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Development Levels Shaping Global Migration Trends

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Abstract

According to estimates by the United Nations' International Organization for Migration, in 2020 the global count of international migrants reached 281 million, nearly doubling the estimate from 1990. While a significant portion of emigration can be attributed to wars and conflicts, less developed countries have witnessed a surge in outward migration over the past few decades, extending beyond forced emigration. Among these migrants there is a considerable number of young, skilled, and educated individuals, whose departure has unfortunate effects on their countries of origin, impacting economic progress and demographics. The level of country development significantly influences migration, as migrants often move from less developed to more developed countries in search of better living conditions and more opportunities.

This paper aims to identify the primary determinants of global migration movement between years 1990 and 2022, with a focus on evaluating the impact of country development level disparities on these flows. According to our static and dynamic estimation results the level of development is a significant driver of emigration while higher GDP per capita is associated with lower net emigration. These results imply that policies aimed at reducing migration pressures should focus on fostering economic development and increasing GDP per capita in low-income countries.

Keywords: global emigration determinants, country economic development levels gap, aging population, education levels, poverty, conflicts

1. Introduction

In recent decades, emigration has emerged as one of the more prominent global issues, with wide-ranging geopolitical, economic, cultural, and security implications. The International Organization for Migration (IOM) estimates that around 3.6 percent of the global population were immigrants in 2020, or approximately 281 million people - an increase of almost 45% compared to 1990 and more than three times the figure in 1970 (McAuliffe and Oucho, 2024). It is now evident that no country or region in the world remains unaffected by this phenomenon, and the situation will likely only grow more complex. With varied signs, intensities, and directions of movement, a broad spectrum of real and potential problems arises, affecting the future of both developed and emerging economies.

The International Monetary Fund (International Monetary Fund [IMF], 2020) estimates that immigrants constitute around 12 percent of the population in developed economies - an increase from 7 percent in 1990 - whereas they represent only 2 percent of the population in emerging economies, primarily as refugees.

Given these dynamics, it is not surprising that immigration has become one of the central political, economic, and social topics in developed countries. For instance, immigration lies at the core of numerous items within the EU budget and the Multiannual Financial Framework (2021–2027), which together represent some of the most important priority areas in the EU's budgetary structure and policy-making. It has also become a fundamental political issue, influencing electoral outcomes in numerous countries, including the U.S., and the EU member states Sweden, the Netherlands, Italy, and Hungary.

Evidently, emigration is becoming an ever more significant challenge for developing nations as well, given that a considerable number of departing individuals are young, educated citizens. Their emigration is likely to adversely affect source economies and societies. For instance, countries of Western Balkans have gained an infamous label of one of the world's leading regions in brain-drain with expected loss of a quarter to half of its skilled and educated young citizens

in the forthcoming decades (Icoski, 2022).

The rapid recovery of migration flows to the pre-pandemic levels after Covid-19 demonstrates the resilience of underlying motivational factors (Almulhim A.I., Alverio G.N., Sharifi A., Shaw R., Huq S., Mahmud M.J, Ahmad S. and Abubakar I.R., 2024) while climate-change related factors are increasingly emerging as a major driver of migration in developing nation, with the potential to negatively impact close to 150 million people in upcoming decades (Benton M, Huang L., Batalova J and Tirado T., 2023).

However, despite the growing gravity and complexity of the situation, as well as the increasing research and policy attention this issue has received, there is still no comprehensive and systematic theory of migration. The following section will delve into the existing theoretical and empirical frameworks in greater detail. Nevertheless, it is important to acknowledge that migration is an extremely complex phenomenon to define, let alone to explain or predict. Most authors use basic distinction between voluntary and forced migration as a starting point to define international movements of people with intention to relocate. Kuhnt (2019) uses motives to migrate as a criteria to broadly define voluntary migration as movement driven by maximization of individual potential, primarily in economic terms, while forced migration is typically a consequence of conflict or violence. Obviously, it is a formidable challenge to draw a fine line between forced and voluntary elements in decision to move due to the lack of job opportunities and severe economic conditions caused by political instability and failing institutions (de Haas, 2011). It is even harder to construct proxy of fear for one's life and to measure it. As a result, the distinction between migrants, refugees, asylum seekers, and other groups are inherently murky. Additionally, it is necessary to differentiate between the desire or aspiration to migrate and the actual ability to do so. A growing body of literature highlights the importance of networks in influencing migration decisions (e.g., Munshi, 2003; Beine, Docquier and Özden, 2011), as well as quantification of financial thresholds that either facilitate or constrain movement (IMF, 2020). These factors represent just a few of the numerous variables researchers must consider when attempting to better understand the basic propositions of migration phenomena. Furthermore, a significant proportion of migration is either illegal or unreported, which means that macro-level data often lags behind. At the micro level, defining, collecting, and estimating individual characteristics, perceptions, and aspirations - particularly when observed continuously over time - poses even greater challenges (Aslany, Carling, Mjelva and Sommerfelt, 2021).

