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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, even though the evidence on whether economic development leads to more or less people emigrating is so far inconclusive. Employing various panel-data approaches, 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. Our findings reveal a universal negative association between income per capita and emigration for all three skill groups and across specifications. 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 is limited due to the modest size of the estimated income effect.

Keywords

Migration, Economic Development, Migrants' Skill Composition

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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 determinant of migration decisions.

However, policy makers' presumption that migration can be reduced by supporting economic development has been challenged in the 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). The social science literature (e.g. de Haas 2010a and 2010b) broadens this income-centred approach by arguing that people's propensity to migrate depends not only on income but on the 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.

In its income-centred version, the hypothesis of a migration hump attributes an important role to liquidity constraints: 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 binding so that further increases in real incomes cause the emigration rate to fall from its peak as predicted by the neoclassical model. The migration hump hypothesis receives empirical support in cross-sectional settings, i.e. 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, locate the turning point at GDP per capita levels between US $8000 and US$ 10000. This finding therefore suggests 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 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 and Schneiderheinze 2020; Böhme et al. 2020; Clist and Restelli 2021; Ortega and 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 in poorer countries. Beine et al. (2021) show for 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.

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, along the lines of Djajic et al. (2016), who focus on the cross-country dimension, we investigate the relationship between income per capita and emigration to OECD countries separately for three different skill groups. These include low-skilled, medium-skilled and high-skilled workers. As highlighted by Borjas (1987) and Dao et al (2018), among others, skill composition of the population is an important factor driving emigration decisions. 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 influencing the migration flows of low-skilled workers, whereas opportunity costs of migration tend to figure more prominently for the highly skilled. Hence, at any initial level of economic development, a rise in income is more likely to lead to higher emigration for low-skilled as compared to high-skilled workers. In their cross-country analysis, Djajic et al. (2016) confirm this hypothesis, obtaining a positive and significant income effect for the group of low-skilled emigrants, whereas at higher skill levels the effect turns negative but loses its statistical significance. Likewise, Dao et al. (2018) obtain results that corroborate the hump relationship - which is weaker for high-skilled workers and stronger in actual than desired emigration.

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 and Peri 2013), while others (e.g. Benček and 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 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. In Section 2, 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 3 presents the estimation results, starting with a baseline specification and then adding a series of robustness checks. Section 4 closes the paper with some concluding remarks.

2. Econometric Specification and Data

Following Adovor et al. (2021) as well as Lanati and Thiele (2020), in our preferred baseline regression we estimate the relationship between income per capita and emigration with a two-step strategy based on a structural dyadic gravity model of international migration. Our econometric specification of the income-emigration link reduces to:

$$\hat{\mathrm{S}}_{i(l),t;t+5} = \beta_i + \beta_t + ln(\mathrm{GDP}_{i,t}) * \gamma + ln(\mathrm{POP}_{i,t}) * \partial + \epsilon_{i(l),t;t+5} \qquad (1)$$

where $\hat{\mathrm{S}}_{i(l),t}$ is the origin-year fixed effect term obtained from estimating the following equation in the first step:

$$\mathrm{M}_{ji(l),t;t+5} = exp\left[S_{i(l),t} + S_{j(l),t} + S_{ij(l)} + \ ln\left(\mathrm{MigStocks}_{ji,t}\right) * \delta + \tau_{ji(l),t;t+5}\right] \qquad (2)$$

$\hat{\mathrm{S}}_{i(l),t}$ 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. $\mathrm{M}_{ji(l),t;t+5}$ denotes emigration flows from i to j; they are calculated as differences of bilateral migrant stocks provided in 5-year intervals (see below). Equation (1) allows us to capture time-varying push factors from the origin countries, including our variable of interest, per-capita income.

In our baseline specification, we model emigration in absolute terms, regressing *migration openness* on absolute GDP and controlling for population size. The main reason for doing so is that population growth exerts an influence on emigration beyond increasing the pool of potential migrants. It shapes age distribution within countries, which in turn affects average emigration propensities. In addition, more populous countries provide more opportunities for internal migration (Haas et al. 2018). Following Clemens' (2020) argument that employing GDP and population separately in the regression could lead to spurious correlations, we alternatively use GDP per capita as the relevant explanatory variable. Along the lines of Beine and Parsons (2017) and Cattaneo and Peri (2016), we start with a parsimonious model which includes only the set of fixed effects with no controls. While 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. In order to test whether omitted-variable bias is an issue, we add several standard origin-specific controls to our baseline specification. These include proxies for the prevalence of conflict and natural disasters as well as a democracy index that captures various elements of electoral competitiveness.

