right]. \tag{2}$$

$\widehat{S}_{i(l),t}$ is a measure of migration openness, indicating the average volume of emigrants a specific origin country sends relative to other sending countries in a given year. $M_{ji(l),t}$ denotes emigration flows from country i to country j; in line with Beine and Parsons (2015), they are calculated as differences of bilateral migrant stocks provided in 5-year intervals (see below).

Through the inclusion of destination-time fixed effects $\left(S_{j(l),t}\right)$ and origin-time fixed effects $\left(S_{i(l),t}\right)$, the first-step Equation (2) absorbs all push and pull factors, leaving the lagged stock of bilateral migrants $\left(\text{MigStocks}_{ji,t}\right)$, the standard proxy of migrant networks or diasporas, as the only covariate estimated in the econometric specification. Additionally, including country-pair fixed effects $\left(S_{ij(l)}\right)$ allows us to fully account for multilateral resistance to migration (Bertoli & Fernandez-Huertas Moraga, 2013), that is the fact that the choice of a potential migrant to move to a given destination country does not only depend on the attractiveness of the country of destination relative to the country of origin but also on how this relates to the opportunities to move to other destinations.

Equation (1) allows us to capture time-varying push factors from the origin countries, including our variable of interest, per-capita income. Besides income per capita, we consider several standard control variables (see below). To account for the possible heterogeneity of effects across income levels, we pursue two strategies: (i) using subsamples of lower-income countries and (ii) including interaction terms. First, based on Clemens and Postel's (2018) suggestion that the turning point of the U curve may lie at around GDP per capita values of \$8000–\$10,000, we introduce income thresholds of \$10,000 and \$8000, and even lower threshold of \$6000 as in Dao et al. (2018), to focus on the poorer population segments for which the income–migration relationship is potentially upward-sloping.[1] Second, we run a model with multiplicative interaction terms between GDP per capita and various indicators for 'poor and very poor countries' (<\$10,000; <\$8000; <\$5000; <\$3000). Our preferred specification is the one with different income thresholds given the setting of a potentially non-linear income-migration link. This is because the multiplicative interaction model relies on the key assumption that the interaction effects are linear, whereas the split sample strategy allows us to depart from that stringent postulation (Hainmueller et al., 2019). Yet, the interaction model also comes with clear advantages, which include a higher number of observations and the option to look at a subset of very poor countries with GDP per capita below \$3000 as we do not have to reduce the sample size when introducing the interaction terms. Below, we therefore also present the results of the interaction model.

[1]Based on the estimated coefficients of a specification that includes a squared GDP per capita term and no time or country fixed effects (column 8 in Table OA1 of the online appendix, which reveals a U-shaped effect of GDP per capita; the U-shape is also shown for various cross-sections in Figure OA1), we calculate the turning point of the U-shaped relationship between per-capita income and emigration to be around \$11,000. Against this background, the thresholds applied in our empirical analysis appear fairly conservative.

Following Adovor et al. (2021) as well as Lanati and Thiele (2020), we apply the pseudo-Poisson maximum likelihood (PPML) method in the first step of our estimation and OLS in the second step. The rationale behind the former is to account for the occurrence of zero observations. According to Silva and Tenreyro (2006), a significant share of zero observations creates a correlation between the covariates and the error term, rendering OLS estimates inconsistent. In addition, OLS is likely to be biased and inconsistent when the error term is heteroskedastic, whereas the PPML estimator is consistent under more general circumstances. Larch et al. (2019) have shown that the underlying heteroskedasticity in structural gravity models leads to an increasing divergence in estimates between PPML and OLS with an increasing number of small countries included in the sample. Given that our sample is characterised by a large number of countries of origin, many of them small, the choice of the PPML estimator therefore matters. In the monadic setting of Equation (1), in which there are no zero observations in the dependent variable, we employ OLS regressions to estimate the effect of per-capita income on $\widehat{S}_{i(l),t}$.

We prefer a strategy based on a structural gravity model over the estimation of a monadic model because our proxy of *migration openness* for a given country, $\widehat{S}_{i(l),t}$, is obtained by exploiting all the dyadic information available. In particular, estimating *migration openness* with a structural gravity model allows us to control for all destination and dyadic specific determinants of emigration, including policies at destination, geographic factors and cultural proximity. Omitting these variables might lead to biased estimates of the income effect. For instance, countries like Mexico and Morocco have relatively higher emigration rates to OECD countries because of their geographical proximity with the US and the EU, respectively. This may wrongly be attributed to their comparably high incomes. In addition, the inclusion of origin-year fixed effects in a gravity model captures corrections for multilateral resistance to migration (see above). As Bertoli and Fernandez-Huertas Moraga (2013) have shown, failing to account for multilateral resistance would lead to overestimated effects of economic conditions at the origin. In a robustness check, we follow previous studies by Benček and Schneiderheinze (2020) as well as Clemens (2020) and estimate a monadic model.

In our baseline specification, we use GDP per capita as the relevant explanatory variable when estimating Equation (1), which allows us to construct income distributions for each country following the methodology proposed by Grogger and Hanson (2011), where percentiles of source-country income are generated by combining information on GDP per capita at purchasing power parity and Gini coefficients.[2] In doing so, we also address Clemens' (2020) concern that the alternative of employing GDP and population separately in the regression could lead to spurious correlations. We prefer using income percentiles based on GDP per capita at purchasing power parity rather than a more direct measure of skill-specific wages because (a) many of the potential emigrants in our developing country sample are not wage-earners, and (b) unlike wages, information on per capita income is available for most of the developing countries. Still, it has to be noted that theories such as the Harris-Todaro model explain migration decisions based on (expected) earning differentials, that is wages are in principle better suited to test these theories than GDP per capita. In an additional robustness test, we therefore focus on wages of selected low-to-medium skilled occupations for which data are available.

The strategy of generating income percentiles has some drawbacks, as it is subject to measurement error and some fairly strong assumptions. First, since informal economic activities are particularly prevalent in developing countries, the Gini index of measured incomes is likely to overstate true income inequality. Second, it assumes that income is log-normally distributed, whereas evidence has shown that there are sometimes significant departures from log normality observed in income data (e.g. Battistin et al., 2009). Third, it leads to a loss in statistical power: When transforming our variable of interest and generating income percentiles, we lose around 25% of observations. We therefore alternatively model emigration in absolute terms, regressing *migration openness* on absolute GDP and controlling for population size. An advantage of doing so is that population growth exerts an influence on emigration that goes beyond increasing the pool of potential migrants. It shapes age distribution within countries, which in turn

[2]Formally, it is assumed that income X is log-normally distributed, that is $ln X \sim N(\mu,\sigma^2)$. Hence, the parameter σ can be obtained from the Gini coefficient (G) using $\sigma = \sqrt{2}\,\Phi^{-1}[(G+1)/2]$, where Φ^{-1} is the inverse of a standard normal cumulative density function. Therefore, each percentile of income X_α can be written as $X_\alpha = E(X)exp(\sigma z_\alpha - \sigma^2/2)$, where z_α denotes the α_{th} percentile of a unit normal random variable and $E(X)$ is substituted with GDP pc in 2011 Const. $ PPP.

affects average emigration propensities. In addition, more populous countries provide more opportunities for internal migration (de Haas et al., 2019). The main drawback of this specification is that we cannot calculate skill-specific incomes but rather have to rely on the very strong assumption that changes in average incomes provide a good approximation of changes along the income distribution.

Our baseline specification includes a set of origin-specific control variables that represent common push factors, namely (i) the average years of schooling attained (aged 15–64), (ii) the total number of natural disasters in a given year, (iii) conflict intensity, (iv) a democracy index and (v) the dependency ratio. Opportunities to migrate and earn a decent living abroad are likely to improve with the level of formal education, which we approximate by school attainment. Following Beine and Parsons (2015), we consider natural disasters as a proxy for the potential role of adverse environmental factors in shaping migration decisions. We use conflict as a standard driver of emigration in accordance with much of the previous empirical literature (e.g. Lanati and Thiele (2018). A lack of democracy, political rights and civil liberties may act as a push factor for migrants seeking greater freedoms, which is most likely the case for those with higher education levels. Giménez-Gómez et al. (2019), for instance, show that African migration to Europe is negatively related to levels of democracy in countries of origin.[3] Finally, we capture demographic push factors at origin by means of the total dependency ratio, that is the total population aged less than 15 or over 64 as a share of the working age population, assuming that a larger pool of working age people at origin increases the likelihood of emigration.

Following Beine and Parsons (2017) as well as Cattaneo and Peri (2016), we also estimated a parsimonious model that includes only the set of fixed effects with no controls. Although this specification is prone to omitted-variable bias, it has the advantage that it does not include control variables that possibly could take up part of the overall income effect.

Although the estimates of Equation (1) are consistent, they might be biased due to reverse causality. Indeed, emigration could exert a reverse effect on income levels in sending countries through numerous channels—including economic and social remittances. We mitigate this problem through the lag structure of our model specification. In addition, we perform an instrumental variable (IV) estimation as a further robustness test. We employ two instruments related to the presence of natural resources in the country of origin, namely (a) total natural resource rents as a share of GDP and (b) the contribution of mining to value added. The validity of the exclusion restriction hinges on the assumption that natural resources affect emigration only through their impact on national per-capita income and the added controls, especially the presence of conflicts and the quality of institutions. This indirect link is in accordance with the evidence obtained in the literature on the natural resource curse, which suggests among other things that resource rents are predominantly captured by elites rather than spent on broad-based development (see, e.g. Ross (2015) for a survey). The Dutch disease literature (e.g. Corden & Neary, 1982) points to the potential negative effects of mineral resource endowments on national income, but there are also studies showing that mining may contribute to socio-economic development (e.g. Ericsson & Olof, 2019; McMahon & Moreira, 2014). To the best of our knowledge, no study establishes a direct link between the importance of resources and emigration from developing countries, but we still caution against a strong causal interpretation of our results. The first-stage Kleibergen–Paap F-statistic and the Hansen J-statistic generally support the validity of our set of instruments (see below).

3.1 | Data

We proxy bilateral emigration flows to 20 selected OECD destinations by taking the difference between cross-sections of bilateral stocks of emigrants for contiguous census rounds with 5-year intervals.[4] Data are from Brücker et al. (2013), which is the only dataset, to the best of our knowledge, which provides panel information for a

[3]Other institutional variables may also affect migration decisions (e.g. Ariu et al., 2016). In a robustness check, we therefore replace the democracy indicator by alternative institutional quality indicators, namely political stability, fractionalization and polarization.

