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Regular Research Article

# Higher economic growth in poor countries, lower migration flows to the OECD – Revisiting the migration hump with panel data

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## ABSTRACT

Comparing emigration rates of countries at different stages of economic development, an inverse u-shape emerges. Since the “migration hump” peaks at an average income of 6000 to 10 000 USD, economic progress in developing countries is often assumed to increase migration consistently. However, it is poorly understood to what extend country-level characteristics, individual incomes and other dimensions of development evoke this pattern, which limits its value for causal inference and concrete policy advice. In this paper we focus on the role of economic growth and investigate whether in developing countries emigration indeed increases with economic progress at shorter more policy-relevant time periods of up to 10 years. Using 35 years of data on migration flows to OECD destinations, we successfully reproduce the hump-shape in the cross-section. However, our more rigorous fixed effects panel estimations that exploit the variation over time robustly feature contrasting results: emigration rates fall as incomes increase. This finding holds independent of the level of income a country starts out at. In contrast to prevailing development emigration narratives, our results imply that rising individual incomes discourage emigration and hence conducive economic policies can reduce emigration. 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.

## 1. Introduction

International migration is as old as nation states. In recent decades, however, migration has increasingly focused on a small number of destination countries. While the global share of international migrants increased only moderately from 2.9 percent in 1990 to 3.5 percent in 2019 (UN, 2019), migration towards OECD destinations has increased at a much higher pace (OECD, 2019). As a result, about half of the 272 million international migrants today reside in just 10 countries (UN, 2019). According to data from the Gallup World Poll this trend is unlikely to shift: Globally 750 million individuals intend to move abroad, and two thirds of them aim at one of just 18 destinations (Espipova et al., 2018). In the years to come, climate change and population growth are forecast to further increase the pool of aspiring migrants (Cattaneo & Peri, 2016; Hanson & McIntosh, 2016). In many destination countries, immigration has become highly politicized and a cultural backlash fuels populist movements (Hooghe & Marks, 2018; Inglehart & Norris, 2016).

In search of common ground, policy makers emphasize the importance of tackling root causes of migration and have identified poverty and low economic development as major drivers.<sup>1</sup> Influencing migration indirectly through development cooperation rather than directly by restrictive immigration policy comes with political and practical advantages. Development policies are more likely to gain public support from voters throughout the political spectrum. Moreover, upholding restrictive immigration policy regimes is extremely expensive and has been shown to shift regular to irregular migration (Czaika & Hobolth, 2016). However, the idea to reduce migration by supporting economic development has been heavily criticized by academics based on recent studies showing middle-income countries to have the highest emigration rates (Clemens & Postel, 2018; de Haas, 2019). These authors argue that country-level income and emigration are related in a hump-shaped pattern (de Haas, 2010; Clemens, 2014; Djajic et al., 2016; Commission, 2018; Dao et al., 2018; Clemens & Postel, 2018), combining cross-sectional evidence with a plausible theory: At low income levels, credit

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constraints prevent aspiring migrants from emigrating, while at higher income levels decreasing economic incentives for emigration dominate ever less binding credit constraints (Dao et al., 2018). In consequence, emigration rates are assumed to follow an inverse u-shape along the economic development path of a country.

Such a relationship would have far-reaching implications: The peak implied by the existing estimates is located roughly at the current per capita income level of Bulgaria, China or Colombia. About two thirds of the world's population lives in countries below this threshold (Dao et al., 2018). Hence, interpreting the migration hump as a causal relationship means that economic growth in developing countries should be expected to boost emigration in the future. Effective development policy could thus raise immigration pressures in most primary destination countries. Clemens and Postel (2018, p. 686) explicitly emphasize this trade-off: *“development assistance to origin countries, to the extent that it is successful in fostering sustained development, is likely to create additional pressure on third-country hosting arrangements by encouraging greater overall emigration.”*

Yet, while this relationship is inherently inter-temporal, many of the above studies rely almost exclusively on cross-sectional evidence. The fact that middle income countries experience higher emigration than their poorer counterparts might be a direct consequence of their income level or it might be due to fundamental differences between low and middle-income countries that simultaneously affect both development and emigration (Lucas, 2019). In that respect, the migration hump hypothesis resembles one of the most heatedly debated concepts in development economics: the Kuznets-curve. Based on the observation that middle-income countries experience higher economic inequality than their poorer and richer counterparts, Kuznets deduced that economic development in poor countries increases inequality (Kuznets, 1955). Only much later it was shown that the hump-shaped cross-country pattern was largely driven by systematic differences between countries and does not represent a natural time path (Deininger & Squire, 1998; Field, 2002).

In this paper, we argue along the same lines for the relationship between economic growth and emigration to OECD countries. We demonstrate that countries at the upwards-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 exogenous characteristics are well-known to influence both development and migration in the same direction and thus likely confound the cross-sectional relationship.

Moreover, the substantive argument about the migration hump aims at the very long run,<sup>2</sup> and might thus not be very informative about short to medium term policy aims. Even if the observed cross-sectional pattern was rooted in a causal relationship at the country level, an important open empirical question is whether and how short to medium term dynamics deviate from the long-term trajectory. Understanding such short to medium term dynamics is crucial for policymakers in trying to anticipate the marginal effects of development policy at reasonable time horizons.

In this paper, we employ a country-level data set recently compiled by Wesselbaum and Aburn (2019) that covers bilateral migration flows between 198 countries of origin and 16 OECD destinations from 1980 to 2014 and test the existence of the migration hump in panel data. In contrasting cross-sectional with panel estimates, we are, to our knowledge, the first to systematically analyze the dynamics underlying the migration hump. Our analysis focuses specifically on developing countries for which the cross-sectional evidence suggests a positive relationship between economic progress and emigration. While we successfully reproduce the hump-shape in the cross-section, our more

<sup>2</sup> Clemens and Postel (2018) demonstrate that at realistic rates of economic growth the poorest quintile of countries might not reach the peak of the migration hump until the year 2198.

rigorous fixed effects panel estimations employing the within variance over time robustly yield contrasting results: emigration rates fall as incomes increase. Our results are robust to using different income ranges, time trends, and controls. Most importantly they also hold for different migration data and different time periods (i.e. five and ten year aggregates). Our results do not imply that financial constraints would not be binding for many individuals. Yet, when economic opportunities improve, few of them seem to utilize their increasing capabilities to migrate.

Our finding casts significant doubt on the validity of the migration hump hypothesis as a universal inter-temporal relationship and consequently questions its relevance for policy making. In contrast to prevailing development emigration narratives, our results imply that conducive economic policies in developing countries can reduce emigration.

The remainder of the paper proceeds as follows: In Section 2 we review the migration and development literature and critically discuss both the theoretical argument and the empirical evidence that underpin the migration hump. After introducing the data in Section 3, Section 4 presents the empirical analysis as well as several robustness checks. Section 5 sums up and concludes.

## 2. The development–emigration nexus: Theory and existing empirical evidence

Studying the relationship between economic development and migration has a long tradition in development economics (e.g. Harris & Michael, 1970). The vast majority of the academic literature used to focus on the influence of migration on development (Beine et al., 2001; Giuliano & Ruiz-Arranz, 2006). How development affects migration has received much less attention. As international migration gained political relevance in destination countries due to large numbers of irregular arrivals of migrants from poor countries, the focus started to shift. Several empirical and theoretical studies have begun to analyze the role of economic development in emigration patterns more systematically (Docquier et al., 2014; Dustmann & Okatenko, 2014; Clemens, 2014; Dao et al., 2018; de Haas et al., 2018; Clemens, 2020a; b). While these authors' empirical findings sometimes diverge, they broadly agree on the main theoretical argument: An individual's decision to migrate generally depends on (i) aspirations and (ii) capabilities to move (Carling & Schewel, 2018).

At the macro level, numerous factors systematically influence aspirations and capabilities. These include economic, political, cultural, environmental, and demographic conditions. Due to the complex relationship between economic progress and these other dimensions of development, their individual effects are difficult to disentangle. Large parts of the literature rely on GDP as a universal measure of development. Economic growth, for example, improves local incomes as well as the state's ability to provide public goods.

A priori, the overall influence of development on emigration is ambiguous. If local livelihoods improve, migration aspirations decrease (Dustmann & Okatenko, 2014). However, higher disposable income simultaneously relaxes budget constraints that may previously have prohibited migration. Hence, economic development decreases migration aspirations but increases migration capabilities. Which of these effects dominates likely differs across countries and between different groups of individuals within countries.

### 2.1. The migration hump: Concept, evidence and interpretation

The migration hump hypothesis (or mobility transition theory) dates back to Zelinsky (1971) and is among the best known stylized facts regarding the development–migration nexus. The hypothesis posits an inverted u-shaped relationship between development and emigration. This fundamentally differs from a traditional neoclassical view of migration, as for example employed in the gravity literature, which

omits credit constraints at the individual level and thus assumes emigration to decrease along the development trajectory as rising living standards at home render migration less attractive. Many scholars have argued in favor of a hump-shaped relationship between development and emigration using different terms, e.g. ‘migration curve’ (Akerman, 1976), ‘migration transition’ (Gould, 1979), ‘migration hump’ (Martin, 1993) and ‘emigration life cycle’ (Hatton & Williamson, 1994).<sup>3</sup> While these scholars broadly agree on the inverse-U shaped pattern, they hold different factors responsible for it (see Clemens (2014) for an excellent review).

Among these are demographic change (Easterlin, 1961; Hatton & Williamson, 1994), financial constraints (Faini & Venturini, 1994; Hatton & Williamson, 1994), information asymmetries (Greenwood, 1969; Massey et al., 1993; Epstein, 2008), structural economic transformation (Zelinsky, 1971), economic inequality (Stark, 2006) and immigration barriers abroad (Hatton & Williamson, 2005). All these proposed determinants are strongly related to development and arguably also to emigration and there are different mechanisms through which they may give rise to a hump-shaped long-term relationship between development and emigration. Yet, such a migration hump is not a unique outcome that will always occur. Even if all these factors operate as suggested, the negative relationship between development and emigration, that is induced by improving living standards and increasing opportunity costs for migration might still prevail.

de Haas (2010) was the first of several researchers who provided empirical evidence in support of the migration hump hypothesis at a global level. Descriptively and by means of bivariate and multivariate regression analysis, he detected a non-linear, hump-shaped relationship between per capita GDP and emigrant stocks with a peak at an income level of 12 000 USD per capita. Using cross-sectional data from the World Bank and the United Nations, Clemens (2014) showed that the migration hump also exists in migration flow data. The highest emigration rates are observed in countries in the middle of the global income distribution, while the richest and the poorest countries experience systematically less emigration. According to his non-parametric regressions, the rate of emigration steadily increases up to a peak around a per capita income of 6000–8000 USD. This pattern holds for each of the decades from 1960 to 2010. In a more recent study, Clemens and Postel (2018) locate the peak to be at a somewhat higher level of 8000–10 000 USD.

Dao et al. (2018), Djajic et al. (2016), and the European Commission (2018) provide similar descriptive evidence.<sup>4</sup> Yet, the location of the peak in their studies varies between 4000 USD (Djajic et al., 2016) and 7000–13000 USD (Commission, 2018). Since these studies differ in terms of their migration and GDP data, time periods, and country selection, varying peak levels do not question the general relationship. Despite differences in the location of the peak, these studies convincingly demonstrates: Emigration is, on average, higher in middle-income countries than it is in either high or low-income countries.