Following Adovor et al. (2021) as well as Lanati and Thiele (2020), we apply the 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, while 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 characterized by a large number of countries of origin, many of them small, the choice of the PPML estimator therefore matters. Our PPML estimations include a standard set of higher-dimensional fixed effects. 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 $\hat{S}_{i(l),t;t+5}$.

While 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 and 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. Ericson and Löf 2019; McMahon and 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).

The two-step estimator chosen here has several potential advantages over the one-step procedure, which we still apply in one of our robustness checks. For instance, when using a 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 and Mayer 2014). In addition, 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). Calculating emigration rates with the population differentiated by the skill level available from the Barro and Lee (2013) dataset as the denominator, for instance, would lead to considerable loss of information due to missing data. Finally, employing a monadic approach in the second step also renders it possible to perform an IV estimation along the lines described above, which can hardly be achieved in a dyadic setting.

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, $\hat{S}_{i(l),t}$, is obtained 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 the so-called multilateral resistance to migration. 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.

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.[1] Data are from Brucker et al (2013) which is the only dataset, to the best of our knowledge, which provides panel information for a sufficiently long time period on bilateral emigration stocks at different skill levels from developing countries. 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 two 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 dependent variable. Table A1 in the Appendix lists the sources and provides a brief description of these variables and 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 and 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 $\hat{S}_{i(l),t}$ 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 zero, assuming that both deaths and return migration are small relative to net migrant flows.[2] 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+5 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 ILO et al. 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 from Penn World Table. As for the control variables, a dummy that takes the value of one in the presence of conflicts 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 are provided by the International Disaster Database of the Centre for Research on the Epidemiology of Disasters (EMDAT 2021), and an index of Legislative and Executive Dimensions of Electoral Competitiveness is from the DPI2020 Database of Political Institutions (Cruz et al. 2021).

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1 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 in the Appendix.

2 While all negative values are set to zero, 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.

3. Results

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). The estimated positive coefficients point to a network effect of the diaspora variable on emigration flows, which is in line with previous studies (see Adovor et al. 2021).[3] The lower part of Table 1 reports the OLS estimates of Equation (1), with standard errors clustered by country of origin.[4] Columns 9-12 contain the results for our preferred specification including a full set of fixed effects. 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$ 10000 as defined by Clemens and Postel (2018).[5] This would be in accordance with the upward-sloping part of an inverted U curve. 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 $\hat{S}_{i(l),t;t+5}$.

The inclusion of country fixed effects in columns 9-12, by contrast, 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. The effect is modest but non-negligible in quantitative terms: in the full sample, a 10 percent increase in GDP per capita lowers emigration flows by about 2.5 percent. It appears to vary little according to skill levels or with levels of per-capita income. 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 and Schneiderheinze 2020; Ortega and Peri 2013).

Our main findings hold when we add the set of control variables introduced above (Table 2). Among the controls, only conflict turns out to be a significant determinant of emigration, with the expected positive sign. The number of natural disasters and the level of democracy in the country of origin do not appear to affect international migration.

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3 The network elasticities reported in the gravity literature are larger, typically ranging between 0.4 and 0.7 (Beine et al. 2015). 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 and Parsons 2015).

4 To account for the possibility that errors are correlated within origin and time dimensions in Equation (1), we followed Faye and Niehaus (2021) and replicated our estimates with standard errors multi-way clustered at origin-time level. While 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. The results with multi-way clustered standard errors are available on request.

5 The GDP coefficients remain statistically significant with a negative sign when we employ Clemens and Postel's (2018) lower bound of US$ 8000 as a threshold. The estimates are available upon request.

Robustness Checks

To investigate the validity of our baseline results and how they relate to the findings of previous studies, we perform a variety of robustness checks. First, 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 $\hat{S}_{i(l),t;t+5}$. We address these data issues by setting the negative values of changes in stocks to zero and using bilateral stocks as the dependent variable, respectively. The estimates reported in Tables 3 and 4 retain the negative sign for our variable of interest once the full set of fixed effects is included in the two-step gravity equation. 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. With migrant stocks as the dependent variable, the negative income coefficient decreases in size for our baseline data (Table 4; columns 1-4) but does not turn positive. The results obtained with the two alternative datasets – columns 5-8 for Docquier et al. (2007); 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. Still, they corroborate the general finding of a negative income-migration link, even though some of the coefficients become statistically not significant at conventional levels.

Second, we employ GDP per capita as the relevant explanatory variable in the regression rather than GDP and population separately. As shown in Table 5, the estimated relationship between income and emigration remains negative and significant for all skill levels, with coefficients that are broadly comparable to the baseline. It is thus unlikely that the correlation we find in our preferred specification is spurious.