[4]The included OECD countries of destination are Australia, Austria, Canada, Chile, Denmark, Finland, France, Germany, Greece, Ireland, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom and United States. The origin countries included in the sample are listed in Table A2. Summary Statistics are reported in Table A3.

sufficiently long time period on bilateral emigration stocks at different skill levels from developing countries. The figures provided in the dataset are aggregates from census data of the 20 OECD destination countries computed as part of a pan-European research project coordinated by the research institute of the German federal employment agency (IAB). They contain information on the total number of foreign-born individuals aged 25 years and older living in each of the 20 considered OECD destination countries by year, gender, country of origin and educational level. Educational levels are distinguished into low, medium and high skilled; they are defined as follows: primary (low-skilled: includes lower secondary, primary and no schooling); secondary (medium-skilled: high-school leaving certificate or equivalent) and tertiary education (high-skilled: higher than high-school leaving certificate or equivalent).[5]

The Brücker et al. (2013) dataset spans six time intervals (1980–1985, 1985–1990, 1990–1995, 1995–1900, 2000–2005 and 2005–2010), from which we obtain 5-year bilateral migration flows by taking the differences between stocks. Two alternative datasets—Docquier et al. (2007) and the OECD DIOC database (OECD, 2021)—cover comparable bilateral emigration stocks at different skill levels for only 2 years, 1990–2000 and 2000–2010, respectively. This renders the panel estimation of Equation (1) with emigration flows impossible. In a robustness test, we ran our two-step model using emigration stocks from these two alternative data sources as the dependent variable.

Table A1 lists the sources and provides a brief description of these variables and the other covariates that are used as controls in the empirical analysis.

A problem with our baseline approach is that negative migration flows result when bilateral migrant stocks decline over time. This might be the result of migrants returning home, moving on to a third-party country, or death (Beine & Parsons, 2015). As argued by Clemens (2020), in particular, emigrant deaths as a source of change in emigrant stocks over a 5-year period would cause a downward bias in the measure of net emigration flows. To address this potential source of bias, we estimate $\widehat{S}_{i(l),t}$ by considering only positive emigration flows and therefore dropping all negative values from the sample. In a robustness check, we follow Beine and Parsons (2015) and set all negative values to 0, assuming that both deaths and return migration are small relative to net migrant flows.[6] Finally, along the lines of Adovor et al. (2021), we alternatively derive the measure of *migration openness* by estimating the first-step gravity equation with bilateral emigration stocks at t as dependent variable.

Figure 1 shows the total volume of emigrant flows disaggregated by skill level to selected OECD destination countries. The highly skilled represent the largest portion of south–north emigration, and their share increased markedly over time (see also Popova, 2015). This highlights the increasingly selective nature of migration in terms of educational attainment (see Borjas, 1987). As a consequence, the negative relationship between income and emigration as found in several previous panel data studies might be the result of the comparatively high average emigrants' skill level. This is because even in the setting of a low-income country, skilled individuals are likely to be able to afford the costs of migrating abroad and at the same time face lower income gains from moving and taking up employment in high-income countries.

Data on deflated GDP (2011 US$ PPP) and population are taken from Penn World Table, version 9.1. The *Occupational Wages around the World* (OWW) Database provides information on hourly wages across professions for different countries according to the International Standard Classification of Occupations 1988 (ISCO-88) under the responsibility of the International Labor Organization, which provides a system for classifying and aggregating occupational information obtained by means of population censuses and other statistical surveys, as well as from administrative records. The occupations we capture include *Construction Workers* (ISCO-88 Code 9312/9313), *Hand Packers and other Manufacturing Labourers* (ISCO-88 Code 9322), *Printing-machine operators* (ISCO-88 Code 8251) and *Metal melters, casters and rolling-mill operators* (ISCO-88 Code 8122). Wages in current US dollars are transformed into PPP constant international dollars using the consumption price deflator from Penn World Tables.

[5]Since it is included in the low-skill category, we cannot separately analyse the group of emigrants with no education to which one of the reviewers pointed us.

[6]Although all negative values are set to 0, we do not augment the original migration flows by the opposite of negative flows in the reverse direction as in Beine and Parsons (2015), because we do not have data on South–South migration. Including return migration along these lines would inflate north–north migration, possibly creating disparities and distortions in the estimates.

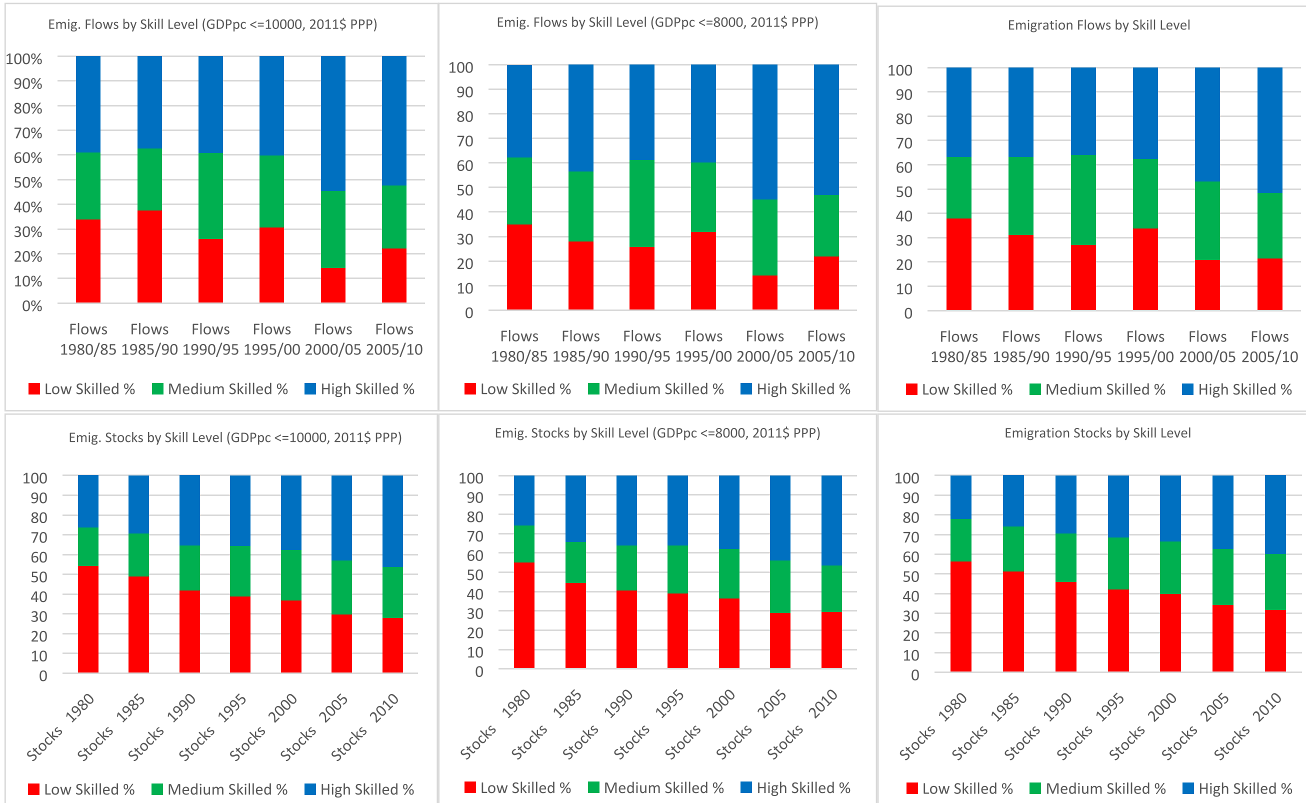

FIGURE 1 **South–north emigration by skill level.** *Note*: Migration flows (panels above) refer to the sum of bilateral emigration flows to selected OECD countries, with negative values set to 0. The bottom panels refer to emigration stocks. The right, centre and left panels refer to emigration from the whole sample of countries of origin, those with per capita income equal to or lower than $10,000 and those equal to or lower than $8000, respectively. [Colour figure can be viewed at wileyonlinelibrary.com]

As for the additional control variables, conflict intensity is depicted by a categorical variable that takes the value of one in the presence of minor conflicts with 25 to 999 battle-related deaths in a given year, and the value of two for wars with at least 1000 battle-related deaths in a given year. It is taken from the Uppsala Conflict Data Program (UCDP) Monadic Conflict Onset and Incidence Dataset (UCDP, 2021). The number of natural disasters in a given year is provided by the International Disaster Database of the Centre for Research on the Epidemiology of Disasters (Centre for Research on the Epidemiology of Disasters [CRED], 2021), and an index of Legislative and Executive Dimensions of Electoral Competitiveness is from the DPI2020 Database of Political Institutions (Cruz et al., 2021). Average years of schooling across countries are taken from the Barro and Lee (2013) dataset, and dependency ratios from the World Bank's World Development Indicators.

4 | RESULTS

In presenting the findings of our empirical analysis, we start with the two-step approach, which—for the reasons outlined above—is our preferred specification. To investigate the validity of our baseline results, we then perform a variety of robustness checks. First, we examine the possible heterogeneity of the income effects on emigration along various dimensions. Second, given that in the absence of panel data on migration flows none of the available options for calculating the dependent variable is clearly superior, we test several alternatives. Third, we proxy our main explanatory variable of interest—income per capita in the baseline—alternatively by separately looking at income and population because population growth may have an effect on migration that goes beyond raising the pool of potential emigrants (see Section 3) and by taking wages for selected low-skilled occupations as a more direct measure of economic opportunities. Fourth, we use two alternatives to the two-step approach—the one-step gravity approach and monadic regressions—that are common in the literature but come at the cost of not allowing us to properly differentiate among skill groups. Finally, we apply an instrumental-variable approach to account for possible reverse causality running from emigration to income per capita, for example as a consequence of a brain drain.

4.1 | Baseline specification

The upper part of Table 1 shows the first-step estimates of the diaspora effect on emigration flows at different skill levels obtained by estimating a structural gravity model (Equation 2). With the exception of low-skilled migrants, the estimated positive coefficients point to a network effect of the diaspora variable on emigration flows, which is in line with previous studies (see, for example Adovor et al., 2021; Collier & Hoeffler, 2018).[7] The lower part of Table 1 reports the OLS estimates of Equation (1), with standard errors clustered by country of origin.[8] As shown in columns 1–4, a basic regression without any fixed effects yields a positive and statistically significant association between income per capita and emigration across all skill levels. The size of the coefficient even rises when the sample is restricted to countries of origin with incomes below the threshold of US$6000, US$8000 and US$10,000 as defined by Dao et al. (2018) and Clemens and Postel (2018). This would be in accordance with the upward-sloping part of an

[7]The network elasticities reported in the gravity literature are larger, typically ranging between 0.4 and 0.7 (Beine et al., 2016). This can be explained by the fact that our analysis fully exploits the panel dimension of the data and focuses on the time variance of the diaspora variable, whereas in the previous literature the network effect is mostly estimated through cross-sectional studies (e.g. Beine et al., 2011) or without the inclusion of country-pair dummies (e.g. Beine & Parsons, 2015).