It is therefore not surprising that much of the research has focused on identifying the determinants of migration, with the goal of explaining its variations and, ultimately, predicting future trends for the purposes of policy control and integration. This paper aims at estimating the significance of the most important emigration determinants on the sample of 194 countries from the world and 32 years of macroeconomic data. After critically reviewing relevant literature and empirical analyses the model and its formation will be explained. Next, the results of the empirical analyses in which migration determinants are estimated will be presented and discussed. Finaly, conclusions will be made based on the empirical findings.

2. Literature Review

An increasing interest in comprehending the fundamental elements and consequences of migratory patterns has sparked the development of migration theories and empirical investigations spanning diverse fields, each utilizing unique viewpoints to explain international migration. As outlined in the previous section, due to the complex nature of the migration process, a comprehensive general theory of international migration is yet to be formulated, as explained by Arango (2000).

Academic research on economics of migration and the motivations behind emigration has a history of over a century, with seminal works such as those by Ravenstein (1885) and Lee (1966) shaping the discourse. Massey (2015) offers a broader framework that incorporates world-systems theory from sociology, institutional theory from economics, segmented labor market theory, and social capital theory in the context of the strong demand for low-wage workers, which has been an inherent feature of markets globalization over the last few decades of the 20th century and the first decade of the new millennium.

A major strand in the literature focuses on gravity models of migration. Beine, Bertoli and Fernández-Huertas Moraga, (2016) provide a comprehensive review of the evolution of gravity trade flow models, starting from Ravenstein (1885, 1889) through Tinbergen (1962) to more recent developments such as those by Head and Mayer (2015). The recent availability of so-called dyadic source-destination data on migration, in the form of migrant stocks as proxies for migration flows, has enabled a surge in empirical studies exploring migration patterns. The classic approach in this group is based on random utility maximization (RUM) models, which offer an elegant method to estimate the utility that potential migrants associate with moving to a particular country at a specific point in time. Beine et al. (2016) also discuss, in detail, the shortcomings and challenges associated with the estimation of RUM models. Chief among these are the distributional assumptions concerning the stochastic component and the specification of the deterministic

component of utility, which basically comes down to the invariability of (perceived) attractiveness among destination countries and individuals, as well as not considering component of time for decision making.

More recently, IMF (2020) conducted a gravity model to estimate the main drivers of bilateral migration flows. The findings highlight the diverse factors influencing migration patterns, including geographical, cultural, demographic, and economic elements. Conflict-driven migration, particularly among refugees, significantly impacts immigration into emerging and developing economies. Additionally, according to their results income levels play a crucial role in shaping migration decisions, with both the income gap between origin and destination countries and the per capita incomes in each location influencing migration dynamics. Their further findings point out that nations with extremely low per capita income, even a small increase in income can elevate the rate of emigration. This suggests the existence of "poverty traps" that hinder very poor individuals from affording migration. However, once income surpasses a certain threshold, additional income growth tends to reduce emigration instead.

Another segment of the literature is grounded in neoclassical economics and neoclassical labor migration theory or push - pull models. Both focus on the motivations of potential migrants. The former assumes that individuals migrate primarily to maximize their lifetime earnings, while the latter posits that migration is a temporary strategy to overcome market constraints in home countries (Massey, 2015). In that light, Lee's (1966) analysis of migration determinants outlines a range of variables categorized into four groups: those related to the country of origin; those associated with the destination country; intervening obstacles and personal factors. Within these categories, factors are further classified into push factors (unbearable or threatening conditions in the home country) and pull factors (incentives in the host countries). Many studies consider both push and pull factors, seeking to understand why individuals leave their country of origin and why they select specific destinations for immigration. However, when using net migration flows as a dependent variable, as we do, it is possible to look at the independent variables (such as GDP per capita, unemployment rate etc.) as both push and pull factors - depending on whether there has been net emigration or net immigration for a certain country and a certain year.