Third, 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 recently proposed by Clemens (2020) as well as Bencek and Schneiderheinze (2020). The estimates using these two alternative approaches, reported in Tables 5 and 6, are again qualitatively the same as the baseline results. The one-step approach even points to a somewhat more pronounced negative association between GDP per capita and emigration. Our monadic results differ from Clemens (2020), who retains a positive income-migration link when using 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.

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.[6] 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 clearly above the rule-of-thumb critical value of 10, while the Hansen-J test confirms the validity of the over-identifying restrictions. In the first stage regression – results are reported in Appendix Table A3 – 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,

[6] Note that the IV estimates are obtained with GDP per capita as (endogenous) variable of interest, rather than including country of origin's income and population separately as in Equation (1). Applying the IV estimator to national income leaves the results roughly unaffected (results are available on request).

the IV estimates generally confirm the negative relationship between the time variation of income levels at the origin and emigration across different skill levels.

4. 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 income channel dominates even for poor and unskilled people, keeping some would-be migrants from going abroad.

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. 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 firmly conclude that policy makers should at least not be 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.

References

Adovor, E., M. Czaika, F. Docquier, and Y. Moullan (2021). Medical Brain Drain: How Many, Where, and Why? *Journal of Health Economics* 76: 102409.

Bazzi, S. (2017). Wealth Heterogeneity and the Income Elasticity of Migration. *American Economic Journal: Applied Economics* 9(2): 219-255.

Beine, M., F. Doquier, and C. Özden (2011). Diasporas. *Journal of Development Economics* 95: 30–41.

Beine, M., and C. Parsons (2015). Climatic Factors as Determinants of International Migration. *Scandinavian Journal of Economics* 117(2): 723-767.

Beine, M., and C. Parsons (2017). Climatic Factors as Determinants of International Migration: Redux. *CESifo Economic Studies* 63(4): 386–402.

Beine, M., L. Bertinelli, R. Cömertpay, A.Litina, and J.-F. Maystadt (2021). A gravity analysis of refugee mobility using mobile phone data. *Journal of Development Economics* 150: 102618.

Benček, D., and C. Schneiderheinze (2020). Higher economic growth in poor countries, lower migration flows to the OECD: Revisiting the migration hump with panel data. Kiel Working Paper 2145, June 2020.

Bertoli, S., and J. Fernandez-Huertas Moraga (2013). Multilateral resistance to migration. *Journal of Development Economics* 102(May): 79-100.

Böhme, M., H., A. Gröger, and T. Stöhr (2020). Searching for a better life: Predicting international migration with online search keywords. *Journal of Development Economics* 142: 102347.

Borjas, G. J. (1987). Self-selection and the earnings of immigrants. *American Economic Review* 77: 531–53.

Brücker H., S. Capuano, and A. Marfouk (2013). Education, gender and international migration: insights from a panel-dataset 1980-2010. Norface Research Programme on Migration: New developments, Spring 2013. Norface Migration: London. 31-32.

Cattaneo, C., and G. Peri (2016). The Migration Response to Increasing Temperatures. *Journal of Development Economics* 122: 127–146.

Clemens, M.A. (2014). Does Development Reduce Migration? In: *International Handbook on Migration and Economic Development* 8592: 152–185.

Clemens, M.A. (2020). The Emigration Life Cycle: How Development Shapes Emigration from Poor Countries. Center for Global Development Working Paper 540, August 2020.

Clemens, M.A., and H.M. Postel (2018). Deterring Emigration with Foreign Aid: An Overview of Evidence from Low-Income Countries. *Population and Development Review* 4: 667–693.

Clist, P., and G. Restelli (2021). Development Aid and International Migration to Italy: Does Aid Reduce Irregular Flows? *The World Economy* 44 (5): 1281-1311.

Corden, W.M., and J.P. Neary (1982). Booming Sector and De-Industrialisation in a Small Open Economy. *The Economic Journal* 92 (December): 825-848.

Cruz, C., P. Keefer, and C. Scartascini (2021). DPI2020 Database of Political Institutions: Changes and Variable Definitions. Interamerican Development Bank, January 2021.

Dao, T.H., F. Docquier, C. Parsons, and G. Peri (2018). Migration and development: Dissecting the anatomy of the mobility transition. *Journal of Development Economics* 132: 88-101.

Djajic, S., M.G. Kirdar, and A. Vinogradova (2016). Source country earnings and emigration. *Journal of International Economics* 99: 46–67.

Docquier, F., O. Lohest, and A. Marfouk (2007). Brain Drain in Developing Countries. *The World Bank Economic Review* 21(2): 193-218.

Dustmann, C., and A. Okatenko (2014). Out-migration, wealth constraints, and the quality of local amenities. *Journal of Development Economics* 110: 52-63.