However, the migration hump’s policy relevance is based on its causal interpretation. Supported by the different theoretical arguments that link development to rising emigration, the cross-sectional evidence for the migration hump is widely interpreted as a natural time path at the country level. For example, Clemens and Postel (2018) suggest a causal relationship when stating that: “economic growth has historically raised emigration in almost all developing countries”. This interpretation typically builds specifically on the role of individual incomes and the feasibility to finance migration. To explain the effect of rising

incomes on emigration in the context of the migration hump, the migration decision is depicted as an investment decision: Any increase in individual income affects both the feasibility of migration by easing the financial constraint and the incentive to stay by increasing the opportunity costs. At low income levels, the former effect dominates, creating a positive income–migration relationship until income is sufficiently high to discourage emigration. In consequence, over the long-term development path of a country, emigration rates are assumed to increase universally until per capita incomes of 6000–10 000 USD are reached. This very intuitive explanation is backed up by microeconomic evidence for Indonesia. Using census data, Bazzi (2017) provides some empirical support for the existence of a capital constraint to international migration in a causal setup. While in poor rural areas of Indonesia Bazzi (2017) finds positive income shocks to increase emigration, the opposite effect occurs for the most developed regions within the country. It has to be noted, however, that this convincing evidence comes from a single country where similarity between different origins is much higher than in the global cross-country samples that underlie the migration hump.

Microeconomic support, a rich and intuitive theoretical foundation and the empirical reproducibility across data sets and time have created a powerful narrative to interpret the migration hump as a universal relationship at the country level. However, a causal interpretation based on cross-sectional evidence, might still be misleading, especially since various omitted variables could govern this relationship.

## 2.2. Risks to causal inference: Poor and middle income countries differ systematically

The causal interpretation of the migration hump hypothesis is based on the assumption that today’s poor and middle income countries are fundamentally similar with respect to important factors such as migration cost. However, if today’s poor countries differ from their richer counterparts in important omitted factors such as for example geographical location, language, or culture, such an assessment could be misguided.

Economically speaking, systematic heterogeneity across countries may endanger valid causal inference. As Lucas (2019, p. 18) puts it: “In the end, cross-country evidence may tell us little about the time-path of emigration as development proceeds; those countries currently in the middle-income range may simply differ in fundamental ways from what their poorer counterparts are evolving into.”

**Table 1**  
Selected country characteristics by income group.

	low income: <5000 GDP pc N = 69	remaining non- OECD N = 84	p-value
av. GDP pc as of 2010 (PPP \$2011)	2367 (1058)	16,489 (17564)	<0.001
distance to OECD country (km)	4744 (1754)	3872 (2359)	0.012
common border with OECD	0.00 (0.00)	0.04 (0.19)	0.083
colonial ties with OECD	0.46 (0.50)	0.70 (0.46)	0.004
landlocked	0.31 (0.47)	0.10 (0.30)	0.002
av. population (millions, 2010)	44.6 (156)	10.1 (23.1)	0.073

Note: Countries are clustered by average income between 1960 and 2010; data sources: Penn World Tables 2015 and CEPII’s GeoDist Database.

We briefly examine differences in basic country characteristics that are known to influence both development and migration. In doing so, we focus on the group of poor countries on the upward-sloping part of the hump and test if these are similar to their richer counterparts (summarized in Table 1). Specifically, the first group consists of all countries

<sup>3</sup> In line with Clemens (2014) we use the term ‘migration hump’, which is the most illustrative in our view.

<sup>4</sup> We label a regression that simply creates a best fit in a two-dimensional model as “descriptive” because it is a way of describing the relationship between the two variables and not an approach that aims at isolating underlying components.

with an average income per capita of less than 5000 USD between 1960 and 2010, while the second group includes all the remaining non-OECD countries.<sup>5</sup> We exclude OECD origin countries for this descriptive table because geographical proximity to these primary destination countries is among the factors we want to investigate. The geographical measures are taken from CEPII's GeoDist Database (Mayer, 2011). The dissimilarities are striking. Poorer countries left of the hump's peak are on average located significantly further away from OECD-countries, less likely to have colonial ties with them and are more frequently landlocked. In addition, these countries host much larger populations. Even after excluding China and India the average population in the poor country group is almost twice as high. Small countries often exhibit higher emigration rates than large ones not least because of a lack of opportunities for specialization (de Haas, 2010). Short distance moves, for example to the next large city, are far more likely to involve crossing international borders if the country's land area is small. Furthermore, leaving a small country is much easier in terms of monetary and physical effort as the nearest border is much closer. It is important to note that all these factors are well known to impact development and migration and at the same time they are plausibly exogenous. More specifically, they are negatively related to both development and emigration, and hence, provide a competing explanation for low emigration rates in poor countries. Such factors are therefore likely to confound any empirical analysis of the relationship between development and emigration that does not account for them.

These insights cast some doubt on the hump's validity as a universal relationship and question inferences based on cross-sectional data. For a robust identification of the link between economic development and emigration we need to control for differences across countries. That is the natural domain of panel studies.

### 2.3. The impact of development on emigration over time: Insights from panel studies

In contrast to cross-sectional studies, time-series approaches allow to account for differences between countries by employing the variation within countries over time. While economic development is included in most studies on migration as an important driver, very few existing studies explicitly focus on the impact of economic development on emigration, and hardly any study accounts for non-linear relationships or explicitly tests the migration hump. Prior to our study we are only aware of two papers that specifically test the migration hump in time series data (Vogler & Rotte, 2000; Telli, 2014). However, these studies only focus on migration to one specific destination country (Germany and the UK, respectively), and both rely exclusively on annual data. Furthermore, and likely to be most problematic, both studies use merely a squared term in their panel regressions to account for a hump-shaped relationship and do not test more flexible frameworks, thus forcing the data to either take a hump shape, a linear shape or no shape at all. Recent econometric studies show that using only a squared term to detect (inverse) u-shaped relationships often leads to false conclusions (Lind & Mehlum, 2010; Haans et al., 2016; Simonsohn, 2018). Most of today's gravity-style migration models focus on the determinants of bilateral migration flows and hence on the destination choice rather than on root causes of emigration in origin countries. In consequence, existing studies yield inconclusive results (Clemens, 2014). While for example Bazzi (2017) and Dao et al. (2018) detect a positive relationship between GDP and migration at low income levels, Ortega and Peri (2013) and Böhme et al. (2019) find a universal negative relationship. Other studies do not return a statistically significant relationship at all (Mayda, 2010; Naudé, 2010; Ruysen et al., 2012). According to

Clemens (2014), existing panel and time series studies that seek to explain the relationship between income at origin and emigration fail to detect the migration hump, because they suffer from three major shortcomings. First, the time horizon they employ (15–20 years) is too short to detect long-term patterns. Second, by using annual data, short-term economic fluctuations mask the influence of income levels and long-term trends. Third, as time-series studies typically do not allow for a non-linear effect, the different direction of impact (negative for richer countries, positive for poorer countries) leads to inconsistent results and coefficients that are close to zero. We agree with this evaluation and specifically design our empirical methodology below to address these limitations (see section 4).

### 3. Data

Data availability is among the main constraints to quantitative migration research in general. This is particularly relevant for studies that investigate long term trends. Any conclusive analysis must be based on a large time dimension in order to be able to identify substantial changes and avoid relying on short term fluctuations in migratory patterns due to exogenous shocks. Furthermore, a large sample of observational units is desirable to prevent biased estimates resulting from idiosyncratic characteristics of individual units.

The migration panel dataset compiled by Aburn and Wesselbaum (2019), meets both of these requirements. By merging information from the 2015 Revision of the United Nations' Population Division with the OECD's migration database and data from Ortega and Peri (2013), the authors compile one of the longest and most exhaustive panel data sets of bilateral net migration flows, covering 198 countries of origin and 16 OECD destinations from 1980 to 2014. Still, the panel is unbalanced because of missing data, especially in the early 1980s when data is available for only about half of the country dyads. But since our research question focuses on the relationship between incomes and emigration, we are not interested in directions of migration flows but rather their variations in total volumes over time (and income). Therefore, we aggregate all bilateral flows by their origin to calculate the number of emigrants per country and year. To a certain extent, this aggregation also mitigates a potential selection bias from missing observations early on in the observation period.

Our main variable of interest is economic development for which we rely on GDP data provided the Penn World Table (Feenstra et al., 2015). In addition, our empirical analysis uses several common control variables: country sizes are measured by their total population (also included in Penn World Table); to account for existing migrant networks, a significant determinant of bilateral migration flows, we control for the size of a country's diaspora population within the 16 OECD destinations in our sample (based on decennial migrant stocks published by the World Bank and Özden et al. (2011)). To incorporate potential shocks from conflict we use UCDP's armed conflict database to construct a categorical variable that distinguishes peace, minor conflict, and war (Pettersson and Eck, 2018; Gleditsch et al., 2002). In addition, we also control for varying political rights and civil liberties using data from Freedom House (2018) (FH) via Teorell et al. (2019). In order to account for changing political trends with respect to migration, we include an index from the International Migration Policy in Comparison Project (IMPIC), measuring the restrictiveness of migration policies among the OECD destinations considered in our sample (Helbling et al., 2017); lastly, we control for the changing cost of migration during the study period by including the number of air travel passengers as a percentage of world population in the model (World Bank, 2019). For a brief description of the data, Fig. 1 visualizes the migration panel and Table 2 provides summary statistics for all variables we employ across different specifications.

<sup>5</sup> The differences between the groups are not sensitive to the threshold value. Table 10 in Appendix B features different threshold values and the significant group difference persist.

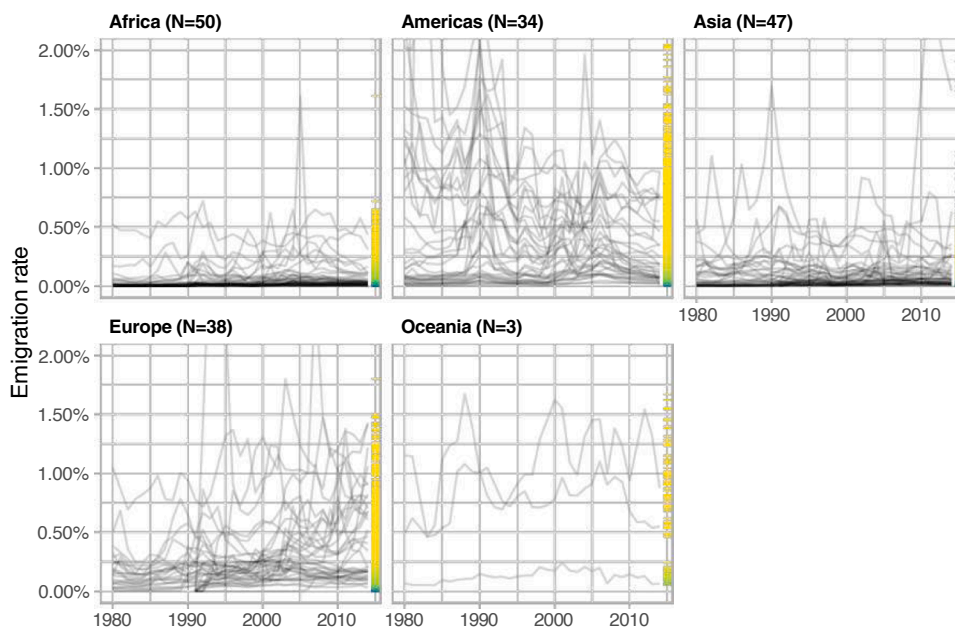


Fig. 1. Emigration rates towards 16 OECD countries across time and continents. Note: Figure 1 depicts the variation in emigration rates towards 16 OECD destination countries across continents and time. The data is based on the 2015 Revision of the United Nations’ Population Division with the OECD’s migration database and data from Ortega and Peri (2013) and was compiled by Aburn & Wesselbaum (2019).