[8]To account for the possibility that errors are correlated within origin and time dimensions in Equation (1), we followed Faye and Niehaus (2012) and replicated our estimates with standard errors multi-way clustered at origin-time level. Although on average the level of statistical significance slightly decreases with this way of clustering standard errors, denoting a potential issue of autocorrelation in the error term of Equation (1), most estimated coefficients are still significant and in the same order of magnitude as the baseline estimates. We also performed second-step estimates with bootstrapped standard errors (1000 iterations). Bootstrapping below the $10,000 cut-off turned out to be impossible because of insufficient observations. Reassuringly, the z-statistics of the coefficients obtained with the whole sample are very similar to our baseline statistics. The results with multi-way clustered standard errors and bootstrapped standard errors are available on request.

TABLE 1 Baseline specification—Emigration flows (only non-negative flows).

First step: PPML				
Dep. var. **Skill**	**(1) Emigrant flows** ***Low***	**(2) Emigrant flows** ***Med***	**(3) Emigrant flows** ***High***	**(4) Emigrant flows** ***Total***
Ln(1 + *Mij,t*)	−0.00286	0.0648**	0.0355*	0.0348*
	(−0.16)	(3.17)	(2.37)	(2.31)
N	12,464	12,424	12,702	13,146
Destination-year FE	X	X	X	X
Origin-year FE	X	X	X	X
Destination-origin FE	X	X	X	X

Second step: OLS												
Dependent var. **Skill** ***Source country income percentile***	**(1)** $\widehat{S}_{i(l),t}$ ***Low*** **10th**	**(2)** $\widehat{S}_{i(l),t}$ ***Med*** **50th**	**(3)** $\widehat{S}_{i(l),t}$ ***High*** **90th**	**(4)** $\widehat{S}_{i(l),t}$ ***Tot*** ***Avg.***	**(5)** $\widehat{S}_{i(l),t}$ ***Low*** **10th**	**(6)** $\widehat{S}_{i(l),t}$ ***Med*** **50th**	**(7)** $\widehat{S}_{i(l),t}$ ***High*** **90th**	**(8)** $\widehat{S}_{i(l),t}$ ***Tot*** ***Avg.***	**(9)** $\widehat{S}_{i(l),t}$ ***Low*** **10th**	**(10)** $\widehat{S}_{i(l),t}$ ***Med*** **50th**	**(11)** $\widehat{S}_{i(l),t}$ ***High*** **90th**	**(12)** $\widehat{S}_{i(l),t}$ ***Tot*** ***Avg***
Ln (GDP pc,i,t)	0.261	0.275	0.161	0.245	0.199	0.215	0.106	0.185	−0.377***	−0.477***	−0.357***	−0.353***
	(1.63)	(1.56)	(0.97)	(1.38)	(1.20)	(1.20)	(0.63)	(1.02)	(−3.52)	(−4.61)	(−4.17)	(−4.40)
Ln (Edu,i,t)	−0.0290	0.286	0.445	0.184	0.0714	0.381	0.550	0.285	1.426***	0.912**	0.575	0.688**
	(−0.06)	(0.63)	(1.14)	(0.42)	(0.14)	(0.83)	(1.37)	(0.64)	(4.38)	(2.13)	(1.64)	(2.55)
Democracy (i,t)	0.0998	0.0781	0.0923	0.0983*	0.124*	0.0960*	0.106*	0.115**	0.0119	−0.00009	−0.00192	−0.0036
	(1.62)	(1.50)	(1.63)	(1.77)	(1.97)	(1.79)	(1.88)	(2.05)	(0.52)	(−0.00)	(−0.14)	(−0.22)
Dep. ratio (i,t)	−0.0155	−0.0156	−0.0183*	−0.019*	−0.0191	−0.0181	−0.0195*	−0.0209*	−0.00862	−0.00621	−0.00105	−0.0033
	(−1.25)	(−1.45)	(−1.85)	(−1.74)	(−1.49)	(−1.64)	(−1.95)	(−1.87)	(−1.22)	(−1.13)	(−0.24)	(−0.74)
Conflict intensity (i,t)	0.445**	0.452***	0.437***	0.426***	0.423**	0.439***	0.429***	0.412***	0.0722	0.122*	0.0768	0.0871*
	(2.57)	(3.25)	(2.73)	(2.81)	(2.43)	(3.09)	(2.65)	(2.68)	(1.00)	(1.82)	(1.38)	(1.76)
Natural disasters (i,t)	0.511***	0.372**	0.348**	0.425**	0.571***	0.383**	0.376**	0.449***	0.0907	−0.0674	−0.0745	−0.0200
	(2.68)	(2.25)	(2.26)	(2.58)	(2.90)	(2.29)	(2.39)	(2.65)	(1.15)	(−0.96)	(−1.42)	(−0.37)

(Continues)

TABLE 1 (Continued)

Second step: OLS												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent var.	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$
Skill	*Low*	*Med*	*High*	*Tot*	*Low*	*Med*	*High*	*Tot*	*Low*	*Med*	*High*	*Tot*
Source country income percentile	10th	50th	90th	*Avg.*	10th	50th	90th	*Avg.*	10th	50th	90th	*Avg*
N	610	610	610	610	610	610	610	610	606	606	606	606
R^2	0.194	0.258	0.284	0.267	0.213	0.272	0.301	0.279	0.888	0.909	0.947	0.946
Adj. R^2	0.1858	0.2506	0.2770	0.2594	0.1984	0.2590	0.2878	0.2656	0.8574	0.8838	0.9322	0.9304
Within R^2	0.1938	0.2580	0.2842	0.2667	0.2095	0.2664	0.2917	0.2740	0.0774	0.0744	0.0826	0.0767
Origin FE					X	X	X	X	X	X	X	X
Year FE									X	X	X	X
GDPpc <=$10,000												
Ln (GDP pc,i,t)	0.686***	0.604***	0.478**	0.596***	0.647***	0.574**	0.430**	0.550**	−0.302***	−0.265**	−0.202*	−0.215**
	(3.28)	(2.64)	(2.37)	(2.70)	(3.01)	(2.40)	(2.00)	(2.33)	(−2.81)	(−2.20)	(−1.94)	(−2.22)
Ln (Edu,i,t)	−0.0288	0.217	0.300	0.0748	0.0230	0.243	0.379	0.131	1.046***	0.224	0.164	0.378
	(−0.05)	(0.45)	(0.73)	(0.17)	(0.04)	(0.49)	(0.89)	(0.28)	(2.88)	(0.46)	(0.40)	(1.26)
Democracy (i,t)	0.0346	0.00992	0.0255	0.0341	0.0575	0.0184	0.0375	0.0459	−0.0279	−0.0312	−0.0174	−0.0241
	(0.62)	(0.23)	(0.51)	(0.69)	(0.97)	(0.39)	(0.73)	(0.89)	(−1.19)	(−1.56)	(−1.31)	(−1.63)
Dep. ratio (i,t)	−0.00729	−0.0114	−0.0184*	−0.0180	−0.00944	−0.0125	−0.0184*	−0.0186	0.0122	0.00909	0.0141**	0.00853
	(−0.56)	(−1.03)	(−1.73)	(−1.61)	(−0.70)	(−1.11)	(−1.68)	(−1.62)	(1.30)	(1.15)	(2.06)	(1.32)
Conflict intensity (i,t)	0.449***	0.478***	0.473***	0.483***	0.432**	0.467***	0.468***	0.474***	0.0905	0.110*	0.0679	0.0943**
	(2.66)	(4.05)	(3.18)	(3.60)	(2.53)	(3.85)	(3.15)	(3.48)	(1.31)	(1.81)	(1.23)	(2.05)
Natural disasters (i,t)	0.510**	0.370*	0.319	0.372*	0.557**	0.338	0.294	0.364*	0.110	0.0245	−0.00920	0.0411
	(2.18)	(1.88)	(1.63)	(1.93)	(2.23)	(1.63)	(1.44)	(1.76)	(1.00)	(0.35)	(−0.16)	(0.62)
N	380	380	380	385	380	380	380	385	378	378	378	378
R^2	0.219	0.255	0.280	0.276	0.234	0.264	0.291	0.281	0.913	0.922	0.952	0.950
Adj. R^2	0.2060	0.2428	0.2681	0.2644	0.2108	0.2416	0.2695	0.2599	0.8831	0.8954	0.9365	0.9332

TABLE 1 (Continued)

Second step: OLS												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent var.	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$
Skill	*Low*	*Med*	*High*	*Tot*	*Low*	*Med*	*High*	*Tot*	*Low*	*Med*	*High*	*Tot*
Source country income percentile	10th	50th	90th	*Avg.*	10th	50th	90th	*Avg.*	10th	50th	90th	*Avg*
Within R^2	0.2185	0.2548	0.2797	0.2759	0.2287	0.2541	0.2805	0.2771	0.0796	0.0497	0.0721	0.0643
Origin FE					X	X	X	X	X	X	X	X
Year FE								X	X	X	X	X
GDPpc <=$8000												
Ln (GDP pc,i,t)	0.815***	0.708***	0.533**	0.750***	0.795***	0.719***	0.478**	0.741***	−0.307***	−0.272**	−0.192*	−0.215**
	(3.81)	(3.11)	(2.42)	(3.35)	(3.62)	(3.08)	(2.37)	(3.09)	(−2.78)	(−2.25)	(−1.78)	(−2.16)
Ln (Edu,i,t)	−0.0344	0.210	0.290	0.0272	−0.00938	0.202	0.300	0.0520	1.025***	0.130	0.0948	0.331
	(−0.06)	(0.43)	(0.70)	(0.06)	(−0.02)	(0.40)	(0.73)	(0.11)	(2.77)	(0.27)	(0.23)	(1.09)
Democracy (i,t)	0.0270	−0.00091	0.0218	0.0222	0.0420	−0.00129	0.0255	0.0246	−0.0226	−0.0330	−0.0153	−0.0226
	(0.49)	(−0.02)	(0.43)	(0.46)	(0.72)	(−0.03)	(0.51)	(0.49)	(−0.93)	(−1.54)	(−1.09)	(−1.42)
Dep. ratio (i,t)	−0.00679	−0.0104	−0.0208*	−0.0166	−0.00837	−0.0104	−0.0184*	−0.0163	0.00840	0.0102	0.0158**	0.00885
	(−0.51)	(−0.94)	(−1.87)	(−1.46)	(−0.62)	(−0.94)	(−1.73)	(−1.41)	(0.92)	(1.22)	(2.21)	(1.32)
Conflict intensity (i,t)	0.428**	0.464***	0.439**	0.482***	0.411**	0.456***	0.473***	0.482***	0.102	0.109	0.0512	0.0883
	(2.33)	(3.62)	(2.63)	(3.31)	(2.20)	(3.48)	(3.18)	(3.28)	(1.38)	(1.59)	(0.82)	(1.66)
Natural disasters (i,t)	0.407	0.278	0.241	0.335*	0.431*	0.228	0.319	0.299	0.0867	0.0169	−0.0178	0.0275
	(1.66)	(1.37)	(1.17)	(1.69)	(1.67)	(1.08)	(1.63)	(1.41)	(0.77)	(0.23)	(−0.28)	(0.40)
N	343	343	343	348	343	343	343	348	342	342	342	342
R^2	0.245	0.260	0.275	0.283	0.256	0.270	0.280	0.289	0.911	0.917	0.951	0.948
Adj. R^2	0.2316	0.2471	0.2722	0.2703	0.2308	0.2463	0.2729	0.2655	0.8807	0.8884	0.9338	0.9297
Within R^2	0.2451	0.2603	0.2850	0.2829	0.2510	0.2593	0.2831	0.2822	0.0718	0.0520	0.0742	0.0598
Origin FE					X	X	X	X	X	X	X	X
Year FE									X	X	X	X