EMDAT (2021). The International Disaster Database. Center for Research on the Epidemiology of Disasters (https://emdat.be).

Ericsson, M., and O. Olof (2019). Mining's contribution to national economies between 1996 and 2016. *Mineral Economics* 32: 223-250.

Faye, M., and P. Niehaus (2012). Political aid cycles. *American Economic Review* 102(7): 3516- 30.

Haas, H. de, M. Czaika, M-L. Flahaux, E. Mahendra, K. Natter, S. Vezzoli, and M. Villares-Varela (2018). International Migration. Trends, Determinants and Policy. IMI Working Paper Series 142: 1-59.

Haas, H. de (2010a). Migration and Development: A Theoretical Perspective. *International Migration Review* 44 (1): 227–264.

Haas, H. de (2010b). Migration transitions: A theoretical and empirical inquiry into the developmental drivers of international migration. Working Paper 24, International Migration Institute, University of Oxford.

Harris, J.R., and M.P. Todaro (1970). Migration, unemployment and development: a two-sector analysis. *American Economic Review* 60 (1): 126–142.

Head, K., and T. Mayer (2014). Gravity Equations: Workhorse, Toolkit, and Cookbook. Handbook of International Economics, Volume 4, Chapter 4: 131-195.

International Labor Organisation (ILO), Organisation for Economic Co-operation and Development (OECD), and World Bank Group (2015). The Contribution of Labour Mobility to Economic Growth.

Lanati, M., and R. Thiele (2018). The Impact of Foreign Aid on Migration Revisited. *World Development* 111: 59-74.

Lanati, M., and R. Thiele (2020). Foreign Assistance and Emigration: Accounting for the Role of Non-Transferred Aid. *The World Economy* 43(7): 1951-1976.

Langella, M., & Manning, A. (2021). Income and the desire to migrate. Working Paper No. 1794, LSE – Centre for Economic Performance.

Larch, M., J. Wanner, Y. Yotov, and T. Zylkin (2019). Currency Unions and Trade: a PPML Re-assessment with High-Dimensional Fixed Effects. *Oxford Bulletin of Economics and Statistics* 19(3): 487-510.

McMahon, G., and S. Moreira (2014). The Contribution of the Mining Sector to Socioeconomic and Human Development. Extractive industries for development series no. 30. The World Bank, Washington, DC.

Moullan, Y. (2013). Can Foreign Health Assistance Reduce the Medical Brain Drain? *Journal of Development Studies* 49(10): 1436-1452.

Qian, N. (2015). Making Progress on Foreign Aid. *Annual Review of Economics* 7 (1): 277–308.

OECD (2021). Database on Immigrants in OECD and non-OECD Countries: DIOC (https://www.oecd.org/els/mig/dioc.htm).

Ortega, F., and G. Peri (2013). The role of income and immigration policies in attracting international migrants. *Migration Studies*, 1(1): 47–74.

Ross, M.L. (2015). What Have We Learned about the Resource Curse? *Annual Review of Political Science* 18: 239-259.