Subsequent literature has traditionally categorized migration determinants into three broad categories (Schmeidl, 1997, as cited in Kuhnt, 2019): (a) root causes, (b) proximate conditions, and (c) intervening factors. Root causes refer to structural, long-term factors, primarily of an economic nature, while proximate conditions encompass factors that have the most significant influence on migration decisions immediately before the move (e.g., political stability, existence of conflict). Intervening factors introduce supplementary elements such as migration traditions, diaspora, migrant networks and so on.

An alternative theoretical framework for migration determinants was developed by Timmerman et al. (Timmerman, Heyse andVan Mol, C. 2010; Timmerman, De Clerck, Hemmerechts, and Willems, 2014) and further refined by Kuhnt (2019) and others. At its core, this approach divides migration determinants into three levels: macro, meso, and micro. One of the strengths of this model is that it allows for the analysis of the same factors in both source and destination countries, as well as accounting for both voluntary and forced migration, alongside migration aspirations and capabilities. The macro level includes factors that affect the entire population of a country, while the micro level focuses on individual, idiosyncratic characteristics of potential migrants. Kuhnt (2019) identifies the most critical macro-level determinants as: violence and conflict; institutions, welfare state, and state fragility; economic opportunities and security; poverty and development; development-induced displacement; migration policies, and environmental changes. At the micro level, factors such as age, educational attainment, gender, risk aversion, and personality traits are emphasized. The meso level comprises subnational or local factors such as migration culture, networks and information, technology, geography and infrastructure, and the role of migrant smugglers. The same study, in a comprehensive review, concludes that the literature consistently finds macro-level factors to be the most influential, with meso- and micro-level determinants playing a supplementary role. This aligns with the approach we adopted in developing the research design for this paper.

Most of the empirical analyses focus on specific country when estimating the migration determinants. There are few studies which focus on regions or the world. Drazenovic, Kunovac and Pripuzic (2018) and Franc et al. (2019) estimate push and pull factors by using fixed effects model to estimate the migration flows from new EU members to "core" EU countries for period 2000-2016. Trpkova-Nestorovska (2019) focuses only on push factors to analyse the emigration determinants in 28 EU countries for the period 1999-2017. Her results imply that emigration is driven by unemployment rate, total population, young male and young female population, while level of corruption, GDP per capita and enrolment in tertiary education do not have statistically significant impact on emigration in the countries of the European Union, according to her analysis. All above mentioned studies focus on EU countries and fail to control for dynamic character of migration and to estimate the significance of belonging to different income-group.

Crippa, Giorgio, Dunne and Luca (2022) investigate the effect of conflicts on migration on the world level data and find

a large effect of conflict on net migration for low-income countries. Their study, however, does not control for other relevant emigration determinants (such as GDP, unemployment) and uses UN migration dataset which has the migration data in five-year sequences. Nielsen (2007) focused also only on push factors in emigration to determine the main brain drain determinants in year 2000 and he used macroeconomic variables in his empirical analysis. He conducted OLS analysis on 105 countries to estimate the effect of GNI per capita, purchasing power parity (as proxies for income), foreign direct investments, polity (democracy and autocracy scores assigned to each state by the Polity IV Project), government spending on education (as a proxy for educational opportunities), CIRI index for physical integrity (as a proxy for level of violence) and level of education on emigration rates. However, he did not get robust results, presumably due to shortcomings in the data for primary and secondary education and due to focus on one year only. Nejad and Young (2016) also focused on macroeconomic determinants of migration and observed 77 countries over 1990-2000 period. They focused on exploring migration self-selection according to institutional quality. They applied OLS and Poisson pseudo-maximum likelihood method (PPML) to gravity model specifications as they were interested in determinants of bilateral migration flows. Their results imply that increases in economic freedom are significantly attractive to potential migrants, while relative political freedoms are not significant once economic freedom is controlled for. However, they do not cover period of the last 20 years which include important world happenings, such as Global financial crises and pandemic. They also fail to control for important determinants such as war/conflict in the country people are emigrating from and the unemployment rate, which are considered to be important push factors.