Table 2  
Summary statistics of the explanatory variables.

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Emigrants (thousands)	5, 768	17.34	37.05	0.00	0.81	18.05	949.10
Emigration rate (%)	5, 768	0.19	0.33	0.00	0.02	0.20	6.52
GDP (PPP billions \$2011)	5, 768	324.89	1, 170.37	0.08	9.09	187.55	16, 395.20
GDP per capita (PPP \$2011)	5, 768	12, 400.51	16, 194.58	223.09	2, 429.61	16, 822.63	215, 721.00
GDP per capita growth(%)	5, 745	2.53	9.12	-69.63	-1.11	6.17	142.68
Population (millions)	5, 768	34.07	125.78	0.01	2.14	21.90	1, 382.79
Diaspora (millions)	5, 768	0.33	0.77	0.00	0.01	0.30	13.12
Conflict	5, 768	1.20	0.50	1	1	1	3
FH index	5, 433	1.87	0.81	1.00	1.00	3.00	3.00
Air passengers	5, 768	25.52	7.71	15.41	19.50	30.60	42.99
Immig. pol. restrictiveness	5, 103	0.40	0.03	0.37	0.38	0.41	0.46

#### 4. Empirical analysis

##### 4.1. Methodology

The main objective of this paper is to test whether the cross-sectional finding of an inverse u-shaped relationship of migration and development holds for the shorter-term relationship between economic growth and emigration at the country level. To investigate this question we employ a panel setup which exploits only the variation within countries over time. As a first step, we replicate the cross-sectional migration hump using our data. For one, this ensures that we can compare our panel estimates with prior cross-sectional analyses and potential discrepancies do not simply result from differences in data sources. For another, replicating the migration hump enables us to identify the critical income threshold up to which emigration is hypothesized to increase and truncate our sample accordingly. As existing empirical studies identify this turning point at different levels between 4000 and 13 000 USD, it is important to identify the upward-sloping range of the migration hump for our specific data set. Hence, our empirical analysis of the influence of economic progress on emigration in poor countries proceeds in three steps:

Employing the same methodology as Clemens (2014), we reproduce the cross-sectional migration hump with the OECD migration data set compiled by Aburn and Wesselbaum (2019).

10 We truncate our sample of countries and only include observations where incomes have remained left of the cross-sectional peak during the entire observation period. This way we specifically focus on the upward-sloping part of the cross-sectional migration hump where we would expect a robust positive relationship between GDP and the number of emigrants.

We estimate a range of fixed effects panel emigration models, which are based on the recent literature and aim at explaining changes in emigration within countries over time by changes in GDP and other control variables.

For the core of our analysis (step 3), we employ a straightforward panel emigration model to test if cross-sectional and panel estimates of the development– emigration nexus concur. The setup of our model is influenced by Mayda (2010) and Ortega and Peri (2013). Departing from their setup, we only model emigration at the level of origin countries instead of bilateral flows because we are not interested in the destination choice. Hence, we do not include destination country factors. In that sense our empirical model is very similar to the “unilateral” (origin-country level) model by Böhme et al. (2019). While the decision to model aggregate emigration instead of bilateral flows is based on our

research question, it comes with the additional advantage of having hardly any zeros in the dependent variable.<sup>6</sup>

Our main specification is

$$y_{it+1} = \alpha + \beta GDP_{it} + \gamma X_{it} + \delta_i + \tau_t + \varepsilon_{it}, \quad (1)$$

where  $y_{it+1}$  denotes the number of emigrants from country  $i$  in year  $t + 1$ .  $GDP_{it}$  is the main variable of interest and represents total GDP for a given country and year.  $X_{it}$  represents a set of control variables that vary over countries and time.  $\delta_i$  and  $\tau_t$  are vectors of country and year fixed effects, respectively, and  $\varepsilon_{it}$  represents the error term.

In comparison to cross-sectional regressions, this panel setup is much less likely to suffer from omitted variable bias, since country and time fixed effects control for unobserved heterogeneity from time-invariant factors such as geographical characteristics, language, national migration narratives or cultural relations, which clearly affect migration flows. Hence, our estimates more likely represent a causal relationship. Moreover, as the subsequent analysis reveals, adding different sets of control variables has very little impact on our core results.

In line with Böhme et al. (2019), we have decided to model emigration in absolute terms. Hence, we regress the absolute number of emigrants on absolute GDP and control for population size.<sup>7</sup> Using the emigration rate and GDP per capita could impede the identification of the true effect of economic progress on emigration as, at least in the short run, variations in these ratios may largely be driven by population growth. Moreover, population growth exerts an influence on emigration beyond increasing the pool of potential migrants. It shapes the age distribution within countries, which affects average emigration propensities, and more populous countries yield higher opportunities for internal migration and thus experience less emigration (de Haas et al., 2018). Beyond that, our emigration data features the absolute number of emigrants for each country and year as observed in destination countries. Computing emigration rates from emigrant numbers and population size risks introducing a measurement error stemming from poor quality population data in developing countries.

We use explanatory variables lagged by one year on the right hand side of equation (1) in order to account for time-consuming preparations that usually go along with migration as well as to mitigate issues of reverse causality.

For all high-magnitude variables (i. e. emigrants, GDP, population and diaspora) we use the inverse hyperbolic sine (IHS) transformation instead of a logarithmic one in our estimations. This has the advantage that observations with zero values do not need to be discarded or altered (by adding a constant) as IHS is defined for any real number (see Burbidge & Magee, 1988; MacKinnon & Magee, 1990). At the same time, IHS retains the properties of a log transformation and we can interpret estimated coefficients as percentage changes or elasticities (Pence, 2006; Bellemare & Wichman, 2019).

Another important feature of any long-term migration model is the way to incorporate time trends in the feasibility of international migration. Global technological progress in communication and transportation likely decreases migration costs over time; immigration policies change (de Haas et al., 2018). We use two different approaches. Most conservatively we include year fixed effects. As an alternative to the strict year fixed effects specification, we employ two variables that reflect migration-relevant technological and political changes: Decreasing transport costs and ease of travel are approximated by the number of air travel passengers per year (as a percentage of world population); changes in migration policies are reflected in the IMPIC-index for restrictiveness of migration policies among the destination

countries.

Besides using year fixed effects to absorb aggregate changes over time (which controls for sudden global shifts in emigration), we tackle the issue of yearly fluctuations on the right hand side of equation (1) by also specifying a model based on 5-year and 7-year averages that smooth the time-series data.<sup>8</sup>

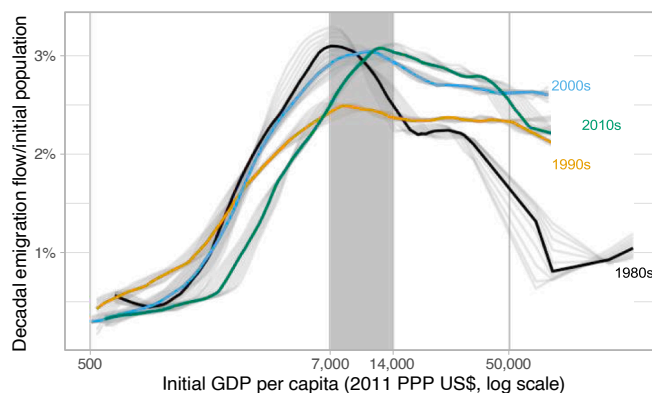
In Appendix D we perform a Monte Carlo Simulation to demonstrate that our econometric setup is well suited to identify the relationship between economic growth and emigration in this specific data structure. Specifically we show that our setup outperforms the more common per capita specification, if emigration is directly affected by population growth or subject to a time trend.

Based on the existing literature, we would expect the panel estimates to resemble their cross-sectional counterparts (Vogler & Rotte, 2000; Telli, 2014; Clemens & Postel, 2018; de Haas et al., 2018). For the poorest countries we would expect a positive relationship between between GDP and emigration to OECD countries.

## 4.2. Results

Even though our migration data only feature OECD destination countries, we are able to replicate Clemens and Postel (2018) cross-sectional result of a hump-shaped income–emigration relationship very closely in Fig. 2. Throughout the decades, emigration peaks somewhere between 7000 and 14 000 USD per capita. Based on these estimates, we restrict the data in the rest of our analysis to those countries with per capita incomes below 7000 USD throughout the entire time period.<sup>9</sup>

That leaves us with a balanced panel of 54 low-income countries. The average per capita GDP over the entire time period is roughly 2000 USD, mean annual economic growth and emigration rates equal 1.52 percent and 0.06 percent, respectively. A complete overview of summary



**Fig. 2.** Non-parametric regression of decadal emigration rates on initial real income per capita, 1980–2014. *Note:* Bold lines are Nadaraya-Watson kernel-weighted local means (Epanechnikov kernel, bandwidth of 0.5 natural log points); transparent lines depict varying bandwidths between 0.4 and 0.6 natural log points; initial GDP per capita means at the beginning of the respective decade; to correct for the shorter 2010 decade in the data we have scaled up the estimated migration flow, allowing for a direct comparison.

<sup>8</sup> We retain the lagged structure of our estimation by matching averaged time periods that are shifted by one year, e.g. the average number of emigrants from 1981 to 85 regressed on averages of our RHS variables from 1980 to 1984.

<sup>9</sup> This sample restriction is based on data exceeding the observation period of our analysis since Feenstra et al. (2015) provide longer time series of GDP and population data. While this distinction barely changes the set of countries under consideration and has no effect on our results, we choose to use all of the information available to us to restrict the sample.

<sup>6</sup> That would bias estimates unless accounted for, e.g., by using a poisson pseudo-maximum likelihood estimator. Given the absence of zeros in our setup, we can stick to a linear panel model.

<sup>7</sup> Our results are robust to modeling this relationship in per capita terms (see Table 11 in appendix C).

statistics for all relevant variables is shown in Table 9 in Appendix B.

Our main estimation results are reported in Table 3, which first includes two pooled specifications of equation (1) without country fixed effects as models 1 and 2. The estimates are in line with the cross-sectional evidence in the migration literature and show a robust positive effect of income on emigration that corresponds to the upward-sloping part of the migration hump. Hence, controlling for time trends and excluding all countries beyond 7000 USD of GDP per capita does not change the positive cross-sectional relationship between GDP and emigration for poorer developing countries. Explicitly including a time trend based on global air passengers and OECD migration policies reflect the increased total number of emigrants and a mild dampening effect of migration restrictiveness, suggesting a 1 percent decrease in emigrants between the most open and the strictest migration policies observed in the data. The estimated effect of income remains unchanged and corresponds to an increase of 0.8 percent in emigration with 1 percent GDP growth. Overall, this pooled estimation is very much in line with the existing migration hump evidence. Yet, the Breusch-Pagan test advises against the use of a pooled model due to heteroskedasticity. The Hausman test favors the fixed-effects estimator.

Turning to the panel estimates in models 3–6 of Table 3, we observe that the cross-sectional relationship does not hold up at the country level. Here, rising incomes actually reduce the total number of emigrants from a given country. This effect is robust to the addition of time-varying country-level control variables (models 5 and 6) as well as to using the time trend variables instead of time fixed effects (models 4 and 6). It also holds if we do not control for time effects at all (see Table 12 in Appendix C). In all cases, GDP growth rates of 1 percent reduce emigration by about 0.5 percent. Our estimates for the effects of institutional environments and the occurrence of violent conflict show the expected signs: Emigration increases as armed conflicts intensify, autocratic regimes exhibit lower emigration rates.<sup>10</sup>

Most importantly, these results do not support a hump-shaped income–emigration relationship and rather suggest that economic progress, on average, reduces emigration towards OECD destinations.