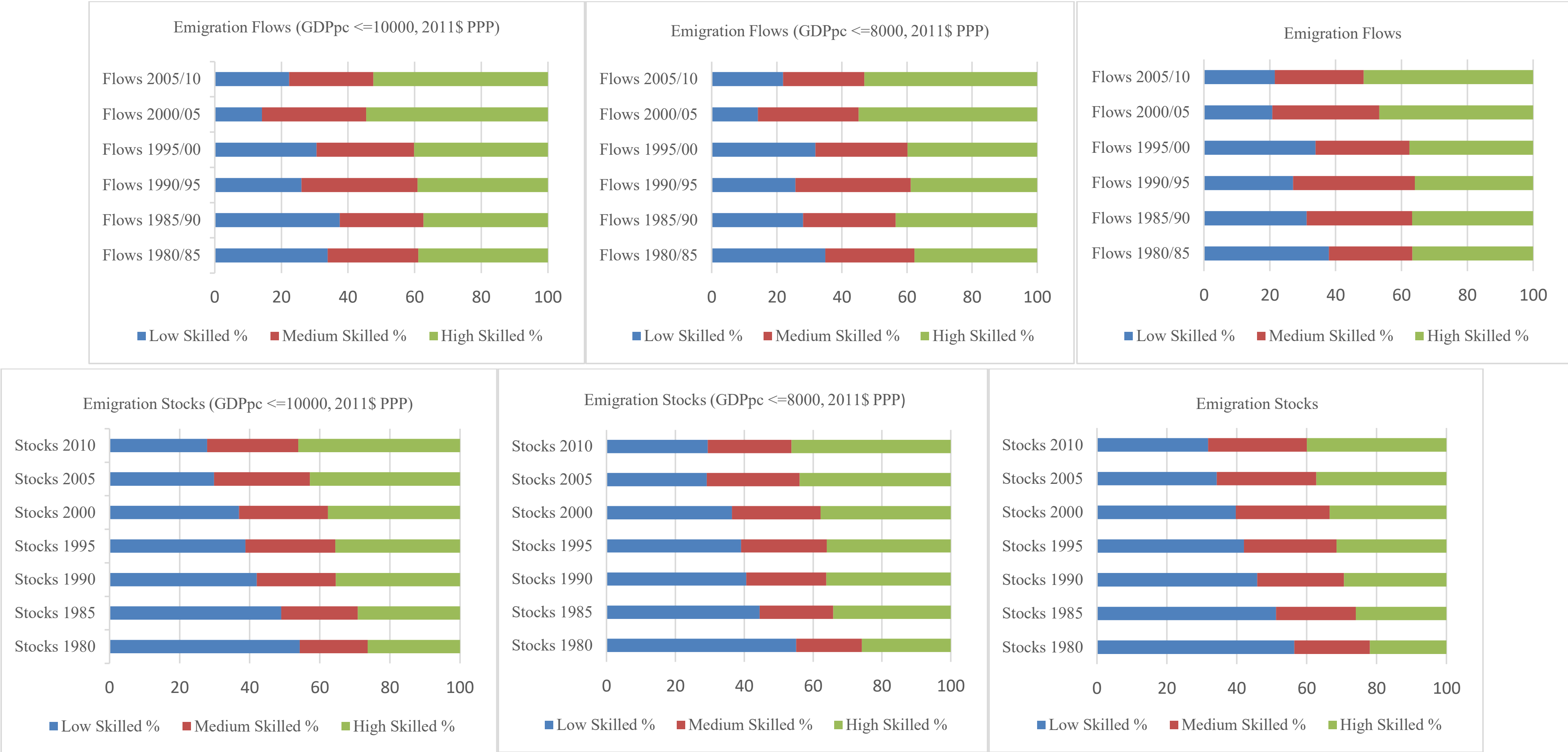
Silva, J.S., and S. Tenreyro (2006). The Log of Gravity. *The Review of Economics and Statistics* 88(4): 641-658.

Sjaastadt, L.A. (1962). The costs and returns of human migration. Journal of Political Economy 70: 80–93.

UCDP (2021). Uppsala Conflict Data Program (https://ucdp.uu.se).

World Bank (2010). The changing wealth of nations: measuring sustainable development in the new millennium. The World Bank, 2010.

Figure 1: South-North Emigration by Skill Level



Notes: Migration flows (panels above) refer to the sum of bilateral emigration flows to selected OECD countries, with negative values set to zero. 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 or lower than 10000$ and those equal or lower than 8000$, respectively.

Table 1: Baseline Specification – Emigration Flows (only non-negative flows)

First Step: PPML

	(1)	(2)	(3)	(4)
Dep. Var.	Emigrant Flows	Emigrant Flows	Emigrant Flows	Emigrant Flows
Skill	*Low*	*Med*	*High*	*Total*
Ln(1+Mij,t)	-0.00286	0.0648**	0.0355*	0.0348*
	(-0.16)	(3.17)	(2.37)	(2.31)
N	12464	12424	12702	13146
Destination-Year FE	X	X	X	X
Origin-Year FE	X	X	X	X
Destination-Origin FE	X	X	X	X

Second Step: OLS

	1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent Var.	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$
Skill	*Low*	*Med*	*High*	*Tot*	*Low*	*Med*	*High*	*Tot*	*Low*	*Med*	*High*	*Tot*
Ln(GDP,i,t)	0.328**	0.433***	0.458***	0.404***	0.334**	0.432***	0.451***	0.402***	-0.248**	-0.306***	-0.215**	-0.245**
	(3.17)	(4.53)	(5.47)	(4.30)	(3.17)	(4.43)	(5.30)	(4.20)	(-2.77)	(-3.42)	(-2.96)	(-3.25)
Ln(Pop,i,t)	0.130	0.0670	0.0968	0.104	0.126	0.0667	0.100	0.105	0.527	1.260***	0.590*	0.634*
	(1.19)	(0.67)	(1.08)	(1.06)	(1.15)	(0.66)	(1.11)	(1.06)	(1.65)	(3.82)	(2.53)	(2.39)
N	947	947	947	947	947	947	947	947	946	946	946	946
R^2	0.230	0.327	0.433	0.343	0.233	0.331	0.438	0.344	0.900	0.918	0.943	0.943
GDPpc <=10000$												
Ln(GDP i,t)	0.760***	0.788***	0.789***	0.762***	0.767***	0.785***	0.782***	0.761***	-0.252*	-0.233*	-0.177*	-0.215*
	(4.31)	(5.15)	(5.55)	(4.92)	(4.34)	(5.12)	(5.47)	(4.89)	(-2.27)	(-2.24)	(-2.07)	(-2.25)
Ln(Pop,i,t)	-0.323	-0.311	-0.249	-0.294	-0.328	-0.313	-0.247	-0.296	-0.482	0.311	-0.170	-0.126
	(-1.63)	(-1.84)	(-1.64)	(-1.74)	(-1.65)	(-1.85)	(-1.62)	(-1.74)	(-1.08)	(0.57)	(-0.45)	(-0.29)
N	626	626	626	626	626	626	626	626	617	617	617	617
R^2	0.236	0.328	0.429	0.326	0.242	0.336	0.435	0.329	0.909	0.920	0.940	0.938
Origin FE									X	X	X	X
Year FE					X	X	X	X	X	X	X	X