Great deal of studies aiming to identify the determinants of emigration primarily rely on survey data, basing their analyses on individual responses. The advantages of utilizing survey data lie in the ability to control for respondents' characteristics and take their direct opinions into account. However, when investigating differences across a large number of countries and/or changes over an extended period within a single country, survey data may not be feasible. Firstly, surveys with identical questions are not universally available across all countries or over extended periods within countries, making cross-country and longitudinal comparisons challenging. Moreover, individuals from different countries may perceive similar situations differently based on their distinct individual experiences and knowledge, potentially leading to subjective interpretations. For instance, individuals may perceive their country's situation negatively if compared to neighbouring countries, despite it being relatively favourable on a global scale. Utilizing macroeconomic data enables more objective comparisons of the impacts of countries' characteristics on emigration on global level. By employing macroeconomic data spanning a 32-year period, we can observe the effects of changes within countries and the impacts of events like wars and conflicts, and changes in the level of development and employment opportunities, on emigration. Taking all these factors into consideration, there is a strong argument for the importance of using macroeconomic data in research seeking to discern differences between countries and within countries over time. Finally, surveys typically only capture a small portion of the citizens, making national data more representative of the entire population.

The main interest of this research is to assess the effect of the *level of development* on net migration flows. Theory clearly recognize differences in various components of economic development between origin and destination countries as one of the primary determinant(s) of migration. These differences are in the core of neoclassical migration theory and push-pull models of migration (see, for example, Borjas, 1990; Lee, 1996). However, empirical evidence has been mixed (Kuhnt, 2019). IMF (2020) and numerous other studies identify and quantify existence of *migration hump*, a phenomenon that reflects discontinuous relation between migration aspiration and capabilities on one side and economic development of a nation on another. In other words, for low-income populations caught in a poverty trap, a marginal increase in the level of development in their home country is not sufficient to deter migration; rather, it facilitates migration to destinations with higher income or other forms of development. Once a upper-level of income threshold is reached, the negative proportional relationship between the level of development and emigration is restored. Given this, both theoretical and empirical evidence consistently and unequivocally indicate that levels of development are crucial determinants of migration, whether as part of the root-causes group in traditional literature or as macro factors in more recent studies.

We utilize macro and micro level of migration determinants within a push-pull framework to identify the crucial drivers of migration. The literature predominantly supports this approach - justifying the omission of meso-level factors. This allows us to account for both global features and national-level characteristics of countries (such as the presence or absence of conflicts, employment opportunities, development levels, political stability, and demographic dynamics) and to analyze their interconnections in order to discern variations in emigration drivers across countries. Additionally, we examine both major components of migration: voluntary and forced migration, which was often missing in traditional approach in the literature. The expanded scope of our research design represents a clear improvement over much of the existing literature, which tends to be narrowly focused and traditionally addresses only one of these migration categories. Moreover, due to the specific construction of the variables we employ, we are able to jointly capture the

effects of both migration aspirations and capabilities.

Our study has a global scope, covering all available countries (a total of 192), over a 32-year period, allowing us to effectively capture the impact of differences in the level of development, the effect of change in GDP growth and other relevant potential determinants. We also estimate the potential differences between poor countries and the those with middle, upper and high income and the differences in the effect of GDP per capita depending to which income group countries belong to. Accordingly, the model is specified.

3. Model, Data and Methodology

We use World Development Indicator (WDI) dataset for most of macroeconomic indicators in the model. These are macro, secondary, longitudinal data in contrast to the dyadic data mostly used in gravity models of migration. The WDI database on migration, with sample of 194 countries, spanning over the period from 1973 until 2022, split in five-year sequences, records migration stocks which serve as an adequate proxy for migration flows (Beine et al., 2016). Also, given the global scope of our study, the choice to use macro, aggregate, statistical data is justified (Aslany et al. 2021).

The dependent variable is net emigration share in population (EMIG) from the World Development Indicator (WDI) dataset. We form a variable so that it is positive when emigration is higher than immigration and negative when immigration is higher; therefore, positive sign of independent variable means that emigration is increasing when the independent variable is increasing. To determine the main independent variables, we begin with traditional migration factors and include root-cause macroeconomic variables and proximate factors (e.g., political stability). These variables are then integrated into the macro- and micro-level framework proposed by Timmerman et al. (2010).

To control for the level of development we use GDP per capita (GDPPC) and expect its negative effect on emigration as people from more developed countries tend to emigrate less than those in less developed ones. Additionally, we include categorical variable which represent income group to which each country belongs to check for the differences between countries that belong to different income groups. This variable is created according to World Bank (WB) classification based on GNI per capita which reflects country's level of development:

- 1 for low-income country group, to which countries with a gross national income (GNI) per capita of $1,135 or less belong to;

- 2 for lower-middle-income country group, to which countries with a GNI per capita between $1,136 and $4,465 belong to;

- 3 for upper-middle-income country group, to which countries with a GNI per capita between $4,466 and $13,845 in 2022 belong to;

- 4 for high-income country group, to which countries with a GNI per capita of $13,846 or more belong to.