Next we investigate the sensitivity of our results to different sample selections, i.e. we employ different GDP per capita thresholds at which we truncate the sample. The initial threshold (7000 USD per capita GDP) is based on the cross-sectional peak and thus the corresponding sample is well-suited to compare cross-sectional and panel results. However, by design our working sample is somewhat unbalanced. It mainly consists of the poorest countries, observations in the 4000 to 7000 USD income range are underrepresented. Increasing the threshold level provides us with a larger sample size and additional country–year observations along the increasing segment of the migration hump. For example, shifting the cut-off level from 7000 to 10 000 USD per capita gives us 15 extra countries and the average per capita GDP is still far below 7000. Yet, it comes at the cost of including countries which have surpassed the peak in recent years. For this sensitivity test, we estimate model 4 from Table 3 with year and country fixed effects on a range of sub-samples that correspond to maximum GDP per capita thresholds between 4000 and 20 000 USD. The lower bound is based on the lowest peak level from the respective literature (Djajic et al., 2016). Yet, since our initial sample already comes with a low average income of about 2000 USD, it is more reasonable to increase our threshold than to decrease it.

We depict the estimated coefficients for GDP and their corresponding 95 percent confidence intervals in Fig. 3. This exercise shows a significantly negative association starting from a threshold level of 4500 USD per capita that increases in size up to our original cutoff point of 7000 USD. At higher t In Appendix C Figure 4 we provide the results based on Model 5 including the additional control variables. Thresholds the

estimate fluctuates slightly around the average value of about  $-0.5$ . The changing size of the estimated coefficient hints to somewhat heterogeneous impacts across countries. That is not surprising as economic progress may affect the economic opportunities of the respective populations differently, and thus we should be careful not to over interpret the exact size of the coefficients. Yet, and more importantly, the negative relationship holds across the whole cut-off range and the size of the estimated coefficients does not change systematically with income levels.

Such aggregate analysis might still mask heterogeneous outcomes across different countries since economic trajectories differ significantly. More specifically, the aggregate analysis does not reveal whether our estimates are particularly driven by high-growth or low-growth countries. For instance, the observed negative relationship between economic growth and emigration might be driven by economic crises spurring out-migration. To investigate heterogeneous impacts across different levels of economic growth, we split our sample further into high performers and low performers. The distinction is made based on the average GDP per capita growth (PPP) over the entire observation period.

The specification is again identical to Model 4 in Table 3 including country and time fixed effects. We distinguish four different subsets of countries for this analysis (presented in Table 4): the low-performing countries with less than 1 percent average growth (column 1), or with less than 2 percent (column 2); and the high-performing countries with more than 1 percent average real economic growth (column 3), or with more than 2 percent growth (column 4). An interesting pattern emerges: For all but the least-performing countries the association between GDP and the number of emigrants is again significantly negative. The higher the average economic growth, the higher is the estimated coefficient. This makes intuitive sense since low growth rates leave most citizens unaffected in the short-term. In consequence, higher growth rates are easier to perceive and thus may be more relevant for the migration decision. Moreover, the small and insignificant coefficient for the worst performing countries with very little economic progress (Column 1) suggests that it is in fact economic growth discouraging emigration and not recessions spurring emigration. To further look into this we test outlier dummies<sup>11</sup> for positive and negative growth years. The results are provided in Table 13 in Appendix C. Notably, these dummies do not return significant coefficients and hardly change the size of the general relationship.

In stark contrast to most of the previous literature, our findings thus indicate a negative impact of rising incomes on emigration in poor countries. We do not find support for a non-linear relationship between economic growth and emigration, i.e. a positive relationship at low average incomes and a negative one at higher levels. Instead the negative relationship is independent of income levels. This suggests that the migration hump in the cross-section is due to omitted variables at the country level.

#### 4.3. Robustness checks

A remaining concern with the robustness of our results may stem from the use of annual data. Clemens (2014) argues that in such kind of panel analysis short term fluctuations may overshadow the true relationship between economic development and emigration.

In order to address these concerns we aggregate our data into five and seven year time intervals and run the same regressions again (see Table 5 Columns 3–6). This way, our estimates are much less vulnerable to short term fluctuations in economic conditions and migration opportunities. Especially business cycle fluctuations should have very little

<sup>10</sup> Results remain unchanged when using Polity IV data instead of the Freedom House index to measure the institutional framework in origin countries (see Table 15 in appendix C).

<sup>11</sup> Specifically, for each country we code years as positive growth outliers if the real annual growth rate exceeds the average value by at least two standard deviations. Negative outlier years are computed in a similar fashion.

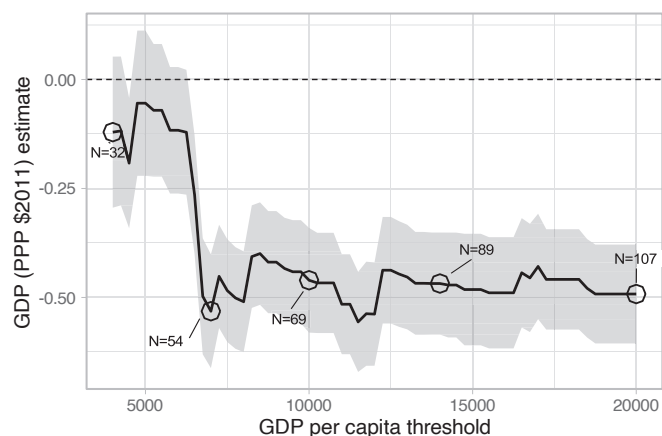


**Table 3**  
Main results: Pooled versus panel regressions.

	Pooled		Panel			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
GDP (PPP \$2011)	0.775* (0.339)	0.788* (0.353)	-0.532*** (0.067)	-0.537*** (0.076)	-0.481*** (0.059)	-0.471*** (0.068)
Population	0.222 (0.361)	0.219 (0.372)	1.591*** (0.280)	2.673*** (0.290)	0.921*** (0.251)	1.768*** (0.268)
Air passengers		0.062*** (0.015)		0.052*** (0.010)		0.045*** (0.009)
Immig. pol. restrictiveness		-10.009*** (1.930)		-4.157*** (1.023)		-4.911*** (0.949)
UCDP: Minor conflict					0.356*** (0.055)	0.335*** (0.062)
UCDP: War					0.508*** (0.076)	0.514*** (0.087)
FH: partly free					0.055 (0.072)	-0.039 (0.079)
FH: not free					-0.107 (0.078)	-0.250** (0.086)
Diaspora size					0.168*** (0.038)	0.254*** (0.040)
Country FE	no	no	yes	yes	yes	yes
Year FE	yes	no	yes	no	yes	no
Num. obs.	1858	1645	1858	1645	1769	1560
R <sup>2</sup> (overall)	0.535	0.513	0.891	0.883	0.916	0.907
R <sup>2</sup> (within)	0.457	0.513	0.047	0.522	0.096	0.565

\*\*\* p < 0.001; \*\* p < 0.01; \*p < 0.05.

Note: The dependent variable is emigration (total number of emigrants). The sample consists of 54 relatively poor countries with less than 7000 USD per capita over the entire observation period (1980 – 2014). The high magnitude variables emigration, GDP, population, and diaspora size are transformed using the inverse hyperbolic sine function. The interpretation of the respective coefficients is similar to logarithmic values. Conflict (UCDP) and political freedom (FH) are captured by categorical variables with three levels each. All explanatory variables are lagged by one year.–.



**Fig. 3.** Estimated coefficient of IHS-transformed GDP (with 95 % confidence interval) conditional on varying GDP per capita thresholds for the underlying sample. Note: This figure depicts country-fixed effects coefficient estimates for the relationship between GDP changes and changes in emigration to OECD countries conditional on the set of countries included. An x-axis value of 10 000 indicates that the sample consist of all countries that do not exceed an income level of 10 000 USD at any moment in the observation period (1980–2014). Moving to the right increases the number of countries in the sample, moving to the left depicts estimates under a stricter exclusion criterion. The grey area visualizes the 95% confidence intervals. The estimates for the influence of GDP on Emigration are based on model 4 in Table 3.

impact on this specification. This estimate can also be interpreted as the more long-term relationship between economic growth and emigration. Naturally, that comes at the cost of reducing the number of observations substantially, which risks insignificant results. To further investigate the robustness of our initial estimate we consider private consumption as an alternative economic measure. Especially for small countries, household consumption is often considered to be a less volatile welfare measure, and it is less influenced by exchange rate fluctuations. The regressions

**Table 4**  
Panel estimation for varying growth sub-samples.

	max 1 % growth	max 2 % growth	min 1 % growth	min 2 % growth
GDP (PPP \$2011)	-0.206 (0.132)	-0.468*** (0.081)	-0.599*** (0.091)	-0.873*** (0.177)
Population	-0.850 (0.492)	-0.708* (0.353)	2.726*** (0.366)	5.810*** (0.533)
Country FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Countries	18	36	36	18
Num. obs.	608	1238	1250	620
R <sup>2</sup> (overall)	0.885	0.904	0.894	0.880
R <sup>2</sup> (within)	0.017	0.046	0.070	0.197

\*\*\* p < 0.001; \*\* p < 0.01; \*p < 0.05.

Note: The dependent variable is Emigration (total number of emigrants). The high magnitude variables Emigration, GDP, Populations, and Diaspora size are transformed using the inverse hyperbolic sine function. The interpretation of the respective coefficients is similar to logarithmic values. Conflict (UCDP) and political freedom (FH) are captured by categorical variables with three levels each. Explanatory variables are lagged by one year. The sample differs across regressions in this table, the selection is based on average GDP per capita growth between 1980 and 2014.

are presented in Table 5 and support our initial findings. Using household consumption instead of GDP returns a slightly larger coefficient, while the regressions with aggregated data yield somewhat smaller coefficients. Yet, the negative relationship between economic progress and emigrations is robust to these alterations.

As a next robustness check, we repeat our estimation with different sets of migration data (Table 6). In column 1 and 3, we utilize the bilateral migration stock data provided by the World Bank (World Bank, 2018). This data set comes with the additional advantage of covering a longer time span, ranging from 1960 to 2018. Moreover it covers the full set of destination countries.

Yet, in contrast to our main migration data, we only get eight points in time and inconsistent time intervals. In order to allow for a

**Table 5**  
Panel estimation: Using household consumption data and multi-year periods.

	Consumption		5-year ave.		7-year ave.	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
HH consumption	-0.636*** (0.090)	-0.624*** (0.081)				
GDP (PPP \$2011)			-0.359** (0.133)	-0.456*** (0.120)	-0.359* (0.157)	-0.473*** (0.140)
Population	1.598*** (0.281)	0.939*** (0.252)	2.177*** (0.512)	1.373** (0.468)	1.953*** (0.571)	1.082* (0.513)
UCDP: Minor conflict		0.341*** (0.055)		0.388*** (0.097)		0.373*** (0.109)
UCDP: War		0.483*** (0.077)		0.573*** (0.134)		0.561*** (0.148)
FH: partly free		0.038 (0.072)		-0.107 (0.153)		-0.106 (0.178)
FH: not free		-0.154 (0.079)		-0.195 (0.165)		-0.241 (0.187)
Diaspora size		0.152*** (0.038)		0.155* (0.074)		0.349*** (0.102)
Country FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
Num. obs.	1858	1769	424	416	318	312
R <sup>2</sup> (overall)	0.890	0.915	0.913	0.928	0.915	0.933
R <sup>2</sup> (within)	0.040	0.092	0.063	0.134	0.060	0.167

\*\*\* p < 0.001; \*\* p < 0.01; \* p < 0.05.