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. 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 dependent variable. The second-step models include the log of population as the only control variable.

Table 2: Baseline Specification with Controls

Second Step: OLS								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Var.	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$
Skill	*Low*	*Med*	*High*	*Tot*	*Low*	*Med*	*High*	*Tot*
GDP pc Threshold	None	None	None	None	<10000$	<10000$	<10000$	<10000$
Ln(GDP i,t)	-0.255**	-0.316***	-0.214**	-0.246**	-0.277*	-0.275**	-0.203*	-0.243*
	(-2.80)	(-3.43)	(-2.79)	(-3.18)	(-2.50)	(-2.69)	(-2.22)	(-2.47)
Ln(POP i,t)	0.703*	1.462***	0.745**	0.754**	-0.566	0.312	-0.113	-0.222
	(2.10)	(4.09)	(3.01)	(2.68)	(-1.17)	(0.49)	(-0.25)	(-0.48)
Democracy	-0.00280	-0.0135	0.00106	-0.00927	-0.0238	-0.0288	-0.00376	-0.0157
	(-0.15)	(-0.72)	(0.07)	(-0.60)	(-1.33)	(-1.70)	(-0.26)	(-1.08)
Conflict	0.161	0.212*	0.205*	0.182**	0.181	0.220**	0.206*	0.171*
	(1.62)	(2.58)	(2.60)	(2.72)	(1.81)	(2.76)	(2.41)	(2.43)
Natural Disasters	0.0617	-0.0715	-0.0900*	-0.0226	0.0906	-0.0167	-0.0687	0.0189
	(0.99)	(-1.25)	(-2.02)	(-0.50)	(1.18)	(-0.26)	(-1.21)	(0.33)
N	875	875	875	875	572	572	572	572
Origin FE	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X
R-sq	0.9075	0.9254	0.9462	0.9488	0.9188	0.9287	0.9436	0.9462

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. 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 non-negative emigration flows as dependent variable.

Table 3: Robustness – Emigration Flows (including negative observations as zeros)

	(1)	(2)	(3)	(4)
Dependent Var.	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$
Skill	*Low*	*Med*	*High*	*Tot*
Ln(GDP,i,t)	-0.246*	-0.309**	-0.237**	-0.302***
	(-2.25)	(-3.25)	(-3.13)	(-3.48)
Ln(Pop,i,t)	0.369	1.280***	0.548*	0.589*
	(1.05)	(4.20)	(2.53)	(2.22)
N	946	946	946	946
R^2	0.866	0.908	0.936	0.927
GDPpc <=10000$				
Ln(GDP i,t)	-0.211	-0.284*	-0.204*	-0.291*
	(-1.47)	(-2.39)	(-2.33)	(-2.59)
Ln(Pop,i,t)	-0.00188	0.511	-0.327	0.101
	(-0.00)	(0.92)	(-0.84)	(0.22)
N	617	617	617	617
R^2	0.877	0.902	0.932	0.924
Origin FE	X	X	X	X
Year FE	X	X	X	X

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. 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 second-step models include the log of population as the only control variable.