To capture the effect of *lack of economic opportunities* we use data for unemployment rate (UNR) and economic growth (GDPG). We expect positive effect of unemployment on emigration since people tend to emigrate if they cannot find job in their country. The data for unemployment rate is from World Development Indicator database and is available for most of the countries from 1990. We expect GDP growth to have negative effect as higher growth should lower the emigration.

Demographic factors are captured by data on the percentage of people with higher education (EDU) and aging population variable (AP). The expected effect of education is positive as more educated people tend to emigrate more (as they are usually more aware of possibilities outside their country and they have more opportunities in other countries). Aging population variable is defined as percentage of 65+ in whole population and we expect positive sign as the older the population is the more (young) people tend to leave their countries of origin.

Further, we capture the effect of *political stability*, which is also likely to force people to emigrate, by using World governance indicator (WGI) about political stability and lack of violence (PS). This variable measures perceptions of the likelihood of political instability and/or politically motivated violence, including terrorism.

Additional political and social factors could be proxied by other World governance indicators such as measures of voice and accountability (VAA), rule of law (ROL), government effectiveness (GE) and control of corruption (CORR) but these variables are highly correlated with GDP per capita so we do not include them[1]. When included in the regression they turned out as insignificant. Furthermore, inadequate access to education and healthcare services may motivate individuals to emigrate to places with better opportunities for education and health so we capture this effect by including the data for government spending on education and healthcare (GEE and GEH, respectively). However, these

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[1] VIF test for multicollinearity indicates variance inflation factor higher than 10 for ROL, GE and CORR variables (Appendix)

variables are also highly correlated with GDP per capita and are highly insignificant when included so we do not include them in our preferred specification.

Additionally, we add forced migration indicator to the mix by controlling for *war and conflict* through including conflict variable from Uppsala Conflict Data Program database. Traditional literature almost always focuses on one or the other, so including them together in the model we use is another important upgrade in existing approaches.

Finally, we include two dummy variables to capture the group effect: Europe and EU, to see whether there is a difference between these groups of the countries and the rest of the world.

$$EMIG_{i,t} = \alpha_0 + \alpha_1 UNR_{i,t} + \alpha_2 GDPPC_{i,t} + \alpha_3 EDU_{i,t} + \alpha_4 GDPG_{i,t} + \alpha_5 AP_{i,t} + \alpha_5 PS_{i,t} + \alpha_6 CONFLICT_{i,t} + \alpha_7 EUROPE_{i,t} + \alpha_8 EU_{i,t} (+ \alpha_9 INCOME\_CATEGORY_{i,t}) + \gamma_t + \varepsilon_{i,t} \tag{1}$$

First, we estimate the model by using pooled OLS (Equation 1) and include time dummy variables (period fixed effects - γ_t) in order to control for "migration shocks", which are usually caused by violent conflicts. However, as we cannot expect to capture all countries' specifics by the exogenous variables we should control for the country effects which is not done within pooled OLS. Migration trends differ between the countries and country specifics should be taken into account when analysing emigration determinants. In order to account for the countries' effects (u_i) a fixed effects (FE) model is next utilised (Equation 2).

$$EMIG_{i,t} = \alpha_0 + \alpha_1 UNR_{i,t} + \alpha_2 GDPPC_{i,t} + \alpha_3 EDU_{i,t} + \alpha_4 GDPG_{i,t} + \alpha_5 AP_{i,t} + \alpha_5 PS_{i,t} + \alpha_6 CONFLICT_{i,t} + \alpha_7 EUROPE_{i,t} + \alpha_8 EU_{i,t} (+ \alpha_9 INCOME\_CATEGORY_{i,t}) + \gamma_t + u_i + \varepsilon_{i,t} \tag{2}$$

Since past migration might affect the current flows of migration (which will also be tested through serial correlation test after FE estimation) we control for the past effects by using GMM dynamic panel model (Equation 3).