Note: The dependent variable is Emigration (total number of emigrants). The sample consists of 54 relatively poor countries with less than 7000 USD per capita over the entire observation period (1980 – 2014). The high magnitude variables Emigration, GDP, Populations, and Diaspora size are transformed using the inverse hyperbolic sine function. The interpretation of the respective coefficients is similar to logarithmic values. Conflict (UCDP) and political freedom (FH) are captured by categorical variables with three levels each. Explanatory variables are lagged by one year.

**Table 6**  
Pooled versus Panel estimation: Using alternative migration data.

	Pooled		Panel	
	World Bank	IAB	World Bank	IAB
GDP (PPP \$2011)	0.871 (0.593)	0.958*** (0.275)	-2.531** (0.798)	-0.227*** (0.068)
Population	-0.025 (0.611)	-0.247 (0.278)	-1.266 (2.341)	-0.436 (0.284)
Country FE	no	no	yes	yes
Year FE	yes	yes	yes	yes
Num. obs.	372	372	372	372
R <sup>2</sup> (overall)	0.138	0.503	0.346	0.968
R <sup>2</sup> (within)	0.062	0.424	0.032	0.047

\*\*\* p < 0.001; \*\* p < 0.01; \* p < 0.05.

Note: The dependent variable is Emigration (total number of emigrants). The sample consists of 54 relatively poor countries with less than 7000 USD per capita over the entire observation period (1980 – 2014). The high magnitude variables Emigration, GDP, Populations, and Diaspora size are transformed using the inverse hyperbolic sine function. The interpretation of the respective coefficients is similar to logarithmic values. Conflict (UCDP) and political freedom (FH) are captured by categorical variables with three levels each. Explanatory variables are lagged by one year.

comparable analysis we restrict the World Bank migration data to OECD destinations. That gives us 14 additional destination countries. We then compute migration flows by subtracting each stock from the previous period. That leaves us with seven observations per country. Given the longer time period of the World Bank data, this regression also serves as an additional test of the long-run relationship between income and emigration. In column 2 and 4, we use the IAB brain drain data (Brücker et al., 2013). This data set consists of seven five year intervals ranging from 1980 to 2010 and covers four additional OECD destinations (20 in total). We restrict our analysis to the same countries at the upwards-sloping part of the migration hump. Similar to Table 3, we use these data to investigate both the between-country and the within-country relationship between economic growth and emigration. In line with the cross-sectional migration hump, we again detect positive estimates in the pooled regressions (though the coefficient is only significant for

the IAB data). Contrasting the cross-sectional results and corroborating the validity of our baseline results, the panel regressions yield significantly negative correlations between economic growth and emigration for both data sets.

For the next robustness check, we use the entire sample of countries and a slightly changed setup. Instead of restricting our analysis to the poor countries at the upward-sloping domain of the cross-sectional migration hump, we compute a categorical variable capturing the location of each individual country year. It consists of three levels: The increasing part (below 7000 USD per capita), the peak (between 7000 and 14 000 USD per capita), and the decreasing part (above 14 000 USD per capita). The cut-offs are based on the cross sectional pattern reported in Table 2. For the subsequent panel regressions, we interact this categorical variable with GDP and, thus, allow for distinct estimates of the income–emigration relationship across these different income levels. Except for the interaction terms, the regressions are identical to model 5 in Table 3. The results are depicted in Table 7. Contrasting the cross-sectional relationship, the panel estimates for the influence of GDP on emigration are negative and significant for all three groups. Moreover, the size of the estimates is almost identical across the three income groups. These results suggest that the negative influence of GDP on emigration holds independent of the income level.

In this paper we deliberately focus on migration towards OECD countries, which is quantitatively and politically particularly momentous. However, omitting regional migration might bias our estimates especially if economic growth was largely driven by economic developments in neighboring countries. In that case good economic performance in neighboring countries might induce positive economic spillovers and at the same time make regional migration more attractive compared to migration to the OECD. Fortunately, we can easily include the economic performance of neighboring countries into our empirical analysis. We measure neighbor-growth as the average per capita GDP growth of all neighboring countries weighted by their GDP. Table 8 provides the results for our core regressions extended by the neighbor-growth variable. Since it remains insignificant across all specifications and our core GDP coefficient even increases slightly in size, we do not detect any evidence for a threat to the validity of our estimates.

**Table 7**  
Panel estimation: Interaction terms (all countries).

	Annual		5 year ave.	
	Model 1	Model 2	Model 3	Model 4
GDP: low income (<7000 USD pc)	-0.358*** (0.049)	-0.159*** (0.037)	-0.177* (0.086)	-0.153* (0.075)
GDP: middle income (7–14000 USD pc)	-0.362*** (0.048)	-0.163*** (0.037)	-0.180* (0.085)	-0.160* (0.074)
GDP: high income (>14000 USD pc)	-0.369*** (0.048)	-0.167*** (0.036)	-0.187* (0.084)	-0.163* (0.074)
Population	1.130*** (0.111)	1.462*** (0.087)	1.570*** (0.179)	1.574*** (0.163)
UCDP: Minor conflict		0.286*** (0.039)		0.289*** (0.072)
UCDP: War		0.433*** (0.056)		0.468*** (0.097)
FH: partly free		-0.084* (0.040)		-0.248** (0.083)
FH: not free		-0.423*** (0.047)		-0.530*** (0.096)
Diaspora size		0.119*** (0.015)		0.106*** (0.029)
Country FE	yes	Yes	yes	yes
Year FE	yes	Yes	yes	yes
Num. obs.	5768	5433	1308	1274
R <sup>2</sup> (overall)	0.856	0.913	0.902	0.921
R <sup>2</sup> (within)	0.035	0.118	0.084	0.163

\*\*\*p < 0.001; \*\* p < 0.01; \*p < 0.05.

*Note:* The dependent variable is Emigration (total number of emigrants). The sample consists of 172 countries observed between 1980 and 2014. The high magnitude variables Emigration, GDP, Populations, and Diaspora size are transformed using the inverse hyperbolic sine function. The interpretation of the respective coefficients is similar to logarithmic values. Conflict (UCDP) and political freedom (FH) are captured by categorical variables with three levels each. Explanatory variables are lagged by one year.

**Table 8**  
Panel estimation: Controlling for economic growth in neighbor countries.

	Model 1	Model 2	Model 3	Model 4
GDP (PPP \$2011)	-0.690*** (0.064)	-0.709*** (0.074)	-0.597*** (0.062)	-0.622*** (0.073)
Population	1.289*** (0.265)	2.488*** (0.280)	1.199*** (0.257)	2.134*** (0.276)
Air passengers		0.065*** (0.010)		0.045*** (0.010)
Immig. pol. restrictiveness		-4.117*** (0.992)		-4.432*** (0.990)
UCDP: Minor conflict			0.413*** (0.056)	0.394*** (0.062)
UCDP: War			0.615*** (0.078)	0.640*** (0.088)
FH: partly free			-0.004 (0.076)	-0.087 (0.083)
FH: not free			-0.141 (0.084)	-0.255** (0.092)
Diaspora size			0.201*** (0.042)	0.273*** (0.042)
Neighbor per capita growth	-0.100 (0.287)	-0.012 (0.285)	-0.095 (0.270)	-0.013 (0.269)
Country FE	yes	yes	yes	yes
Year FE	yes	no	yes	no
Num. obs.	1647	1458	1599	1410
R <sup>2</sup> (overall)	0.894	0.884	0.905	0.897
R <sup>2</sup> (within)	0.075	0.565	0.128	0.592

\*p < 0.001; \*\* p < 0.01; \*p < 0.05.

*Note:* The dependent variable is Emigration (total number of emigrants). The sample consists of 172 countries observed between 1980 and 2014. The high magnitude variables Emigration, GDP, Populations, and Diaspora size are transformed using the inverse hyperbolic sine function. The interpretation of the respective coefficients is similar to logarithmic values. Conflict (UCDP) and political freedom (FH) are captured by categorical variables with three levels each. Explanatory variables are lagged by one year.

Another potential issue that warrants attention pertains to the differential impact of measurement inaccuracies. This is particularly relevant when considering data related to Gross Domestic Product (GDP) and population figures, which may be susceptible to errors, especially in the context of less economically developed nations.

The incorporation of fixed effects into our analysis could potentially exacerbate the susceptibility of our estimates to these measurement errors. However, it is important to note that classical measurement errors in explanatory variables are not necessarily a cause for significant concern. The reason for this is that such errors typically bias the estimates towards zero. Consequently, our estimates could be viewed as providing a conservative approximation of the actual relationship.

A more challenging issue arises when measurement errors occur in variables that are highly interrelated. This can lead to biased and inconsistent estimators, making it difficult to draw accurate conclusions from the data. However, in our specific context, we anticipate this issue to be less prevalent. This expectation is based on the understanding that changes in a country's annual population figures are largely predetermined by its demographic characteristics. Therefore, the likelihood of encountering substantial measurement errors in these variables is relatively low. It's unfortunate that we cannot test for measurement errors in our data directly since we don't have the actual values. However, we have conducted three robustness checks to ensure the validity of our results. Firstly, we replaced the population data from the World Penn Table with the World Bank population estimates and conducted our main regression. Secondly, we replaced our GDP data with the United Nations Statistics Office-provided data while keeping the original population data. Finally, we used a GMM model that can handle endogeneity issues and employs lagged values as instruments, which makes them more robust against measurement errors. We used varying lags in the population variable for this model. The results consistently showed a negatively significant coefficient for the relationship between GDP and emigration, whether we lagged the population by one, two, or three years. Therefore, we found no evidence that measurement errors threaten the validity of our empirical results.

Furthermore, our results are robust to including country-specific dummies for periods of unusually high or low growth (Table 13), excluding small countries (Table 14), and the use of different institutional variables (Table 15). The corresponding tables can be found in Appendix C.

## 5. Concluding remarks

In this paper we revisit the relationship between economic progress in low income countries and migration to OECD destinations. Throughout the past decades, the highest average emigration rates are observed in countries in an income range of 7000 to 14 000 USD. Different scholars ascribe this to a universal mobility transition, which systematically shapes feasibility and aspirations to migrate along any country's development path and, thereby, causes a hump-shaped development–migration nexus at the country level (de Haas, 2010; Clemens, 2014). In consequence, economic development in poor countries today is expected to boost global emigration in the future. From a destination country perspective, such an interpretation implies a policy trade-off between supporting development in poor countries and reducing immigration pressures. We question this causal interpretation of the cross-sectional evidence. Middle- and low-income countries differ in terms of exogenous characteristics that shape development and migration. At least to some degree, middle-income countries experience higher levels of emigration because they are smaller, closer to primary destinations, and more frequently have past colonial ties. To account for these and other unobserved differences we employ a panel setup and investigate the relationship between economic development and emigration within countries. Using annual data we identify a robust negative relationship between economic growth and migration to the OECD for countries located in the upward-sloping segment of the

migration hump. This stands in stark contrast to the cross-sectional evidence on the migration hump or, more precisely, its interpretation. Our results are robust to using different income ranges, time trends, and controls. Most importantly they also hold for different migration data and different time periods (i.e. five and ten year intervals).