Table 4: Emigration Stocks – GDP per capita lagged 5-years / Comparison with Alternative Datasets

Second Step: OLS

Dataset	***Brucker et al 2013***				***Docquier et al 2007 (1990-2000)***				***DIOC (2000-2010)***			
	(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*
Ln(GDP,i,t-5)	-0.138**	-0.143*	-0.120**	-0.148**	-0.130	-0.138*	-0.0692	-0.133*	-0.0964	-0.120	-0.132*	-0.110
	(-2.70)	(-2.46)	(-2.65)	(-3.12)	(-1.46)	(-2.04)	(-1.44)	(-2.46)	(-0.85)	(-1.71)	(-2.20)	(-1.41)
Ln(Pop,i,t-5)	0.756***	0.725***	0.210	0.606***	0.743*	0.902***	0.770***	0.862***	1.048***	0.400*	0.377	0.617**
	(4.26)	(4.35)	(1.62)	(4.39)	(2.37)	(3.36)	(4.60)	(4.04)	(3.90)	(2.01)	(1.95)	(3.10)
N	946	946	946	946	292	292	292	292	348	348	348	348
R^2	0.978	0.977	0.981	0.983	0.989	0.992	0.995	0.994	0.982	0.991	0.994	0.990
GDPpc <=10000$												
Ln(GDP,i,t-5)	-0.142*	-0.121	-0.104*	-0.159**	-0.0866	-0.0952	-0.0127	-0.115*	-0.0832	-0.0860	-0.136*	-0.0918
	(-2.25)	(-1.85)	(-2.03)	(-2.91)	(-1.01)	(-1.36)	(-0.25)	(-2.06)	(-0.87)	(-1.36)	(-2.41)	(-1.36)
Ln(Pop,i,t-5)	0.374	-0.386	-0.375	-0.175	-0.216	0.209	0.0791	0.177	0.374	-0.386	-0.375	-0.175
	(0.79)	(-1.29)	(-1.47)	(-0.52)	(-0.54)	(0.74)	(0.35)	(0.66)	(0.79)	(-1.29)	(-1.47)	(-0.52)
N	617	617	617	617	186	186	186	186	188	188	188	188
R^2	0.978	0.976	0.978	0.982	0.993	0.994	0.994	0.995	0.975	0.989	0.992	0.986
Origin FE	X	X	X	X	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X	X	X	X	X

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. 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 the dependent variable is bilateral emigrant stocks. The second-step models include both the log of population as well as GDP variables lagged at t-5.

Table 5: Robustness – GDP Per Capita

Second Step: OLS	***First Step:*** *Only Non-Neg. Flows*				***First Step:*** *Neg. Flows as Zeros*				***First Step:*** *Emigration stocks*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent Var.	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$
Skill	*Low*	*Med*	*High*	*Tot*	*Low*	*Med*	*High*	*Tot*	*Low*	*Med*	*High*	*Tot*
Ln(GDPpc,i,t)	-0.276**	-0.401***	-0.253***	-0.284***	-0.259*	-0.406***	-0.268***	-0.331***	-0.200***	-0.201***	-0.129**	-0.194***
	(-3.19)	(-4.49)	(-3.53)	(-3.86)	(-2.43)	(-4.58)	(-3.91)	(-4.03)	(-4.13)	(-4.10)	(-3.23)	(-4.84)
N	946	946	946	946	946	946	946	946	946	946	946	946
R^2	0.900	0.916	0.942	0.942	0.866	0.906	0.936	0.927	0.977	0.976	0.981	0.982
GDPpc <=10000$												
Ln(GDPpc i,t)	-0.206	-0.238*	-0.156	-0.194*	-0.198	-0.298*	-0.172	-0.280*	-0.126*	-0.105	-0.0690	-0.142**
	(-1.85)	(-2.28)	(-1.84)	(-2.05)	(-1.41)	(-2.56)	(-1.96)	(-2.55)	(-2.04)	(-1.64)	(-1.29)	(-2.67)
N	617	617	617	617	617	617	617	617	617	617	617	617
R^2	0.909	0.920	0.940	0.938	0.877	0.902	0.931	0.924	0.978	0.975	0.977	0.981
Origin FE	X	X	X	X	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X	X	X	X	X

t statistics in parentheses* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard Errors are Clustered by Country of Origin.

Table 6 – One-step approach a la Beine and Parsons (2015)

Estimator: PPML				
GDP pc Threshold	None	<10000$	None	<10000$
Rates constructed with	*Bilateral Stocks as numerator*	*Bilateral Stocks as numerator*	*Bilateral Flows as numerator*	*Bilateral Flows as numerator*
	(1)	(2)	(3)	(4)
Dep. Var.	Em. Rate	Em. Rate	Em. Rate	Em. Rate
Skill	*Total*	*Total*	*Total*	*Total*
Ln(GDP i,t)	-0.098*	-0175***	-0.443***	-0.580***
	(-2.19)	(-3.58)	(-3.42)	(-3.94)
N	18820	12516	18675	12413
Origin FE	X	X	X	X
Destination*Year FE	X	X	X	X

t statistics in parentheses* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard Errors are Clustered by Country of Origin. The regressions include the log of population and log of the lagged bilateral stocks as the only control variables, whose coefficients are not reported.