$$EMIG_{i,t} = \alpha_0 + \alpha_1 EMIG_{i,t-1} + \alpha_2 UNR_{i,t} + \alpha_3 GDPPC_{i,t} + \alpha_4 EDU_{i,t} + \alpha_5 GDPG_{i,t} + \alpha_6 AP_{i,t} + \alpha_7 PS_{i,t} + \alpha_8 CONFLICT_{i,t} + \alpha_9 EUROPE_{i,t} + \alpha_{10} EU_{i,t} (+ \alpha_{11} INCOME\_CATEGORY_{i,t}) + \gamma_t + \varepsilon_{i,t} \tag{3}$$

where $\varepsilon_{i,t} = u_i + v_{i,t}$ (u_i is a group-specific effect and $v_{i,t}$ is a white noise)

Advantages of the GMM are that distributional assumptions, such as normality, are not required and that it enables us to control for unobserved heterogeneity of the same countries over time (Verbeek, 2000). We use the Arellano-Bover/Blundell-Bond (so called 'system' GMM) that builds a system of two equations: a difference equation which is instrumented by levels; and a levels equation instrumented by first differences. The 'system' GMM is more comprehensive than "difference" GMM, since lagged levels (used in 'difference' GMM) are argued to be rather poor instruments for first differenced variables, especially for variables that are close to a random walk, which is frequently the case with macroeconomic variables (Baum, 2006, p.234).

$$EMIG_{i,t} = \alpha_0 + \alpha_1 EMIG_{i,t-1} + \alpha_2 UNR_{i,t} + \alpha_3 GDPPC_{i,t} + \alpha_4 EDU_{i,t} + \alpha_5 GDPG_{i,t} + \alpha_6 AP_{i,t} + \alpha_7 PS_{i,t} + \alpha_8 CONFLICT_{i,t} + \alpha_9 EUROPE_{i,t} + \alpha_{10} EU_{i,t} + \alpha_{11} INCOME\_CATEGORY_{i,t} + \alpha_{12} GDPG_{i,t}*INCOME\_CATEGORY_{i,t} + \gamma_t + \varepsilon_{i,t} \tag{4}$$

Finally, we investigate the effect of the interaction term between GDP per capita and income group variables in order to test for the potential difference in the effect of GDP per capita depending on the income-group the country belong to.

4. Discussion of the Results

We start with the pooled OLS estimation and the results suggest, as expected, negative effect of GDP growth and GDP per capita, implying that, on average, the higher the level of development and the higher the growth are the lower net emigration will be. The results on the additional variable INCOME_CATEGORY, for which the base category (1) is low-income country group suggest the higher the income group the lower the net emigration flow (OLS results are presented in the second and third column in Table 1). However, these results might be biased as diagnostic tests indicate that the assumptions of normality, linearity and homoscedasticity cannot be accepted at all conventional levels of significance (Appendix 1). Furthermore, we cannot expect to capture all countries' specifics by the exogenous variables (which is the case with pooled OLS), so we next control for the country effects by estimating the fixed effects (FE) model (Equation 2). The results have the same implications as those after the OLS estimation (see Table 1).

Table 1. The results from the static estimations (OLS and FE)

	(OLS no income group)	(OLS with income group)	(FE no income group)	(FE with income group)
Dependent variable: Net migration flows				
UNR	0.0109***	0.0122***	0.0247***	0.0222***
Unemployment rate	(0.00284)	(0.00284)	(0.00611)	(0.00627)
GDPPC	-1.66e-05***	-1.06e-05***	-7.41e-06***	-8.08e-06***
GDP per capita	(1.10e-06)	(1.38e-06)	(2.58e-06)	(2.63e-06)
EDU	0.00127	0.00425***	0.00155	0.00234
Education	(0.000840)	(0.000858)	(0.00170)	(0.00174)
AP	0.00569***	0.00250**	0.0126***	0.0123***
Aging population	(0.00112)	(0.00127)	(0.00313)	(0.00318)
GDPG	-0.0162***	-0.0169***	-0.00977***	-0.00984***
GDP growth	(0.00376)	(0.00320)	(0.00351)	(0.00351)
EUROPE	0.365***	0.288***		
1 if country is in Europe	(0.0486)	(0.0484)		
EU	-0.279***	-0.146***		
1 if country is EU member	(0.0530)	(0.0548)		
PS	-0.0188	0.0216	-0.00593	0.0125
Political stability	(0.0250)	(0.0245)	(0.0430)	(0.0435)
CONFLICT	-0.138***	-0.121**	0.0768	0.0871
1 if country had conflict in certain year	(0.0513)	(0.0500)	(0.0630)	(0.0629)
INCOME CATEGORY (Base category: low income countries)				
2.INCOME_CATEGORY		-0.0910*		-0.152**
Lower-middle income		(0.0509)		(0.0661)
3.INCOME_CATEGORY		-0.426***		-0.245**
Upper-middle income		(0.0645)		(0.0972)
4.INCOME_CATEGORY		-0.682***		-0.484***
High income		(0.0874)		(0.130)
Time dummies	yes	yes	yes	yes
Constant	-0.111	0.0817	-0.780***	-0.486**
	(0.125)	(0.116)	(0.218)	(0.246)
Observations	2 666	2 666	2 666	2 666
R-squared	0.180	0.201	0.034	0.040
Number of countries			168	168