Our results do not imply that financial constraints would not be binding for many individuals. Yet, when economic opportunities improve, few of them seem to utilize their increasing capabilities to migrate.

This interpretation is backed by recent micro-level evidence on the link between migration aspirations and economic conditions. Using data from the Gallup World Poll, Migali and Scipioni (2019) study determinants of migration intentions in developing countries. Among the most significant explanatory factors are individual perceptions of economic change. Individuals that expect local economic conditions or their living standards to improve state substantially lower emigration intentions. In addition, employment is negatively related to migration intentions. The influence of these factors is found to be much larger than individual income levels. To investigate the link between incomes and migration aspirations specifically, Langella and Manning (2021) employ cross-country micro data from the Gallup World Poll and the US diversity visa lottery. They detect little evidence for the upwards-sloping part of the migration hump and conclude that higher GDP per capita rather decreases the desire to emigrate. Most recently, our findings have been affirmed by another macro-level study. Using decadal global migration data, similar to our Table 6, Berthiaume et al. (2021) confirm the inconsistencies between cross-sectional and panel estimates of the development-emigration nexus that we present in this paper. Our results relate well to two other strands of literature: The literature on the relationship between development aid and migration and the literature on environmentally-induced migration. Lanati and Thiele (2018) have recently provided empirical evidence for a negative relationship between development aid and migration. The negative relationship between economic growth and emigration that we demonstrate in this paper provides a plausible explanation for their finding. The expected impacts of climate change on migration crucially depend on the assumptions regarding the relationship between economic growth and migration decisions. Consistent with our findings, Falco et al. (2019) show that climate shocks that reduce agricultural productivity in developing countries lead to more emigration. That contrasts previous findings by Cattaneo and Peri (2016). Most recently Rikani et al. (2022) have investigated how future climate-induced migration depends on the assumed nexus between economic growth and emigration. Specifically, they contrast our estimates with the implications of an inter-temporal migration hump and highlight the relevance of this strand of literature for assessing future climate-induced migration flows. Still, it is important to emphasize that our results do not necessarily contradict the

existence of a migration hump at the country level. In the very long-run and especially in the absence of positive economic trends, higher income levels, most certainly, empower a larger number of people to migrate. Moreover, other factors that are associated with development but not closely related to rising incomes, might still contribute to rising emigration in the long-run. In order to better understand the relationship between long-run development and emigration, future research needs to better identify the actual impact that different dimensions of development have. However, in policy-relevant time periods of 5 to 10 years economic growth coincides with less emigration. Hence, policy makers should not be too concerned about trade-offs between development cooperation and immigration control. Even in very poor countries improving economic conditions rather discourage people from migrating, at least at the margin. Yet, given the reasonably small size of the effect and the struggle of development cooperation to sustainably increase economic growth, the scope to affect migration through this channel remains limited.

### CRediT authorship contribution statement

**David Benček:** Methodology, Software, Validation, Formal analysis, Writing – original draft, Visualization. **Claas Schneiderheinze:** Conceptualization, Methodology, Software, Validation, Formal analysis, Writing – original draft, Visualization, Writing – review & editing.

### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

### Data availability

Data will be made available on request.

### Acknowledgment

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## Descriptives

**Table 9**

Summary statistics for our working sample of 54 low-income countries (GDP per capita < 7000 USD).

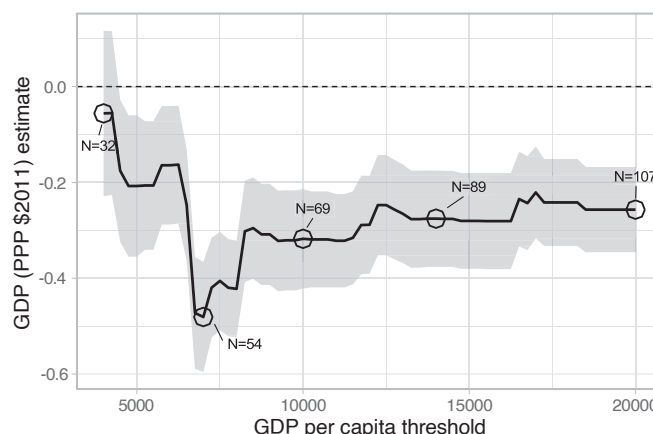
Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Emigrants (thousands)	1, 858	8.42	23.84	0.00	0.28	5.77	286.69
Emigration rate (%)	1, 858	0.06	0.12	0.00	0.004	0.05	1.66
GDP (PPP billion \$2011)	1, 858	74.94	379.30	0.18	5.55	33.20	6, 361.84
GDP per capita (PPP \$2011)	1, 858	1, 944.21	1, 099.26	223.09	1, 104.61	2, 566.72	6, 918.86
GDP per capita growth(%)	1, 855	1.52	9.16	-51.61	-2.47	5.54	91.86
Population (million)	1, 858	35.57	135.84	0.09	4.18	18.34	1, 278.56
Diaspora (million)	1, 858	0.12	0.32	0.0001	0.003	0.07	4.13
Conflict	1, 858	1.33	0.62	1	1	1	3
FH index	1, 769	2.34	0.68	1.00	2.00	3.00	3.00
Air passengers	1, 858	25.32	7.72	15.41	19.50	30.60	42.99
Immig. pol. restrictiveness	1, 645	0.40	0.03	0.37	0.38	0.41	0.46

**Table 10**  
Selected country characteristics by income group: Employing different threshold values.

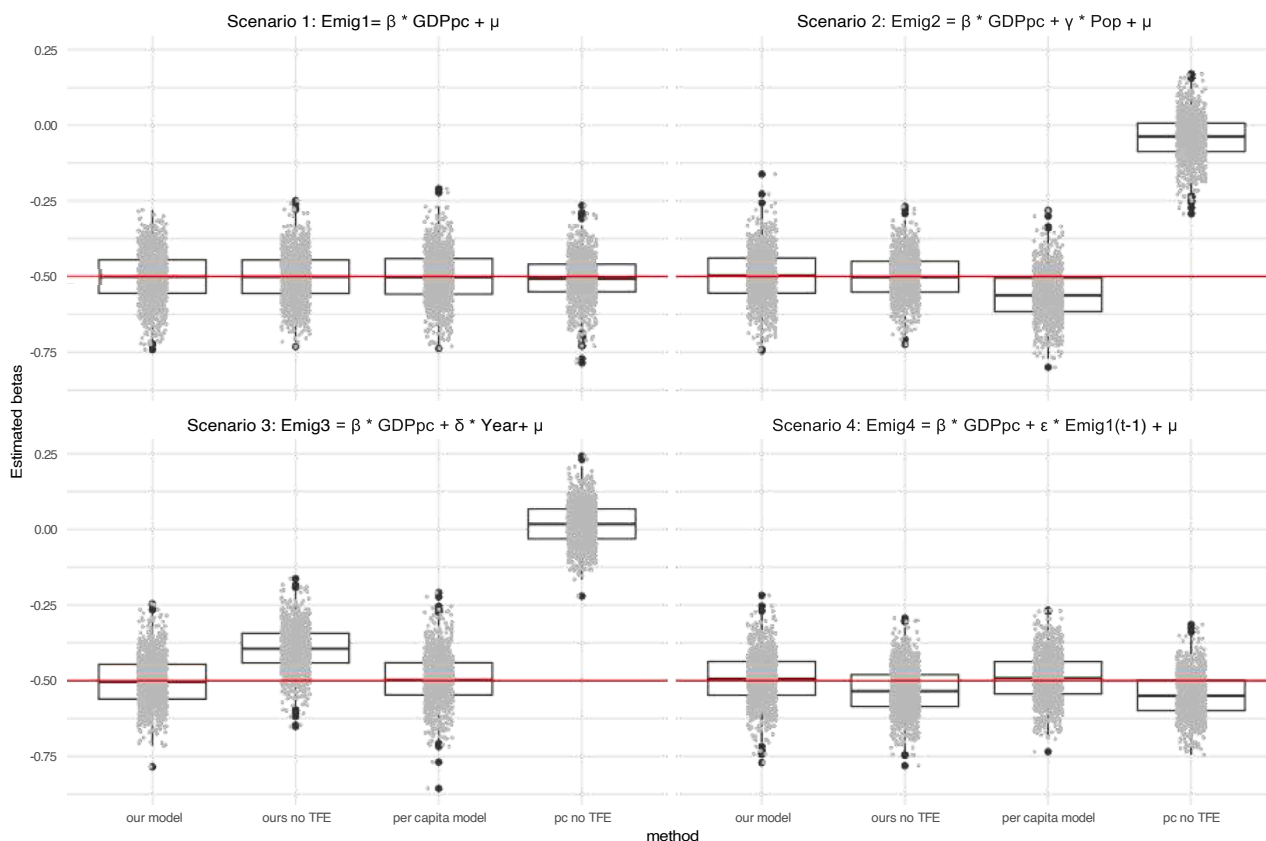
	low income	remaining non-OECD	p-value
<b>GDPpc threshold = 4000 USD:</b>			
GDPpc as of 2010 (PPP \$2011)	2238 (944)	15,943 (17340)	<0.001
Distance to OECD country(km)	4742 (1735)	3916 (2352)	0.016
Common border with OECD	0.00 (0.00)	0.04 (0.19)	0.083
Colonial ties with OECD	0.43 (0.50)	0.71 (0.46)	0.001
landlocked	0.33 (0.48)	0.10 (0.30)	0.001
Population (millions, in 2010)	46.7 (16.0)	10.2 (22.6)	0.073
<b>GDPpc threshold = 5000 USD:</b>			
GDPpc as of 2010 (PPP \$2011)	2367 (1058)	16,489 (17564)	<0.001
Distance to OECD country(km)	4744 (1754)	3872 (2359)	0.012
Common border with OECD	0.00 (0.00)	0.04 (0.19)	0.083
Colonial ties with OECD	0.46 (0.50)	0.70 (0.46)	0.004
landlocked	0.31 (0.47)	0.10 (0.30)	0.002
Population (millions, in 2010)	44.6 (15.6)	10.1 (23.1)	0.073
<b>GDPpc threshold = 6000 USD:</b>			
GDPpc as of 2010 (PPP \$2011)	2810 (1491)	18,132 (18296)	<0.001
Distance to OECD country(km)	4572 (1875)	3929 (2378)	0.075
Common border with OECD	0.00 (0.00)	0.04 (0.21)	0.083
Colonial ties with OECD	0.46 (0.50)	0.74 (0.44)	0.001
landlocked	0.31 (0.46)	0.07 (0.26)	<0.001
Population (millions, in 2010)	39.8 (14.5)	10.1 (24.2)	0.075
<b>GDPpc threshold = 7000 USD:</b>			
GDPpc as of 2010 (PPP \$2011)	3247 (1833)	20,209 (19131)	<0.001
Distance to OECD country(km)	4596 (1934)	3767 (2359)	0.029
Common border with OECD	0.00 (0.00)	0.05 (0.23)	0.083
Colonial ties with OECD	0.51 (0.50)	0.72 (0.45)	0.009
landlocked	0.28 (0.45)	0.07 (0.26)	<0.001
Population (millions, in 2010)	37.6 (13.7)	8.09 (20.1)	0.045
<b>GDPpc threshold = 8000 USD:</b>			
GDPpc as of 2010 (PPP \$2011)	3605 (2136)	22,065 (19850)	<0.001
Distance to OECD country(km)	4556 (1941)	3711 (2415)	0.037
Common border with OECD	0.00 (0.00)	0.06 (0.24)	0.083
Colonial ties with OECD	0.53 (0.50)	0.71 (0.46)	0.025
landlocked	0.27 (0.45)	0.06 (0.24)	<0.001
Population (millions, in 2010)	35.5 (13.1)	7.58 (20.5)	0.041

Note: Countries are clustered by average income between 1960 and 2010; data sources: Penn World Tables 2015 and CEPII's GeoDist Database.