Table 7: Aggregate Monadic Model

	Emigrant Flows	*Emigrant Stocks*
	(1)	(2)
Dependent Var.	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$
Skill	*Tot*	*Tot*
Ln(GDP,i,t)	-0.297**	-0.157**
	(-3.12)	(-2.77)
N	946	946
GDPpc <=10000$		
Ln(GDP i,t)	-0.279*	-0.165*
	(-2.21)	(-2.50)
N	617	617
Origin FE	X	X
Year FE	X	X

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The dependent variable is the total number of emigrants from a given country of origin to selected OECD destinations divided by country's total population. The estimates are obtained with emigration rates as dependent variable calculated using as numerator the sum of bilateral emigration flows (Columns 1-3) and bilateral emigration stocks (Columns 4-6). The regressions include the log of population as the only control variable, whose coefficients are not reported.

Table 8 – Robustness Check: IV – *Per Capita GDP*

Over Identified Model: Two Instruments / One Endogenous Var

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Var.	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$	$\hat{S}_{i(l),t}$
Skill	*Low*	*Low*	*Med*	*Med*	*High*	*High*	*Tot*	*Tot*
GDP pc Threshold	*None*	*None*	*None*	*None*	*None*	*None*	*None*	*None*
1st Step Dep. Var.	*Neg. as Zeros*	*Only Pos.*	*Neg. as Zeros*	*Only Pos.*	*Neg. as Zeros*	*Only Pos.*	*Neg. as Zeros*	*Only Pos.*
Ln(GDP pc i,t)	-1.343**	-0.787*	-0.739*	-0.990**	-0.204	-0.294	-0.686*	-0.552*
	(-2.91)	(-2.39)	(-2.40)	(-3.25)	(-0.68)	(-1.25)	(-2.31)	(-2.32)
N	796	796	796	796	796	796	796	796
Origin FE	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X
K-Paap F-Stat	19.859	16.055	16.055	16.055	16.055	16.055	16.055	16.055
Hansen J Stat (P-Val)	0.3149	0.8959	0.9708	0.5267	0.8477	0.5628	0.4015	0.9634
GDP pc<=10000								
Ln(GDP pc i,t)	-1.092	-0.724	-0.552	-0.460	0.107	-0.198	-0.655	-0.414
	(-1.92)	(-1.66)	(-1.10)	(-1.18)	(0.24)	(-0.58)	(-1.40)	(-1.17)
N	511	511	511	511	511	511	511	511
Origin FE	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X
K-Paap F-Stat	14.452	11.723	11.723	11.723	11.723	11.723	11.723	11.723
Hansen J Stat (P-Val)	0.4870	0.9173	0.4670	0.7639	0.5297	0.9564	0.3911	0.9879

t statistics in parentheses; * p < 0.05, ** p < 0.01, *** p < 0.001. Standard Errors are clustered by origin.

First Stage Statistics are reported in Table A3 in the Appendix. The included instruments are the *Total natural resources rents (% of GDP)* and the *Contribution of mining to value added at current prices (%).*

Appendix - Table A1: Variables Used and Related Sources

Variable	Short description	Source
Dependent variable		
Emigration Flows	Bilateral Emigration Flows at different skill levels (low, medium, high) calculated as differences of bilateral migrant stocks provided in 5-year intervals	Brucker et al (2013)
Emigration Stocks	Bilateral Emigration Stocks at different skill levels (low, medium, high) provided in 5-year intervals	Brucker 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
Diaspora	Bilateral Stock of migrants born in country i and resident in country n at time t-5.	Brucker et al (2013)
Democracy	Legislative and Executive Index of Electoral Competitiveness (LIEC)	Database of Political Institutions 2020. Inter-American Development Bank
Conflict	Dummy = 1 in the presence of conflict in the country of origin, 0 otherwise	UCDP Monadic Conflict Onset and Incidence 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
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

Appendix – 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
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	

Notes: in **bold** the countries with per-capita GDP levels below 10000$ (PPP, Constant) included in the second-step sample for which data on GDP and Population are available (source: Penn World Tables).

Appendix - Table A3: First Stage Statistics

	(1)	(2)
Dep. Var.	*Ln*(GDP pc i,t)	*Ln*(GDP pc i,t)
GDP pc Threshold	None	<10000$
IV Model	Over Identified	Over Identified
Total natural resources rents (% GDP)	-0.163***	-0.161***
	(-6.24)	(-5.16)
Contribution of mining to VA (%)	0.066**	0.075**
	(2.35)	(2.58)
N	796	511
Origin FE	X	X
Year FE	X	X

t statistics in parentheses; * p < 0.05, ** p < 0.01, *** p < 0.001. Standard Errors are clustered by origin.

The statistics refer to the first stage of the IV model estimates reported in Table 8 with migration flows as dependent variable.

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