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Alternatively, we could use the random effects instead of fixed effect estimation. When estimating the model with random effects the results are very similar and Hausman test indicating that there is no significant difference between the two, so the fixed effect results are only presented. Moreover, the random effects require the strict exogeneity of regressors and orthogonality between regressors and unit effects, which is a rarely-fulfilled condition. As Plumper and Troeger (2004, p.6) argued: "the real world data rarely satisfied the conditions under which RE estimators are consistent". Controlling for robust standard errors and cluster robust standard errors did not alter the findings, underscoring their stability. However, the test for serial correlation after fixed effects (FE) estimation suggests that serial correlation may be a concern, indicating a systematic relationship between observations within a sequence. To address these dynamics, we employ the Generalized Method of Moments (GMM) next.

All GMM techniques for estimating dynamic panel models are argued to be suitable for panels with wide cross section (N) and shorter time series (T), which is the case with our sample (168 countries and 32 years of data). We treat aging population, unemployment rate, and GDP growth as endogenous variables as it could be argued that there is simultaneity with the dependent variable: when emigration from the country is high the population tend to be older (Zimmermann, 1995), unemployment rate decreases as mostly unemployed people leave the country (Hatton and Williamson, 1998) and GDP growth might decrease with the increase in emigration (Faini, 2007)

Hansen test suggests that the instruments used in the system GMM estimation are valid and not correlated with the error term (Appendix)[2]. Moreover, tests for the first (m1) and second order autocorrelation (m2) suggest no problem with autocorrelation in the difference residuals, which is consistent with instrument validity[3]. Finally, we investigated the

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[2] Sargan test is not heteroskedasticity robust, which is why the Hansen test – which is heteroskedasticity-robust - is usually preferred (except, possibly, when the number of instruments is "too many" in relation to the number of groups).

[3] The m2+m1 procedure requires rejection of the null of m1, meaning that there is first-order autocorrelation, and

effect of the interaction term between GDP per capita and income group variables (Equation 4) in order to test for the potential difference in the effect of GDP per capita depending on the income-group the country belong to, but it was highly insignificant in all estimations, so we do not report the results from this estimation.

Table 2. The results of the dynamic estimation

	(GMM no income group and time dummies)	(GMM with income group and time dummies)
Dependent variable: Net migration flows		
L.EMIG	0.446***	0.445***
Lagged net migration flows	(0.104)	(0.100)
UNR	0.0190	0.0146
Unemployment rate	(0.0165)	(0.0122)
GDPPC	-8.08e-06***	-5.46e-06***
GDP per capita	(2.48e-06)	(2.04e-06)
EDU	0.00198	0.00279**
Education	(0.00136)	(0.00126)
AP	0.00907**	0.00632
Aging population	(0.00406)	(0.00455)
GDPG	-0.00434	-0.00855*
GDP growth	(0.00603)	(0.00464)
EUROPE	0.180	0.152
1 if country is in Europe	(0.122)	(0.103)
EU	-0.177*	-0.111
1 if country is EU member	(0.0989)	(0.0847)
PS	0.0530	0.0575*
Political stability	(0.0399)	(0.0342)
CONFLICT	0.0633	0.0638
1 if country had conflict in certain year	(0.0928)	(0.0870)
INCOME CATEGORY (Base category: low income countries)		
2.INCOME_CATEGORY		0.00149
Lower-middle income		(0.0601)
3.INCOME_CATEGORY		-0.150*
Upper-middle income		(0.0892)
4.INCOME_CATEGORY		-0.280***
High income		(0.0981)
Constant	0	-0.403
	(0)	(0.407)
Time dummies included		
Observations	2,657	2,657
Number of countries	168	168

Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

The significance of the lagged dependent variable suggests that past migration trends are likely to affect current migration flows and that dynamic model should be applied. Other results of interest are similar to those from the static estimations. They again imply significant and negative relationship between GDP per capita and net emigration flows (Table 2). The findings presented in the third column, which include the income group variable, indicate that there is a lower probability of emigration from countries that belong to upper-middle and high-income countries compared to low-income countries. By demonstrating that migration behaviour varies significantly across income groups, the results seem to confirm the existence of the "migration hump". The statistical significance of other results differs depending on the model specification and the estimation method but the signs are consistent and will be briefly discussed next.