**Robustness checks**



**Fig. 4.** Estimated coefficient of IHS-transformed GDP (with 95 % confidence interval) conditional on varying GDP per capita thresholds for the underlying sample..  
Note: The estimates for the influence of GDP on Emigration are based on model 5 in Table 3.



**Fig. 5.** Comparing different empirical specifications: A Monte Carlo simulation. *Note:* The boxplots in this figure feature the mean and the 95 percent confidence intervals for the GDPpc estimates from four different regression models. The dependent variable (emigration flows) is simulated 1000 times as a function of GDPpc and varying other factors (as specified in parentheses). The parameters are set to the following values:  $\beta = -0.50$ ;  $\gamma = 2$ ;  $\delta = 0.05$ ; and  $E = 0.20$ . In each panel, the first two boxplots represent estimation results from our regression setup in absolute terms with and without time fixed-effects. The third and fourth boxplot are based on estimates from the regression in per capita terms. The red line represents the true beta of  $-0.5$ .

**Table 11**  
Panel regression using GDP per capita.

	Emigration	Emigration	Emigration rate	Emigration rate
GDP per capita	-4.593** (0.486)	-4.343** (0.439)	-0.235** (0.043)	-0.184** (0.046)
Population	1.593** (0.556)	0.237 (0.505)		
UCDP: Minor conflict		0.353** (0.055)		0.008 (0.006)
UCDP: War		0.502** (0.076)		0.023** (0.008)
FH: partly free		0.045 (0.071)		0.028** (0.008)
FH: not free		-0.112 (0.078)		0.022** (0.008)
Diaspora size		0.397** (0.097)		-0.002 (0.010)
Country FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Num. obs.	1858	1769	1858	1769
R <sup>2</sup> (overall)	0.892	0.917	0.661	0.675
R <sup>2</sup> (within)	0.060	0.111	0.016	0.026

\*\*\* p < 0.001; \*\* p < 0.01; \* p < 0.05.

*Note:* The dependent variable is emigration (total number of emigrants) divided by population size. The sample consists of 54 relatively poor countries with less than 7000 USD per capita over the entire observation period (1980 – 2014). Conflict (UCDP) and political freedom (FH) are captured by categorical variables with three levels each. All explanatory variables are lagged by one year.

**Table 12**  
Pooled and panel regressions without time control.

	Pooled		-	Panel	
	Model 1	Model 2		Model 3	Model 4
GDP (PPP \$2011)	0.917** (0.324)	0.045 (0.192)		-0.490*** (0.063)	-0.461*** (0.057)
Population	0.146 (0.352)	0.234 (0.211)		3.953*** (0.113)	2.953*** (0.129)
UCDP: Minor conflict		0.199 (0.171)			0.372*** (0.058)
UCDP: War		0.126 (0.251)			0.485*** (0.081)
FH: partly free		-0.044 (0.229)			-0.095 (0.075)
FH: not free		-0.127 (0.195)			-0.303*** (0.081)
Diaspora size		0.818*** (0.050)			0.253*** (0.033)
Country FE	no	no		yes	yes
Year FE	no	no		no	no
Num. obs.	1858	1769		1858	1769
R <sup>2</sup> (overall)	0.471	0.769		0.878	0.902
R <sup>2</sup> (within)	0.471	0.769		0.527	0.572

\*\*\* p < 0.001; \*\* p < 0.01; \*p < 0.05.

Note: The dependent variable is emigration (total number of emigrants). The sample consists of 54 relatively poor countries with less than 7000 USD per capita over the entire observation period (1980 – 2014). The high magnitude variables emigration, GDP, population, and diaspora size are transformed using the inverse hyperbolic sine function. The interpretation of the respective coefficients is similar to logarithmic values. Conflict (UCDP) and political freedom (FH) are captured by categorical variables with three levels each. All explanatory variables are lagged by one year.

**Table 13**  
Panel regressions with outlier dummies for high and low growth.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
GDP (PPP \$2011)	0.406*** (0.065)	0.396*** (0.074)	0.417*** (0.064)	0.417*** (0.074)	0.408*** (0.065)	0.407*** (0.074)
Population	1.942*** (0.268)	2.955*** (0.279)	1.967*** (0.267)	2.983*** (0.277)	1.944*** (0.268)	2.955*** (0.279)
Air passengers		0.034*** (0.010)		0.033*** (0.010)		0.034*** (0.010)
Immigration policy restrictiveness		-3.852*** (0.972)		-3.884*** (0.972)		-3.890*** (0.972)
High growth	-0.059 (0.059)	-0.051 (0.064)			-0.060 (0.059)	-0.061 (0.064)
Low growth			-0.009 (0.056)	-0.082 (0.060)	-0.014 (0.057)	-0.088 (0.060)
Country FE	yes	yes	yes	yes	yes	yes
Year FE	yes	no	yes	no	yes	no
Num. obs.	1855	1642	1855	1642	1855	1642
R <sup>2</sup> (overall)	0.900	0.893	0.900	0.893	0.900	0.893
R <sup>2</sup> (within)	0.048	0.542	0.048	0.542	0.048	0.542

\*\*\* p < 0.001; \*\* p < 0.01; \*p < 0.05.

Note: The dependent variable is emigration (total number of emigrants). The sample consists of 54 relatively poor countries with less than 7000 USD per capita over the entire observation period (1980 – 2014). The high magnitude variables emigration, GDP, population, and diaspora size are transformed using the inverse hyperbolic sine function. The interpretation of the respective coefficients is similar to logarithmic values. Conflict (UCDP) and political freedom (FH) are captured by categorical variables with three levels each. All explanatory variables are lagged by one year.

**Table 14**  
Panel regressions without small countries.

	pop. > 2.5mio	pop. > 2.5mio	pop. > 5mio	pop. > 5mio
GDP (PPP \$2011)	-0.626*** (0.071)	-0.618*** (0.081)	-0.337*** (0.093)	-0.148 (0.099)
Population	-0.697* (0.322)	0.841* (0.331)	-1.460*** (0.407)	0.422 (0.392)
Air passengers		0.111*** (0.012)		0.086*** (0.015)
Immigration policy restrictiveness		-3.546** (1.159)		-4.373*** (1.301)
Country FE	yes	yes	yes	yes
Year FE	yes	no	yes	no
Num. obs.	1263	1118	714	632
R <sup>2</sup> (overall)	0.867	0.854	0.898	0.888
R <sup>2</sup> (within)	0.066	0.500	0.034	0.502

\*\*\* p < 0.001, \*\* p < 0.01, \*p < 0.05.

Note: The dependent variable is emigration (total number of emigrants). The sample consists of 54 relatively poor countries with less than 7000 USD per capita over the entire observation period (1980 – 2014). The high magnitude variables emigration, GDP, population, and diaspora size are transformed using the inverse hyperbolic sine function. The interpretation of the respective coefficients is similar to logarithmic values. Conflict (UCDP) and political freedom (FH) are captured by categorical variables with three levels each. All explanatory variables are lagged by one year.

**Table 15**  
Panel regressions with different institutional variables.

	Model 1	Model 2	Model 3
GDP (PPP \$2011)	-0.481*** (0.059)	-0.553*** (0.061)	-0.423*** (0.058)
Population	0.921*** (0.251)	1.257*** (0.247)	1.136*** (0.241)
UCDP: Minor conflict	0.356*** (0.055)	0.231*** (0.060)	0.292*** (0.054)
UCDP: War	0.508*** (0.076)	0.356*** (0.084)	0.481*** (0.074)
FH: partly free	0.055 (0.072)		
FH: not free	-0.107 (0.078)		
Diaspora size	0.168*** (0.038)	0.191*** (0.038)	0.212*** (0.039)
Polity IV			0.006 (0.005)
Political Terror Score		0.177** (0.028)	
Country FE	yes	yes	yes
Year FE	yes	yes	yes
Num. obs.	1769	1721	1774
R <sup>2</sup> (overall)	0.916	0.918	0.912
R <sup>2</sup> (within)	0.096	0.141	0.090

\*\*\*p < 0.001; \*\*p < 0.01; \*p < 0.05.

Note: The dependent variable is emigration (total number of emigrants). The sample consists of 54 relatively poor countries with less than 7000 USD per capita over the entire observation period (1980 – 2014). The high magnitude variables emigration, GDP, population, and diaspora size are transformed using the inverse hyperbolic sine function. The interpretation of the respective coefficients is similar to logarithmic values. Conflict (UCDP) and political freedom (FH) are captured by categorical variables with three levels each. All explanatory variables are lagged by one year.

**Table 16**  
Panel regressions: 5-year averages with emigration rate and GDP pc.

	Emigration rate		-	Emigration rate (log)	
	Model 1	Model 2		Model 3	Model 4
GDP per capita	-0.037*** (0.010)	-0.034** (0.011)		-0.031*** (0.008)	-0.029*** (0.009)
Air passengers		0.002*** (0.000)			0.001*** (0.000)
Immig. pol. restrictiveness		0.109 (0.133)			0.068 (0.106)
Country FE	yes	yes		yes	yes
Year FE	yes	no		yes	no
Num. obs.	424	373		424	373
R <sup>2</sup> (overall)	0.774	0.781		0.790	0.797
R <sup>2</sup> (within)	0.039	0.050		0.042	0.063

\*\*\* p < 0.001; \*\* p < 0.01; \*p < 0.05

Note: The dependent variable is emigration (total number of emigrants). The sample consists of 54 relatively poor countries with less than 7000 USD per capita over the entire observation period (1980 – 2014). The high magnitude variables emigration, GDP, population, and diaspora size are transformed using the inverse hyperbolic sine function. The interpretation of the respective coefficients is similar to logarithmic values. Conflict (UCDP) and political freedom (FH) are captured by categorical variables with three levels each. All explanatory variables are lagged by one year.

**Table 17**  
Fixed effects vs. First difference regressions.

	Fixed Effects		First Difference	
	Model 1	Model 2	Model 3	Model 4
GDP (PPP \$2011)	-0.359** (0.133)	-0.456*** (0.120)	-0.381* (0.150)	-0.418** (0.144)
Population	2.177*** (0.512)	1.373** (0.468)	2.978*** (0.325)	2.768*** (0.345)

(continued on next page)



**Table 17** (continued)

	Fixed Effects		First Difference	
	Model 1	Model 2	Model 3	Model 4
UCDP: Minor conflict		0.388*** (0.097)		-0.050 (0.097)
UCDP: War		0.573*** (0.134)		
FH: partly free		-0.107 (0.153)		-0.318* (0.146)
FH: not free		-0.195 (0.165)		-0.503** (0.156)
Diaspora size		0.155* (0.074)		0.011 (0.046)
Country FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Num. obs.	424	416	370	363
R <sup>2</sup> (full model)	0.913	0.928		
R <sup>2</sup> (proj model)	0.063	0.134		
R <sup>2</sup>			0.010	0.034

\*\*\* p < 0.001; \*\* p < 0.01; \*p < 0.05.