(Continues)

TABLE 1 (Continued)

Second step: OLS												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent var.	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$
Skill	*Low*	*Med*	*High*	*Tot*	*Low*	*Med*	*High*	*Tot*	*Low*	*Med*	*High*	*Tot*
Source country income percentile	10th	50th	90th	*Avg.*	10th	50th	90th	*Avg.*	10th	50th	90th	*Avg*
GDPpc <=$6000												
Ln (GDP pc,i,t)	0.929***	0.909***	0.767***	1.029***	0.904***	0.908***	0.732***	1.012***	−0.270***	−0.270**	−0.224*	−0.220**
	(4.18)	(3.70)	(3.25)	(4.36)	(3.97)	(3.56)	(2.78)	(3.87)	(−2.67)	(−2.07)	(−1.93)	(−2.27)
Ln (Edu,i,t)	0.0666	0.260	0.272	0.0210	0.129	0.254	0.325	0.0421	1.090***	0.162	0.231	0.491*
	(0.12)	(0.53)	(0.65)	(0.05)	(0.23)	(0.50)	(0.73)	(0.09)	(3.75)	(0.31)	(0.46)	(1.71)
Democracy (i,t)	0.0555	0.0146	0.0397	0.0379	0.0905	0.0215	0.0467	0.0426	−0.0172	−0.0237	−0.0139	−0.0201
	(1.04)	(0.32)	(0.78)	(0.80)	(1.63)	(0.44)	(0.90)	(0.87)	(−0.72)	(−1.28)	(−1.00)	(−1.34)
Dep. ratio (i,t)	−0.00506	−0.00695	−0.0186	−0.0145	−0.00808	−0.00784	−0.0187	−0.0149	0.000484	0.00180	0.0142*	0.00377
	(−0.36)	(−0.60)	(−1.61)	(−1.25)	(−0.58)	(−0.67)	(−1.56)	(−1.24)	(0.05)	(0.22)	(1.84)	(0.56)
Conflict Intensity (i,t)	0.345*	0.401***	0.429**	0.445***	0.296	0.382**	0.423**	0.435**	0.154**	0.162**	0.0724	0.126**
	(1.73)	(2.80)	(2.35)	(2.72)	(1.47)	(2.61)	(2.31)	(2.63)	(2.16)	(2.54)	(1.11)	(2.52)
Natural disasters (i,t)	0.366	0.289	0.300	0.353	0.447	0.258	0.279	0.339	0.106	0.00990	−0.0302	0.0158
	(1.36)	(1.20)	(1.28)	(1.51)	(1.60)	(1.04)	(1.15)	(1.39)	(0.88)	(0.12)	(−0.42)	(0.21)
N	291	291	291	295	291	291	291	295	290	290	290	290
R^2	0.287	0.296	0.317	0.331	0.315	0.306	0.324	0.334	0.922	0.934	0.949	0.954
Adj. R^2	0.2721	0.2811	0.3028	0.3172	0.2879	0.2789	0.2971	0.3086	0.8937	0.9109	0.9309	0.9375
Within R^2	0.2872	0.2960	0.3172	0.3312	0.3102	0.2953	0.3161	0.3305	0.0825	0.0599	0.0796	0.0725
Origin FE					X	X	X	X	X	X	X	X
Year FE									X	X	X	X

Note: *t* statistics in parentheses. Standard errors are clustered by country of origin. The dependent variables are the estimates of origin-year fixed effects obtained from a fully specified PPML gravity model with dyadic fixed effects, which include positive emigration flows as the dependent variable. The various percentiles of source country income across skill groups are generated by combining information on GDP per capita and Gini coefficients along the lines of Grogger and Hanson (2011).
$^*p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

inverted U curve where liquidity constraints are assumed to be binding. Adding year fixed effects to the specification (columns 5–8) leaves the estimates of our main variable of interest virtually unaffected. As indicated by minor changes in the R-squared, year fixed effects only explain a very small portion of the variability in $\widehat{S}_{i(l),t}$.

Columns 9–12 contain the results for our preferred specification including a full set of fixed effects. In contrast to year fixed effects, the inclusion of country fixed effects adds a lot of explanatory power, raising the R-squared from around 0.3 to above 0.9 and turning regression results around. Once origin-specific time-invariant characteristics are accounted for, we obtain a significant negative effect of per-capita income on emigration for all income thresholds. The effect is modest but non-negligible in quantitative terms: taking our point estimates at face value, a 10% increase in GDP per capita lowers emigration flows in a 5-year period on average by about 3%, which roughly corresponds to 0.6% per year. Given the sample mean of dyadic emigration is 3119.797, the 5-year average immigration flow is 93 immigrants per-dyad (we have 195 origins per destination in the first stage), that is 3627 yearly immigrants per destination $[(93 \times 195 = 18{,}135)/5 = 3627]$. To put this into perspective, two mid-sized immigrant countries—Belgium and the Netherlands—attracted 77,411 and 63,415 immigrants in 2005, respectively (*Source*: OECD—International Migration Database). The average impact of a 10% increase in GDP per capita would thus roughly amount to a 5% reduction in these numbers.

The effect appears to vary fairly little according to skill levels or with different income thresholds. Hence, our findings suggest that even for low-skilled would-be migrants in low-income countries, any migration-enhancing liquidity effects of rising incomes are more than offset by migration-reducing incentive effects through falling income gaps. The estimates are complementary to the results reported by Langella and Manning (2021), who also found a negative relationship across income groups when focusing on migration aspirations. The switch from a positive to a universal negative relationship we observe when controlling for cross-country heterogeneity is in line with what several previous studies have found (e.g. Benček & Schneiderheinze, 2020; Ortega & Peri, 2013).[9]

Among the controls, in our preferred specification only conflict and education turn out to be significant determinants of emigration in some cases, with the expected positive sign.[10] In the absence of country fixed effects, the conflict variable becomes significantly positive throughout, that is variations in conflict intensity across countries are an important predictor of international migration flows. The number of natural disasters, the dependency ratio and the level of democracy in the country of origin do not appear to affect international migration over time.[11] For natural disasters, this corroborates existing evidence (e.g. Beine & Parsons, 2015).[12] Democracy indicators such as the World Bank's voice and accountability measures have also previously been shown to be unrelated to emigration from developing countries (e.g. Lanati & Thiele, 2018). Generally speaking, including a full set of fixed effects absorbs much of the variation that would otherwise be accounted for by the control variables.

When alternatively running a model with interaction terms between GDP per capita and various income thresholds, our main finding holds: the estimated coefficient of GDP per capita remains at around -0.4, whereas all interaction coefficients are not statistically significant (see Table 2), which implies that the relationship between GDP per capita and $\widehat{S}_{i(l),t}$ is negative and fairly stable across different subsamples of lower income countries. Further robustness checks reported in Tables OA10–OA12 of the online appendix largely support this conclusion. A notable exception can be found in the one-step model (Table OA12), where the \$3000 interaction is significantly negative, somewhat surprisingly pointing to a particularly strong negative effect for the lowest income group.

[9]Our main findings generally hold when we employ a parsimonious specification that only includes fixed effects without controls. This is not only true for the baseline but also for the robustness checks (see Tables OA2–OA7).

[10]Following the suggestion of a reviewer, we perform a robustness check including migrant remittances as an additional control variable, which also have a positive and significant impact on emigration without substantially affecting our parameter of interest (see Table QA8).

[11]This finding remains unaffected if we replace democracy by other institutional indicators including political stability, fractionalization and polarization (see Table OA9).

[12]Xu and Sylwester (2016) find, however, that low environmental quality constitutes a factor that encourages emigration, in particular among more educated people. Our estimates also show that migration is positively associated with the number of disasters when looking at the cross-country dimension, that is without country fixed effects.

TABLE 2 Baseline specification—Emigration flows (only non-negative flows) with interaction terms.

Dependent var. Skill *Source country income percentile*	(1) $\widehat{S}_{i(l),t}$ *Low* 10th	(2) $\widehat{S}_{i(l),t}$ *Med* 50th	(3) $\widehat{S}_{i(l),t}$ *High* 90th	(4) $\widehat{S}_{i(l),t}$ *Tot* *Avg*
Ln (GDP pc,i,t)	−0.379***	−0.480***	−0.386***	−0.374***
	(−3.46)	(−4.04)	(−3.98)	(−3.89)
Ln (GDP pc,i,t)$10,000 Dum*	−0.0128	0.0122	0.00128	0.00292
	(−0.60)	(0.98)	(0.13)	(0.28)
Ln (GDP pc,i,t)$8000 Dum*	0.00453	−0.0109	−0.00786	−0.00685
	(0.26)	(−0.90)	(−0.94)	(−0.76)
Ln (GDP pc,i,t)$5000 Dum*	0.00322	−0.00171	−0.00343	−0.00163
	(0.14)	(−0.10)	(−0.38)	(−0.14)
Ln (GDP pc,i,t)$3000 Dum*	−0.00136	−0.00131	−0.00664	−0.00613
	(−0.07)	(−0.08)	(−0.59)	(−0.52)
Ln (Edu,i,t)	1.450***	0.893**	0.568	0.680**
	(4.36)	(2.03)	(1.59)	(2.48)
Democracy (i,t)	0.0111	0.000416	−0.00334	−0.00443
	(0.48)	(0.02)	(−0.24)	(−0.28)
Dep. ratio (i,t)	−0.00850	−0.00599	−0.000216	−0.00277
	(−1.11)	(−1.07)	(−0.05)	(−0.59)
Conflict intensity (i,t)	0.0724	0.120*	0.0764	0.0868*
	(0.99)	(1.77)	(1.36)	(1.72)
Natural disasters (i,t)	0.0873	−0.0650	−0.0751	−0.0204
	(1.12)	(−0.91)	(−1.43)	(−0.38)
N	606	606	606	606
R^2	0.889	0.909	0.947	0.946
Origin FE	X	X	X	X
Year FE	X	X	X	X

Note: t statistics in parentheses. Standard errors are clustered by country of origin. The dependent variables are the estimates of origin-year fixed effects obtained from a fully specified PPML gravity model with dyadic fixed effects, which include positive emigration flows as the dependent variable. The various percentiles of source-country income across skill groups are generated by combining information on GDP per capita and Gini coefficients along the lines of Grogger and Hanson (2011).
$^*p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

4.2 | Accounting for heterogeneity

Having shown that the negative income effect on migration extends to countries with very low incomes, we perform further robustness tests for two sub-samples representing low levels of development: (i) African countries and (ii) countries with low institutional quality. As can be seen in Tables OA13 and OA14, the negative income–migration relationship holds for these two country groups.

In addition, we interact the per-capita GDP variable with several origin-specific covariates, including (i) a dummy for landlocked countries (*Source*: CEPII), (ii) latitude (*Source*: CEPII), (iii) yearly growth rates (*Source*: World Bank),

(iv) English as a national language (*Source*: CEPII) and (v) natural disasters.[13] The results of this exercise are shown in Table OA15. We find that the negative association between per-capita income and emigration is robust across specifications; the interaction effects with the variables listed above are always non-significant.

4.3 | Alternative definitions of dependent variable

In Tables 1 and 2, the dependent variable is given as migrant flows derived from changes in stocks, where negative values have been removed from the sample. The omission of negative flows could lead to an upward bias in the estimates of *migration openness*, whereas taking the difference between cross-sections ignores emigrant deaths as a potential source of change in emigrant stocks and therefore could lead to a downward bias in $\widehat{S}_{i(l),t}$. We address these data issues by setting the negative values of changes in stocks to 0 and using bilateral stocks as the dependent variable, respectively.[14] In addition, we increase the interval of the migration stocks used for calculating emigration flows from 5 to 10 years. Finally, even though our main interest is on south–north migration, we re-estimate the baseline model with our preferred two-step procedure for south–south emigration. The estimates reported in Table 3 reveal that the omission of negative flows does not appear to matter much: Employing the two alternative specifications of the flow variables yields quantitatively very similar results for the relationship between GDP per capita and emigration. The same holds for the extension of intervals, but only if we do not include the control variables (see Table OA4). With controls, coefficients turn insignificant, arguably as a result of the low number of observations.

With migrant stocks as the dependent variable, the negative income coefficient decreases in size for our baseline data (Table OA16; columns 1–4) but stays significant and does not turn positive.[15] The results obtained with the two alternative datasets—columns 5–8 for Docquier et al. (2007) and columns 9–12 for OECD DIOC—have to be interpreted with great caution because of the limited time variation and a fairly low number of observations. They corroborate the general finding of a negative income–migration link, but in particular, when using the OECD DIOC dataset most of the coefficients become statistically not significant at conventional levels.

To estimate south–south migration, we use the World Bank 1960–2000 Global Migration Dataset, which provides bilateral migration stocks with 10-year intervals. We integrate this dataset with the 2010 extension and end up with a short panel of three time intervals (1980/1990–1990/1900–2000/2010), which leads to a second-step regression with a fairly limited number of observations. In contrast to north–north migration, the results reported in Table OA17 reveal a non-significant relationship between south–south emigration and per-capita GDP.

4.4 | Alternative definitions of explanatory variables

We first employ GDP and population separately as the relevant explanatory variable in the regression rather than GDP per capita. In doing so, we have to rely on average incomes instead of skill-specific percentiles of the income distribution. As shown in Table 4, the estimated relationship between income and emigration remains negative and significant for all skill groups irrespective of whether income thresholds are introduced, with coefficients that are in the same order of magnitude as in the baseline. Clemens' (2020) critique that in a specification that includes both GDP and population, the correlations obtained are likely to be spurious, does not appear to be valid in our case. With one exception—medium-skilled emigrants in the full sample—population is not significantly related to emigration when only considering the time dimension.

[13]We thank one of the reviewers for suggesting to consider these interactions.

[14]Note that we have the same number of observations as in the case of dropping the zeros. This is due to the first-step structural gravity regression, where origin-year fixed effects (the second-step dependent variable) are estimated. If a given dyad is dropped or set to zero in a gravity model, the origin-year fixed effect is still estimated.

[15]Given the limited time variation of the alternative datasets that provide information on bilateral migration across skill levels, in Table OA12, we rely on average incomes and employ GDP and population separately instead of generating skill-specific percentiles of the income distribution, as the latter strategy would lead to a further significant drop in the number of observations.

TABLE 3 Emigration flows (including negative observations as zeros).

Dependent var. Skill *Source country income percentile*	(1) $\widehat{S}_{i(l),t}$ *Low* 10th	(2) $\widehat{S}_{i(l),t}$ *Med* 50th	(3) $\widehat{S}_{i(l),t}$ *High* 90th	(4) $\widehat{S}_{i(l),t}$ *Tot* Avg
Ln (GDP pc,i,t)	−0.383***	−0.405***	−0.363***	−0.392***
	(−2.96)	(−3.51)	(−4.78)	(−4.01)
Ln (Edu,i,t)	1.035***	0.928*	0.840**	0.933***
	(3.01)	(1.96)	(2.27)	(3.12)
Democracy (i,t)	0.00216	0.00748	−0.00792	−0.0113
	(0.07)	(0.37)	(−0.54)	(−0.68)
Dep. ratio (i,t)	−0.00101	−0.0115*	−0.00283	0.00282
	(−0.12)	(−1.69)	(−0.61)	(0.50)
Conflict intensity (i,t)	0.207**	0.144	0.0837	0.145**
	(2.20)	(1.36)	(1.50)	(2.60)
Natural disasters (i,t)	0.125	0.0506	−0.0693	0.0368
	(1.24)	(0.72)	(−1.22)	(0.56)
N	606	606	606	606
R^2	0.861	0.917	0.941	0.934
GDPpc <=$10,000				
Ln (GDP pc,i,t)	−0.324***	−0.238*	−0.246**	−0.333***
	(−2.73)	(−1.68)	(−2.43)	(−2.78)
Ln (Edu,i,t)	0.740**	0.276	0.379	0.688*
	(2.30)	(0.54)	(0.84)	(1.98)
Democracy (i,t)	−0.0380	−0.0363	−0.0255*	−0.0357**
	(−1.24)	(−1.66)	(−1.70)	(−2.24)
Dep. ratio (i,t)	0.00988	0.00583	0.00496	0.00713
	(1.01)	(0.69)	(0.74)	(0.96)
Conflict intensity (i,t)	0.143	0.115	0.0886*	0.130***
	(1.52)	(1.58)	(1.70)	(2.85)
Natural disasters (i,t)	0.103	0.107	−0.0564	0.0771
	(0.88)	(1.13)	(−0.79)	(0.98)
N	378	378	378	378
R^2	0.900	0.923	0.941	0.943
GDPpc <=$8000				
Ln (GDP pc,i,t)	−0.341***	−0.224	−0.168*	−0.281**
	(−2.77)	(−1.57)	(−1.78)	(−2.44)
Ln (Edu,i,t)	0.641*	0.0963	0.160	0.444
	(1.89)	(0.20)	(0.37)	(1.35)
Democracy (i,t)	−0.0367	−0.0353	−0.0206	−0.0349**
	(−1.16)	(−1.58)	(−1.35)	(−2.24)
Dep. ratio (i,t)	0.00529	0.00539	0.00304	0.00576
	(0.53)	(0.63)	(0.45)	(0.75)

TABLE 3 (Continued)

Dependent var. Skill *Source country income percentile*	(1) $\widehat{S}_{i(l),t}$ *Low* 10th	(2) $\widehat{S}_{i(l),t}$ *Med* 50th	(3) $\widehat{S}_{i(l),t}$ *High* 90th	(4) $\widehat{S}_{i(l),t}$ *Tot* *Avg*
Conflict intensity (i,t)	0.207**	0.173**	0.105*	0.161***
	(2.21)	(2.55)	(1.83)	(3.38)
Natural disasters (i,t)	0.139	0.131	−0.0697	0.0898
	(1.12)	(1.35)	(−1.13)	(1.19)
N	342	342	342	342
R^2	0.899	0.931	0.954	0.951
GDPpc <=$6000				
Ln (GDP pc,i,t)	−0.354***	−0.238	−0.150	−0.257**
	(−3.01)	(−1.54)	(−1.43)	(−2.13)
Ln (Edu,i,t)	0.880***	0.151	0.331	0.635*
	(2.90)	(0.28)	(0.66)	(1.80)
Democracy (i,t)	−0.0136	−0.0276	−0.0187	−0.0259*
	(−0.45)	(−1.22)	(−1.24)	(−1.86)
Dep. ratio (i,t)	0.00320	0.00477	0.00229	0.00631
	(0.29)	(0.53)	(0.34)	(0.79)
Conflict intensity (i,t)	0.258***	0.198***	0.111*	0.174***
	(2.90)	(2.92)	(1.90)	(3.82)
Natural disasters (i,t)	0.208	0.0969	−0.127*	0.0565
	(1.50)	(0.85)	(−1.84)	(0.63)
N	290	290	290	290
R^2	0.909	0.935	0.954	0.953
Origin FE	X	X	X	X
Year FE	X	X	X	X

Note: *t* statistics in parentheses. Standard errors are clustered by country of origin. The dependent variables are the estimates of origin-year fixed effects obtained from a fully specified PPML gravity model with dyadic fixed effects, in which negative values of the dependent variable are set to 0. The various percentiles of source-country income across skill groups are generated by combining information on GDP per capita and Gini coefficients along the lines of Grogger and Hanson (2011).
*$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$.

Replacing skill-specific GDP per capita by directly looking at wages of selected low-to-medium skill occupations as our main variable of interest (Table 5) corroborates again—without any exception—that even poorer population segments in developing countries, for whom liquidity constraints are considered to be particularly binding, are less likely to emigrate as their incomes rise.

4.5 | Alternative econometric approaches

We apply two alternatives to our preferred two-step gravity specification: the one-step approach for total emigrants adopted by Beine and Parsons (2015), among others, using total population as the denominator for bilateral emigration rates and the monadic model for total emigrants recently proposed by Clemens (2020) as well as Benček and

TABLE 4 Alternative specification—GDP and population estimated separately.