Note: The dependent variable is emigration (total number of emigrants). The sample consists of 54 relatively poor countries with less than 7000 USD per capita over the entire observation period (1980 – 2014). The high magnitude variables emigration, GDP, population, and diaspora size are transformed using the inverse hyperbolic sine function. The interpretation of the respective coefficients is similar to logarithmic values. Conflict (UCDP) and political freedom (FH) are captured by categorical variables with three levels each. All explanatory variables are lagged by one year.

**Table 18**

Pooled vs. Panel regression: Using log transformation instead of IHS.

	Pooled		Panel			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
GDP (PPP \$2011)	0.786* (0.335)	0.799* (0.349)	-0.522*** (0.064)	-0.527*** (0.073)	-0.468*** (0.058)	-0.459*** (0.067)
Population	0.198 (0.355)	0.194 (0.366)	1.522*** (0.269)	2.601*** (0.279)	0.924*** (0.247)	1.772*** (0.264)
Air passengers		0.061*** (0.015)		0.052*** (0.010)		0.044*** (0.009)
Immig. pol. restrictiveness		-9.677*** (1.908)		-3.894*** (0.983)		-4.686*** (0.933)
UCDP: Minor conflict					0.351*** (0.054)	0.331*** (0.061)
UCDP: War					0.499*** (0.075)	0.505*** (0.085)
FH: partly free					0.068 (0.071)	-0.023 (0.078)
FH: not free					-0.079 (0.077)	-0.216* (0.084)
Diaspora size					0.173*** (0.038)	0.253*** (0.040)
Country FE	no	no	yes	yes	yes	yes
Year FE	yes	no	yes	no	yes	no
Num. obs.	1858	1645	1858	1645	1769	1560
R <sup>2</sup> (overall)	0.538	0.516	0.895	0.888	0.917	0.908
R <sup>2</sup> (within)	0.460	0.516	0.048	0.531	0.096	0.567

\*\*\* p < 0.001; \*\* p < 0.01; \*p < 0.05.

Note: The dependent variable is emigration (total number of emigrants). The sample consists of 54 relatively poor countries with less than 7000 USD per capita over the entire observation period (1980 – 2014). The high magnitude variables Emigration, GDP, Populations, and Diaspora size are transformed using log transformation Conflict (UCDP) and political freedom (FH) are captured by categorical variables with three levels each. All explanatory variables are lagged by one year.

**Table 19**

Pooled vs. Panel regression: Alternative GDP measure.

	Pooled		Panel			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
GDP UN (PPP \$2011)	0.614* (0.309)	0.624* (0.312)	-0.573*** (0.082)	-0.572*** (0.094)	-0.470*** (0.074)	-0.464*** (0.086)
Population	0.404 (0.319)	0.402 (0.321)	1.855*** (0.289)	2.899*** (0.305)	1.110*** (0.259)	1.897*** (0.281)
Air passengers		0.068*** (0.014)		0.048*** (0.011)		0.041*** (0.010)
Immig. pol. restrictiveness		-9.546*** (1.725)		-4.599*** (1.053)		-5.406*** (0.978)

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**Table 19** (continued)

	Pooled		-	Panel			
	Model 1	Model 2		Model 3	Model 4	Model 5	Model 6
UCDP: Minor conflict						0.355*** (0.057)	0.338*** (0.063)
UCDP: War						0.431*** (0.082)	0.462*** (0.093)
FH: partly free						0.080 (0.073)	-0.013 (0.081)
FH: not free						-0.144 (0.080)	-0.296*** (0.088)
Diaspora size						0.163*** (0.040)	0.249*** (0.042)
Country FE	no	no		yes	yes	yes	yes
Year FE	yes	no		yes	no	yes	no
Num. obs.	1783	1576		1783	1576	1697	1494
R <sup>2</sup> (full model)	0.534	0.513		0.891	0.883	0.916	0.908
R <sup>2</sup> (proj model)	0.452	0.513		0.044	0.520	0.089	0.563

\*\*\* p < 0.001; \*\* p < 0.01; \* p < 0.05.

Note: The dependent variable is emigration (total number of emigrants). The sample consists of 54 relatively poor countries with less than 7000 USD per capita over the entire observation period (1980 – 2014). The high magnitude variables emigration, GDP, population, and diaspora size are transformed using the inverse hyperbolic sine function. The interpretation of the respective coefficients is similar to logarithmic values. Conflict (UCDP) and political freedom (FH) are captured by categorical variables with three levels each. All explanatory variables are lagged by one year.

**Table 20**

Pooled vs. Panel regression: Alternative population measure.

	Pooled		Panel			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
GDP (PPP \$2011)	0.823* (0.324)	0.834* (0.336)	-0.622*** (0.064)	-0.610*** (0.073)	-0.478*** (0.060)	-0.464*** (0.069)
Air passengers		0.058*** (0.014)		0.083*** (0.010)		0.056*** (0.009)
Immig. pol. restrictiveness		-9.088*** (2.180)		-4.852*** (0.971)		-5.604*** (0.945)
UCDP: Minor conflict					0.353*** (0.056)	0.334*** (0.062)
UCDP: War					0.513*** (0.077)	0.516*** (0.087)
FH: partly free					0.046 (0.073)	-0.037 (0.080)
FH: not free					-0.132 (0.080)	-0.249** (0.086)
Diaspora size					0.179*** (0.039)	0.265*** (0.041)
Country FE	no	no	yes	yes	yes	yes
Year FE	yes	no	yes	no	yes	no
Num. obs.	1797	1635	1797	1635	1719	1560
R <sup>2</sup> (full model)	0.537	0.518	0.895	0.886	0.916	0.906
R <sup>2</sup> (proj model)	0.468	0.518	0.053	0.520	0.094	0.561

\*\*\* p < 0.001; \*\* p < 0.01; \* p < 0.05.

Note: The dependent variable is emigration (total number of emigrants). The sample consists of 54 relatively poor countries with less than 7000 USD per capita over the entire observation period (1980 – 2014). The high magnitude variables emigration, GDP, population, and diaspora size are transformed using the inverse hyperbolic sine function. The interpretation of the respective coefficients is similar to logarithmic values. Conflict (UCDP) and political freedom (FH) are captured by categorical variables with three levels each. All explanatory variables are lagged by one year.

**Table 21**

GMM estimation: Varying population lags.

	Model 1	Model 2	Model 3
GDP	-1.29* (0.55)	-1.17*(0.57)	-1.07*(0.52)
lag(Population, 1)	10.44 (14.63)		
lag(Population, 2)		11.08 (12.02)	
lag(Population, 3)			16.54(14.37)
n	54	54	54
T	35	35	35
Num. obs.	1858	1858	1858
Num. obs. used	1750	1696	1642
Sargan Test: chisq	32.08	30.80	30.83
Sargan Test: df	159.00	157.00	154.00

(continued on next page)

**Table 21** (continued)

	Model 1	Model 2	Model 3
Sargan Test: p-value	1.00	1.00	1.00
Wald Test Coefficients: chisq	5.70	4.30	4.58
Wald Test Coefficients: df	2	2	2
Wald Test Coefficients: p-value	0.06	0.12	0.10
Wald Test Time Dummies: chisq	539.81	506.46	473.47
Wald Test Time Dummies: df	33	32	31
Wald Test Time Dummies: p-value	0.00	0.00	0.00

\*\*\* $p < 0.001$ ; \*\* $p < 0.01$ ; \* $p < 0.05$ .

Note: The dependent variable is emigration (total number of emigrants). The sample consists of 54 relatively poor countries with less than 7000 USD per capita over the entire observation period (1980 – 2014). The high magnitude variables emigration, GDP, population, and diaspora size are transformed using the inverse hyperbolic sine function. Conflict (UCDP) and political freedom (FH) are captured by categorical variables with three levels each. All explanatory variables are lagged by one year.

**Comparing different empirical specifications: A Monte Carlo simulation**

This paper features a distinct empirical setup. In slight contrast to most other papers in this field we decided to use absolute emigration as the dependent variable and control for absolute GDP and Population separately – instead of regressing emigration rates on GDP per capita. We thereby want to better account for the influence of demographic factors on emigration and reduce the likelihood of measurement error (see section 4.1 for a more detailed discussion on these issues). In this section we use a basic, yet powerful, Monte Carlo simulation to compare different empirical setups across different scenarios. This is to some extent motivated by recent concerns that our empirical specification might produce spurious results (Clemens, 2020b). Specifically, Clemens (2020b) argues that including time fixed effects could mask the true relationship between per capita incomes and emigration, and that two non-stationary regressors (GDP and Population) would give rise to spurious correlation. This simulation exercise is based on the same real world GDP and Population data for 54 countries over 35 years that was used throughout the paper (source: World Penn Tables).<sup>12</sup> In consequence, any issues related to underlying time trends and a non-stationary relationship between these two variables are well-captured. We then simulate emigration flows as a function of GDP per capita. Note that GDP per capita is non-stationary and consequently the simulated emigration variable is non-stationary as well. For this task, we employ annual data because at this higher frequency our estimates are most vulnerable to biases associated with non-stationarity.

Specifically we compute emigration flows according to four different scenarios:

- In the first scenario emigration only depends on GDP per capita and an error term.

Scenario 1:

$$Emig1_{it} = \beta * GDPpc_{it} + \mu_{it}, \tag{2}$$

- For the second scenario we assume population to positively influence emigration. High population growth might put pressure on local labor markets and is related to young populations, which plausibly increases average migration propensities.

Scenario 2:

$$Emig2_{it} = \beta * GDPpc_{it} + \gamma * Pop_{it} + \mu_{it} \tag{3}$$

In scenario three, we assume a linear positive time trend for international migration. Real world migration trends, transport infrastructure development and an average global liberalization of immigration policies make this a realistic assumption.

Scenario 3:

$$Emig3_{it} = \beta * GDPpc_{it} + \delta * \tau_t + \mu_{it}, \tag{4}$$

- In the fourth scenario, we induce auto-correlation. That is in line with the importance of networks for migration.

Scenario 4:

$$Emig4_{it} = \beta * GDPpc_{it} + E * Emig1_{it-1} + \mu_{it}, \tag{5}$$

95 percent confidence intervals for the GDPpc estimates from the respective regressions. The first two boxplots represent estimation results from our absolute regression setup with and without time fixed-effects. The third and fourth boxplot in each panel are based on estimates from the regression in per capita terms (with and without time fixed-effects).

In the first scenario (without any additional influence) the results are very similar across the different methods (upper left panel). Despite the non-stationary nature of all our variables of interest all four specifications produce on average unbiased estimates. Moreover, we do not detect any distortions resulting from the inclusion of time fixed effects. In scenario two first systematic differences become apparent (upper right panel). While our working model still performs well, the per capita specification produces significant biases. With time fixed effects we observe a downwards bias, without time fixed effects an even larger upwards bias appears. The third scenario shows the crucial need for time-fixed effects (bottom left panel). If

<sup>12</sup> Similar to the rest of the paper we use the inverse hyperbolic sine function to transform these high magnitude variables.

we do not control for a time trend in international migration via time fixed-effects, both models produce upwards biased estimates. With time-fixed effects both specifications retain unbiased estimates again. A similar lesson can be learned from scenario four (bottom right panel). Time-fixed effects even help against autocorrelation in the dependent variable. Altogether, this simulation task provides valuable insights into strengths and weaknesses of different empirical setups in different scenarios. Omitting time fixed-effects creates substantial biases if emigration flows are non-stationary. Using the same GDP and Population data as in our core analysis, we do not find any evidence for a higher risk for spurious results with our empirical approach. To the contrary, our specification clearly outperforms the more standard per-capita setup in two of the four scenarios.

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