Second step: OLS	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent var.	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$
Skill	***Low***	***Med***	***High***	***Tot***	***Low***	***Med***	***High***	***Tot***	***Low***	***Med***	***High***	***Tot***
Source country income percentile	***Avg.***	***Avg.***	***Avg.***	***Avg.***	***Avg.***	***Avg.***	***Avg.***	***Avg.***	***Avg.***	***Avg.***	***Avg.***	***Avg***
Ln (GDP,*i*,*t*)	0.0600	0.127	0.157	0.142	−0.00332	0.0911	0.130	0.107	−0.320***	−0.321***	−0.276***	−0.300***
	(0.33)	(0.74)	(1.08)	(0.86)	(−0.02)	(0.52)	(0.86)	(0.62)	(−3.09)	(−2.95)	(−3.03)	(−3.43)
Ln (Pop,*i*,*t*)	0.503***	0.414***	0.380***	0.407***	0.559***	0.449***	0.405***	0.440***	0.238	1.109***	0.414	0.402
	(3.07)	(2.62)	(2.87)	(2.72)	(3.26)	(2.71)	(2.92)	(2.81)	(0.61)	(2.65)	(1.32)	(1.21)
N	740	740	740	740	740	740	740	740	739	739	739	739
R^2	0.365	0.428	0.493	0.456	0.378	0.436	0.502	0.462	0.903	0.922	0.941	0.947
GDPpc <=$10,000												
Ln (GDP *i*,*t*)	0.580**	0.552***	0.585***	0.596***	0.529**	0.553**	0.580***	0.580***	−0.357***	−0.254**	−0.257**	−0.307***
	(2.47)	(2.69)	(3.19)	(3.00)	(2.10)	(2.53)	(2.97)	(2.72)	(−2.77)	(−2.14)	(−2.34)	(−2.86)
Ln (Pop,*i*,*t*)	0.0620	0.0107	−0.0239	−0.0278	0.110	0.0112	−0.0149	−0.00974	−0.881	−0.320	−0.823	−0.760
	(0.24)	(0.05)	(−0.13)	(−0.14)	(0.41)	(0.05)	(−0.08)	(−0.04)	(−1.47)	(−0.43)	(−1.55)	(−1.40)
N	465	465	465	465	465	465	465	465	457	457	457	457
R^2	0.405	0.444	0.504	0.472	0.415	0.450	0.510	0.475	0.915	0.927	0.940	0.945
GDPpc <=$8000												
Ln (GDP *i*,*t*)	0.740***	0.613***	0.627***	0.685***	0.709***	0.639***	0.634***	0.683***	−0.363***	−0.271**	−0.257**	−0.314***
	(3.03)	(2.83)	(3.12)	(3.27)	(2.70)	(2.79)	(2.99)	(3.05)	(−2.69)	(−2.19)	(−2.21)	(−2.75)
Ln (Pop,*i*,*t*)	−0.0851	−0.0462	−0.0662	−0.111	−0.0549	−0.0696	−0.0685	−0.107	−1.053*	−0.378	−0.919	−0.860
	(−0.33)	(−0.20)	(−0.33)	(−0.52)	(−0.20)	(−0.29)	(−0.33)	(−0.47)	(−1.70)	(−0.48)	(−1.66)	(−1.52)
N	426	426	426	426	426	426	426	426	420	420	420	420
R^2	0.413	0.430	0.490	0.465	0.419	0.438	0.497	0.468	0.913	0.922	0.936	0.942

TABLE 4 (Continued)

Second step: OLS	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent var.	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$
Skill	***Low***	***Med***	***High***	***Tot***	***Low***	***Med***	***High***	***Tot***	***Low***	***Med***	***High***	***Tot***
Source country income percentile	***Avg.***	***Avg.***	***Avg.***	***Avg.***	***Avg.***	***Avg.***	***Avg.***	***Avg.***	***Avg.***	***Avg.***	***Avg.***	***Avg***
GDPpc <=$6000												
Ln (GDP *i,t*)	0.961***	0.727***	0.699***	0.817***	0.925***	0.766***	0.721***	0.826***	−0.353**	−0.207	−0.212	−0.251**
	(3.57)	(3.10)	(3.08)	(3.50)	(3.21)	(3.16)	(3.02)	(3.34)	(−2.44)	(−1.51)	(−1.67)	(−2.14)
Ln (Pop,*i,t*)	−0.355	−0.198	−0.183	−0.291	−0.319	−0.236	−0.201	−0.297	−0.788	−0.332	−0.738	−0.541
	(−1.23)	(−0.78)	(−0.79)	(−1.18)	(−1.04)	(−0.90)	(−0.83)	(−1.15)	(−1.38)	(−0.49)	(−1.15)	(−1.03)
N	369	369	369	369	369	369	369	369	364	364	364	364
R^2	0.418	0.420	0.470	0.447	0.426	0.429	0.475	0.449	0.923	0.937	0.934	0.949
Origin FE					X	X	X	X	X	X	X	X
Year FE									X	X	X	X

Note: *t* statistics in parentheses. Standard errors are clustered by country of origin. The dependent variables are the estimates of origin-year fixed effects obtained from a fully specified PPML gravity model with dyadic fixed effects, which include positive emigration flows as the dependent variable. GDP per capita is not transformed according to different skill groups: the assumption is that income distribution at the country level remains constant. The controls are included in the regressions but the coefficients are not reported in the Table.
*p < 0.10, **p < 0.05, and ***p < 0.01.

TABLE 5 Alternative specification—Wages for low-skilled occupations.

Dependent var. Skill (l) Occupation	(1) $\widehat{S}_{i(l),t}$ Low *Construction*	(2) $\widehat{S}_{i(l),t}$ Low *Construction*	(3) $\widehat{S}_{i(l),t}$ Low *Hand Packers and other*	(4) $\widehat{S}_{i(l),t}$ Low *Hand Packers and other*	(5) $\widehat{S}_{i(l),t}$ Low *Metal Melters and other*	(6) $\widehat{S}_{i(l),t}$ Low *Metal Melters and other*	(7) $\widehat{S}_{i(l),t}$ Low *Printing-machine operators*	(8) $\widehat{S}_{i(l),t}$ Low *Printing-machine operators*
ISCO-Code	***9312/9313***	***9312/9313***	***9322***	***9322***	***8122***	***8122***	***8251***	***8251***
Percentile in wage distribution	*10th*	*10th*	*10th*	*10th*	*10th*	*10th*	*10th*	*10th*
Ln (*Wages i,t*)	0.428***	−0.208*	0.480***	−0.179*	0.350**	−0.322**	0.229	−0.367***
	(3.43)	(−1.94)	(3.61)	(−1.81)	(2.35)	(−2.34)	(1.46)	(−2.81)
N	372	352	399	385	349	330	286	267
R^2	0.098	0.911	0.110	0.915	0.058	0.907	0.034	0.875
GDPpc <=$10,000								
Ln (*Wages i,t*)	0.679***	−0.212**	0.617***	−0.149*	0.356	−0.344**	0.331	−0.389***
	(4.65)	(−2.18)	(4.14)	(−1.68)	(1.50)	(−2.31)	(1.54)	(−3.26)
N	206	188	229	215	192	177	156	144
R^2	0.121	0.938	0.112	0.938	0.022	0.935	0.034	0.916
Origin FE	X	X	X	X	X	X	X	X
Year FE		X		X		X		X

Note: *t* statistics in parentheses. Standard errors are clustered by country of origin. The selected low-skill ISCO-88 occupations are *Construction* (ISCO-88 Code 9312/9313, columns 1 and 2); *Hand Packers and other Manufacturing Labourers* (ISCO-88 Code 9322, columns 3 and 4); Printing machine operators (ISCO-88 Code 8251, columns 5 and 6); Metal melters, casters and rolling mill operators (ISCO-88 Code 8122, columns 7 and 8). Wages in current US dollars have been transformed in PPP constant international dollars using the '*pl_con*' deflator from Penn World Tables. The various percentiles of source-country wages across skill groups are generated by combining information on GDP per capita and Gini coefficients along the lines of Grogger and Hanson (2011). The regressions do not include control variables.

**p* < 0.10, ***p* < 0.05, and ****p* < 0.01.

TABLE 6 One-step approach a la Beine and Parsons (2015).

	Estimator: PPML				
GDP pc threshold	None	<$10,000	<$8000	<$6000	None
Rates obtained with	*Bilateral flows as numerator*	*Bilateral flows as numerator*	*Bilateral flows as numerator*	*Bilateral flows as numerator*	*Bilateral flows as numerator*
Ln(1 + *Mij,t*)	0.573***	0.591***	0.580***	0.554***	0.580***
	(15.95)	(19.85)	(19.10)	(18.42)	(14.52)
Ln (GDPpc *i,t*)	−0.331***	−0.469***	−0.548***	−0.404**	−0.236*
	(−2.79)	(−3.53)	(−3.40)	(−2.47)	(−1.71)
Ln (Distance *ij*)					−0.432***
					(−7.76)
Comlang Et. *ij*					0.521***
					(5.51)
Contig *ij*					−0.235
					(−1.42)
Colony *ij*					0.259*
					(1.94)
Ln (Edu *i,t*)					0.543
					(0.98)
Dep ratio *i,t*					0.00839
					(1.52)
Conflict *i,t*					0.117*
					(1.75)
Disasters *i,t*					−0.0333
					(−0.73)
N	17,070	11,591	10,678	9,186	13,620
Origin FE	X	X	X	X	X
Dest*Year FE	X	X	X	X	X
Pair FE					

(Continues)

TABLE 6 (Continued)

	Estimator: PPML				
GDP pc threshold	None	<$10,000	<$8000	<$6000	None
Rates obtained with	*Bilateral flows as numerator*	*Bilateral flows as numerator*	*Bilateral flows as numerator*	*Bilateral flows as numerator*	*Bilateral flows as numerator*

Note: t statistics in parentheses. Standard errors are clustered by country of origin. The dependent variable is emigration rates calculated as (MigFlow t, $t+5$/Population, i,t), where MigFlow t, $t+5$ is obtained as the difference in migration stocks between $t+5$ and t. Proxies of bilateral migration costs—namely geographical distance, common language, common colony and common border—are from CEPII.

$^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

TABLE 6 (Continued)

	Estimator: PPML						
GDP pc threshold	<$10,000	<$8000	<$6000	None	<$10,000	<$8000	<$6000
Rates obtained with	*Bilateral flows as numerator*	*Bilateral flows as numerator*	*Bilateral flows as numerator*	*Bilateral flows as numerator*	*Bilateral flows as numerator*	*Bilateral flows as numerator*	*Bilateral flows as numerator*
Ln(1 + *Mij,t*)	0.523***	0.514***	0.496***	0.00393	−0.00628	0.00454	0.0326*
	(10.04)	(8.59)	(7.82)	(0.15)	(−0.30)	(0.20)	(1.79)
Ln (GDPpc *i,t*)	−0.475**	−0.499**	−0.208	−0.338***	−0.484***	−0.484***	−0.274*
	(−2.19)	(−2.15)	(−1.25)	(−3.14)	(−3.06)	(−2.99)	(−1.72)
Ln (Distance *ij*)	−0.465***	−0.481***					
	(−5.45)	(−4.24)					
Comlang Et. *ij*	0.597***	0.593***					
	(4.29)	(3.94)					
Contig *ij*	0.480	0.516					
	(1.33)	(1.34)					
Colony *ij*	0.284	0.212					
	(1.37)	(1.00)					
Ln (Edu *i,t*)	0.843	0.728		0.819**	0.679*	0.613*	−0.0254
	(1.28)	(1.12)		(2.49)	(1.79)	(1.67)	(−0.12)

TABLE 6 (Continued)

	Estimator: PPML						
GDP pc threshold	**<$10,000**	**<$8000**	**<$6000**	**None**	**<$10,000**	**<$8000**	**<$6000**
Rates obtained with	***Bilateral flows as numerator***	***Bilateral flows as numerator***	***Bilateral flows as numerator***	***Bilateral flows as numerator***	***Bilateral flows as numerator***	***Bilateral flows as numerator***	***Bilateral flows as numerator***
Dep ratio *i,t*	−0.00352	−0.00124		0.00398	0.00601	0.00736	0.00177
	(−0.52)	(−0.18)		(0.79)	(0.89)	(1.05)	(0.26)
Conflict *i,t*	0.0515	0.0577		0.0587	0.0510	0.0588	0.118*
	(0.78)	(0.84)		(1.04)	(0.74)	(0.80)	(1.90)
Disasters *i,t*	−0.0219	−0.00832		−0.00594	0.0146	0.0186	0.0798
	(−0.43)	(−0.16)		(−0.14)	(0.28)	(0.34)	(1.52)
N	8844	8137	7003	12,494	7863	7233	6210
Origin FE	X	X	X	X	X	X	X
Dest*Year FE	X	X	X				
Pair FE				X	X	X	X

Note: t statistics in parentheses. Standard errors are clustered by country of origin. The dependent variable is emigration rates calculated as (MigFlow t, $t+5$/Population, i,t), where MigFlow t, $t+5$ is obtained as the difference in migration stocks between $t+5$ and t. Proxies of bilateral migration costs—namely geographical distance, common language, common colony and common border—are from CEPII.

*$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$.

TABLE 7 Aggregate monadic model.

Dependent var. Skill Numerator	(1) *Emigration rate* *Tot* *Emig. flows*	(1) *Emigration rate* *Tot* *Emig. stocks*
Ln (GDP,i,t)	−0.337***	−0.234***
	(−2.80)	(−3.47)
N	739	739
R^2	0.859	0.972
GDPpc <=$10,000		
Ln (GDP,i,t)	−0.404**	−0.197***
	(−2.41)	(−2.83)
N	457	457
R^2	0.868	0.972
GDPpc <=$8000		
Ln (GDP,i,t)	−0.371**	−0.182**
	(−2.13)	(−2.49)
N	420	420
R^2	0.877	0.973
GDPpc <=$6000		
Ln (GDP,i,t)	−0.275*	−0.112
	(−1.70)	(−1.39)
N	364	364
R^2	0.892	0.974

Note: *t* statistics in parentheses. The dependent variable is emigration rates that are calculated as the total number of emigrants from a given country of origin to selected OECD destinations divided by country's total population. The rates are obtained using as numerator the sum of bilateral emigration flows (column 1) and bilateral emigration stocks (column 2), respectively. The regressions include the log of population as well as the standard set of controls, whose coefficients are not reported.
*p < 0.10, **p < 0.05, and ***p < 0.01.

Schneiderheinze (2020). The estimates using these two alternative approaches, reported in Tables 6 and 7, are again qualitatively the same as the baseline results.

In the setting of the Beine and Parsons specification with destination-time fixed effects, the negative effect we report in Table 6 for GDP per capita at origin is equivalent to a positive effect of the same size for the GDP per capita ratio between destination and origin country because changes in GDP per capita at destination are fully absorbed by the fixed effects. Our finding is thus in line with the basic prediction of the Harris–Todaro model that migration is positively related to income gaps.

Our monadic results in Table 7 differ from Clemens (2020), who retains a positive income–migration link when introducing both time and country fixed effects. This discrepancy may at least partly be due to the fact that Clemens (2020) includes non-OECD destinations, where incentive effects might matter less because of lower average income gaps.

4.6 | Instrumental variable estimation

Lastly, we address potential endogeneity due to reserve causality by instrumenting per capita income at the origin with the above-mentioned set of instruments related to the presence of natural resources. Due to the loss of a

TABLE 8 Instrumental variable approach. Over-identified model: Two instruments/one endogenous variable (source country income across skill groups).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent var.	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$	$\widehat{S}_{i(l),t}$
Skill	***Low***	***Low***	***Med***	***Med***	***High***	***High***	***Tot***	***Tot***
GDP pc threshold	***None***	***None Only***	***None***	***None Only***	***None***	***None Only***	***None***	***None Only***
1st Step dep. var	***Neg. as Zeros***	***Pos***	***Neg. as Zeros***	***Pos***	***Neg. as Zeros***	***Pos***	***Neg. as Zeros***	***Pos***
Source country income percentile	***10th***	***10th***	***50th***	***50th***	***90th***	***90th***	***Avg***	***Avg***
Ln (GDP pc,i,t)	−1.307***	−0.718*	−0.641	−0.701**	−0.133	−0.0764	−0.718*	−0.446*
	(−2.63)	(−1.77)	(−1.63)	(−2.02)	(−0.34)	(−0.28)	(−1.77)	(−1.92)
Ln (Edu,i,t)	1.239**	1.504***	0.903*	0.813*	0.824**	0.553	1.504***	0.778***
	(2.52)	(3.86)	(1.79)	(1.79)	(2.03)	(1.40)	(3.86)	(2.67)
Democracy (i,t)	0.00336	0.00909	0.00636	−0.00658	0.00680	0.00559	0.00909	−0.000103
	(0.11)	(0.41)	(0.30)	(−0.29)	(0.38)	(0.35)	(0.41)	(−0.75)
Dep. ratio (i,t)	−0.00434	−0.00858	−0.0116*	−0.00720	−0.00175	0.000561	−0.00858	−0.00130
	(−0.50)	(−1.24)	(−1.70)	(−1.29)	(−0.36)	(0.12)	(−1.24)	(−0.30)
Conflict intensity (i,t)	0.160	0.0623	0.162	0.136*	0.134**	0.107	0.0623	0.112**
	(1.44)	(0.80)	(1.40)	(1.77)	(2.00)	(1.63)	(0.80)	(2.32)
Natural disasters (i,t)	0.0728	0.0562	0.0627	−0.0701	−0.0660	−0.0644	0.0562	−0.0391
	(0.64)	(0.71)	(0.83)	(−0.93)	(−1.03)	(−1.15)	(0.71)	(−0.77)
N	556	556	556	556	556	556	669	669
Origin FE	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X
Cragg–Donald Wald F stat	28.949	28.949	41.746	41.746	34.927	34.927	40.970	40.970
Kleibergen–Paap F stat	12.217	12.217	14.907	14.907	13.759	13.759	18.190	18.190
Hansen–J Stat (P val)	0.3541	0.8422	0.8091	0.3967	0.9886	0.6404	0.4569	0.9603

Note: *t* statistics in parentheses. Standard errors are clustered by origin. First-stage statistics are reported in Table A4. The included instruments are the *Total natural resources rents (% of GDP)* and the *Contribution of mining to value added at current prices (%)*.
$^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

significant number of observations in the IV analysis, we do not restrict the sample according to income thresholds, but we still generate income percentiles corresponding to skill groups along the lines of Grogger and Hanson (2011). As shown in Table 8, our assumptions regarding the validity of the instruments are supported by the first-stage statistics. The KP F-statistic is well above the rule-of-thumb critical value of 10 in all specifications, whereas the Hansen–J test confirms the validity of the over-identifying restrictions. In the first-stage regression—results are reported in Table A4—both instrumental variables turn out to be statistically significant. As suggested by the resource curse hypothesis, the sign of resource rents is negative, whereas the sign of mining's share in value added is positive. The latter is in accordance with previous evidence showing that mining has the potential to contribute to economic development. Despite a loss in statistical power due to a lower number of observations compared to the baseline regressions, the IV estimates for the full sample generally confirm the negative relationship between the time variation of income levels at the origin and emigration across different skill levels. Therefore, reverse causality should not be a major issue in our estimation, but we still refrain from making strong causal claims regarding the link between per-capita income and emigration.

5 | CONCLUSION

In summary, by employing various panel data models we obtain robust evidence supporting the neoclassical view that—irrespective of initial skills and income levels—rising per-capita GDP leads to less emigration from developing countries by closing income gaps between origins and destinations. This is not to deny that a loosening of liquidity constraints through higher incomes, which facilitates emigration, may also play a role. Our results suggest, however, that on balance the incentive effect dominates even for poor and unskilled people, keeping some would-be migrants from going abroad. An interesting avenue for further research would be to disentangle the channels through which income affects emigration from developing countries in detailed micro-level studies.

The limited importance of relaxed liquidity constraints for migration decisions that our empirical analysis suggests may be due to the focus on south–north migration where moving costs tend to be prohibitive for many people. We cannot consider south–south migration, for which the liquidity constraint channel is likely to be more relevant, as panel data are not available by skill level. Furthermore, the panel data regressions we present refer to the short-to-medium run and therefore do not allow for statements on the existence of a long-run migration hump. Our findings do not rule out that other slow-moving development dimensions such as educational advancement, demographic change, and structural economic transformation could still increase migration in the long term. Finally, by restricting our analysis to the income dimension we leave out important non-monetary aspects of the development-migration nexus. Dustmann and Okatenko (2014), for example, show that improved quality of local amenities such as public services has a significant (negative) impact on migration propensities. Likewise, according to Lanati and Thiele (2018), donors can dampen emigration from developing countries by providing aid for social infrastructure.

All these limitations do not affect the policy relevance of the analysis. This is because containing south–north migration in the next few years through local income and employment generation is what policy makers in developed countries usually have in mind when talking about ways to tackle the root causes of migration. Our findings are sufficiently robust to conclude that policy makers should at least not be too concerned about potential trade-offs between (successful) development cooperation and immigration management. At the same time, the scope for using development cooperation as a migration policy instrument can be considered to be limited given the modest size of the estimated income effect in combination with the difficulties donors face when it comes to fostering economic growth in developing countries (see, for example Qian, 2015). From a development perspective, one would also argue that promising anti-poverty measures such as the provision of improved seed varieties for farmers that are likely to raise their income should be pursued even if they eventually lead to a slight increase in emigration to donor countries. More generally speaking, in line with the Tinbergen rule of effective policy assignment, there is a case for using development cooperation exclusively as a means of reaching development goals rather than additionally serving the goal of managing migration.

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CONFLICT OF INTEREST STATEMENT

The authors certify that they have no affiliations with or involvement in any organisation or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

DATA AVAILABILITY STATEMENT

Data used in the analysis are publicly available. STATA codes are available on request from the authors.

ORCID

Mauro Lanati https://orcid.org/0000-0001-9411-6845

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SUPPORTING INFORMATION

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APPENDIX A

TABLE A1 Variables used and related sources.

Variable	Short description	Source
Dependent variable		
Emigration Flows	Bilateral emigration flows at different skill levels (low, medium and high) calculated as differences in bilateral migrant stocks provided in 5-year intervals	Brücker et al. (2013)
Emigration Stocks	Bilateral emigration stocks at different skill levels (low, medium and high) provided in 5-year intervals	Brücker et al. (2013); OECD-DIOC Database; Docquier et al. (2007)
Explanatory variables		
GDP	Origin GDP, current PPP (2011 thousand US $)	Penn World Tables
Population	Origin Population, total (in thousands)	Penn World Tables
Dependency ratio	Age dependency ratio (% of working-age population)	World Bank
Average years of schooling	Average years of schooling attained (age 15–64)	Barro, Robert J and Jong Wha Lee. 2013. 'A New Data Set of Educational Attainment in the World, 1950–2010'. Journal of Development Economics 104: 184–98.
Diaspora	Bilateral Stock of migrants born in country *i* and resident in country *n* at time *t*-5.	Brücker et al. (2013)
Democracy	Legislative and Executive Index of Electoral Competitiveness (LIEC)	Database of Political Institutions 2020. Inter-American Development Bank
Conflict Intensity	0 = Absence of conflict 1 = Minor: between 25 and 999 battle-related deaths in a given year. 2 = War: at least 1000 battle-related deaths in a given year.	UCDP/PRIO Armed Conflict Dataset
Natural Disasters	Calculated as the total number of natural disasters in a given year	International Disaster Database, Centre for Research on the Epidemiology of Disasters
Occupational Wages	Hourly Wages—Variable: *hw3wl_current*	Occupational Wages around the World (OWW) Database. Source: https://www.nber.org/research/data/occupational-wages-around-world-oww-database
Distance (bilateral)	Population-weighted average distance between the most populated cities of each country, arithmetic mean, in km	CEPII
Contig (bilateral)	Dummy which equals 1 if the countries are contiguous (neighbors), 0 otherwise.	CEPII
Colony (bilateral)	Dummy which equals 1 if country pair was ever in colonial relationship, 0 otherwise.	CEPII
Comlang Ethno (bilateral)	Dummy which equals 1 if countries share a common language spoken by at least 9% of the population, 0 otherwise.	CEPII

TABLE A1 (Continued)

Variable	Short description	Source
Instrumental Variable Analysis		
Total natural resources rents (% of GDP)	Total natural resources rents are the sum of oil rents, natural gas rents, coal rents (hard and soft), mineral rents, and forest rents.	Estimates based on sources and methods described in "*The Changing Wealth of Nations: Measuring Sustainable Development in the New Millennium*" (World Bank, 2010).
Contribution of mining to value added at current prices (%)	Contribution of mining to total value added is the proportion of value added in the mining and quarrying sector of total value added for all sectors in the country or area	UNSD National Accounts Main Aggregates Database: http://unstats.un.org/unsd/snaama/Introduction.asp

TABLE A2 List of origin countries.

Afghanistan	**Congo, Dem. Rep. of the**	**Iran**	**Myanmar**	**Somalia**
Albania	**Congo, Rep. of the**	**Iraq**	**Namibia**	**South Africa**
Algeria	**Costa Rica**	Ireland	Nauru	Spain
Andorra	**Cote d'Ivoire**	Israel	**Nepal**	**Sri Lanka**
Angola	**Croatia**	Italy	Netherlands	Sudan
Antigua and Barbuda	Cuba	**Jamaica**	New Zealand	**Suriname**
Argentina	Cyprus	Japan	**Nicaragua**	**Swaziland**
Armenia	Czech Republic	**Jordan**	**Niger**	Sweden
Australia	Denmark	**Kazakhstan**	**Nigeria**	Switzerland
Austria	**Djibouti**	**Kenya**	Norway	**Syria**
Azerbaijan	**Dominica**	Kiribati	**Occupied Palestinian Territory**	**Taiwan**
Bahamas, The	**Dominican Republic**	**Korea**	Oman	**Tajikistan**
Bahrain	**Ecuador**	Kuwait	**Pakistan**	**Tanzania**
Bangladesh	**Egypt**	**Kyrgyzstan**	Palau	**Thailand**
Barbados	**El Salvador**	**Laos**	**Panama**	Timor-Leste
Belarus	**Equatorial Guinea**	**Latvia**	Papua New Guinea	**Togo**
Belgium	Eritrea	**Lebanon**	**Paraguay**	Tonga
Belize	**Estonia**	**Lesotho**	**Peru**	**Trinidad and Tobago**
Benin	**Ethiopia**	**Liberia**	**Philippines**	**Tunisia**
Bhutan	**Fiji**	Libya	**Poland**	**Turkey**
Bolivia	Finland	Liechtenstein	**Portugal**	**Turkmenistan**
Bosnia and Herzegovina	France	**Lithuania**	Qatar	Tuvalu
Botswana	**Gabon**	Luxembourg	**Romania**	**Uganda**
Brazil	**Gambia, The**	**Macedonia**	**Russia**	**Ukraine**
Brunei	**Georgia**	**Madagascar**	**Rwanda**	United Arab Emirates
Bulgaria	Germany	**Malawi**	**St Kitts and Nevis**	United Kingdom

(Continues)

TABLE A2 (Continued)

Burkina Faso	**Ghana**	**Malaysia**	**St Lucia**	United States
Burundi	Greece	**Maldives**	**St Vincent and the Grenadines**	**Uruguay**
Cambodia	**Grenada**	**Mali**	Samoa	**Uzbekistan**
Cameroon	**Guatemala**	**Malta**	San Marino	Vanuatu
Canada	**Guinea**	Marshall Islands	**Sao Tome and Principe**	**Venezuela**
Cape Verde	**Guinea-Bissau**	**Mauritania**	Saudi Arabia	**Vietnam**
Central African Republic	Guyana	**Mauritius**	**Senegal**	**Yemen**
Chad	**Haiti**	Mexico	Serbia and Montenegro	**Zambia**
Chile	Holy See (Vatican City)	Micronesia	Seychelles	**Zimbabwe**
China	**Honduras**	**Moldova**	**Sierra Leone**	
China, Hong Kong SAR	**Hungary**	Monaco	Singapore	
China, Macao SAR	Iceland	**Mongolia**	Slovakia	
Colombia	**India**	**Morocco**	Slovenia	
Comoros	**Indonesia**	**Mozambique**	Solomon Islands	

Note: In **bold**, the countries with per-capita GDP levels below 10,000$ (PPP, Constant) are included in the second-step sample for which data on GDP and population are available (*Source*: Penn World Tables).

TABLE A3 Summary statistics.

First step						
Variable	**Emigrant flows**	**Emigrant flows**	**Emigrant flows**	**Emigrant flows**		
Skill	**Low**	***Med***	***High***	***Total***	***Ln*(1 + $M_{ij,t}$)**	
Mean	1014.165	949.4442	1156.188	3119.797	4.310846	
Standard deviation	19686.27	12366.09	9285.799	36811.13	3.338575	
Min	0	0	0	0	0	
Max	1,415,811	1,142,824	458,438	2,992,111	15.92265	
N	13,146	13,146	13,146	13,146	13,146	
Second step: Avg skill						
Variable	***Ln (GDP pc)***	***Ln (Edu)***	***Democracy***	***Dep. ratio***	***Conflict intensity***	***Natural disasters***
Mean	8.73245	1.851713	6.02377	68.67891	0.2459016	0.6770492
Standard deviation	1.171354	0.5349159	1.71677	18.91659	0.5453411	0.4679878
Min	5.463819	−0.4049653	1	37.09029	0	0
Max	11.24072	2.572994	7	114.3035	2	1
N	610	610	610	610	610	610
Second step: <10,000$						
Variable	***Ln (GDP pc)***	***Ln (Edu)***	***Democracy***	***Dep. ratio***	***Conflict intensity***	***Natural disasters***
Mean	7.999069	1.616696	5.587013	78.33301	0.3298701	0.6753247
Standard deviation	0.7671122	0.52541	1.934699	16.42162	0.6231357	0.4688627
Min	5.463819	−0.4049653	1	38.08612	0	0
Max	9.209674	2.445386	7	114.3035	2	1
N	385	385	385	385	385	385
Second step: <8000$						
Variable	***Ln (GDP pc)***	***Ln (Edu)***	***Democracy***	***Dep. ratio***	***Conflict intensity***	***Natural disasters***
Mean	7.882549	1.578775	5.511494	79.93302	0.3304598	0.6867816
Standard deviation	0.7135045	0.5328762	1.973494	15.8693	0.6190937	0.4644702
Min	5.463819	−0.4049653	1	38.08612	0	0
Max	8.977571	2.443911	7	114.3035	2	1
N	348	348	348	348	348	348

Note: The statistics below refer to the baseline statistics.

TABLE A4 First stage statistics of the instrumental variable regression.

Dep. var. GDP pc threshold IV model	(1) *Ln* (GDP pc *i,t*) None Over identified
Total natural resources rents (% GDP)	−0.167***
	(−5.92)
Contribution of mining to VA (%)	0.092***
	(3.45)
Income Perc: 10th	
Total natural resources rents (% GDP)	−0.162***
	(−4.35)
Contribution of mining to VA (%)	0.126***
	(3.57)
Income Perc: 50th	
Total natural resources rents (% GDP)	−0.161***
	(−5.03)
Contribution of mining to VA (%)	0.104***
	(3.60)
Income Perc: 90th	
Total natural resources rents (% GDP)	−0.160***
	(−5.01)
Contribution of mining to VA (%)	0.081**
	(2.68)
Origin FE	X
Year FE	X

Note: *t* statistics in parentheses. Standard errors are clustered by origin. The statistics refer to the first stage of the IV model estimates reported in Table 8 where $\widehat{S}_{i(l),t}$ is obtained with a structural gravity model in which negative values are dropped. **p* < 0.05, ***p* < 0.01, and ****p* < 0.001.