Findings on the relationship between GDP growth and migration are particularly insightful. They show a consistent negative relationship between GDP growth and net migration, indicating that higher economic growth tends to reduce emigration. This is a crucial finding for policymakers aiming to mitigate migration pressures through economic

---

"acceptance" of m2 null, meaning that there is no second-order autocorrelation; conditions which are satisfied in all specifications.

development. It suggests that policies focused on fostering economic growth and creating employment opportunities can be effective in reducing emigration. Nonetheless, the results also indicate that this effect is not uniform across all countries, with low-income countries experiencing a different migration trajectory compared to middle- and high-income countries, which is consistent with findings regarding the role of development levels discussed above.

The results indicate that higher unemployment rates in origin countries are associated with increased emigration, which expectedly promotes unemployment as one of the key "push factors" in migration. Therefore, policies aimed at reducing unemployment, particularly among young and skilled workers, could have a significant impact on emigration rates. We also find that education levels are positively associated with emigration, reinforcing the notion that skilled and educated individuals are more likely and in better position to migrate. This presents a challenge for developing countries that are already struggling with "brain drain" as they lose valuable human capital to more developed economies.

The inclusion of political stability and conflict variables adds depth to the findings by acknowledging that migration is not solely driven by economic factors. Political instability, violence, and conflict are significant drivers of forced migration, as individuals flee their countries in search of safety. While the effects of political stability and conflict on migration were not as statistically robust in all models, their inclusion is still important for understanding the broader context of migration, particularly in regions experiencing significant political unrest or war. This suggests that policies aimed at reducing migration must also address political and security concerns, particularly in conflict-prone regions. Development policies that focus solely on economic growth without addressing political stability and governance issues may not be sufficient to reduce migration pressures.

Regarding the aging population variable, the results indicate a positive relationship with net emigration, suggesting that countries with a higher proportion of elderly individuals experience higher emigration rates. This can be interpreted as an indirect effect of population dynamics where younger, economically active individuals tend to emigrate, leaving behind an aging population. The youth, in pursuit of better opportunities abroad, contribute to a demographic imbalance in their home countries. As the working-age population decreases, the relative proportion of older people increases, exacerbating the vicious cycle spiral. The departure of the younger workforce could also reduce economic vibrancy, creating a cycle where the remaining population is older, leading to further emigration pressures. This finding highlights the long-term demographic challenges associated with emigration, especially in countries already facing population aging.

However, several limitations of the study should be addressed. The exclusion of governance indicators—such as corruption, rule of law, and accountability—due to multicollinearity with GDP per capita may limit the comprehensiveness of the analysis. These factors are known to play a crucial role in shaping migration decisions, particularly in low- and middle-income countries, where weak institutions and corruption often exacerbate economic and political instability. Moreover, future research should attempt to fill the gap in understanding relative position and importance in the hierarchy of various migration determinants. Moreover, it would be useful to distinguish between voluntary and non-voluntary migration since the determinants are likely to differ. While we refrained from pursuing this due to the limitations of available data and existing theoretical frameworks, addressing this gap could provide valuable insights into the complex interplay between migration drivers.

5. Conclusion

In this paper we have conducted a comprehensive examination of the macroeconomic determinants of global migration, using an extensive dataset spanning 192 countries and 32 years. By using both static and dynamic panel models, the analysis captures the complexities of migration flows while considering a wide array of factors such as GDP per capita, unemployment, education, political stability, and conflict. Moreover, the study effectively captures the differential impact of income groups on migration behaviors, adding nuance to the existing literature on migration economics.

The study provides robust evidence that economic development, demographics, and political factors are among key drivers of global migration. The findings suggest that policies aimed at reducing migration should focus on fostering economic growth, creating job opportunities, and addressing political instability in origin countries. However, the results also indicate that migration behaviour is complex and varies across different income groups and regions, highlighting the need for targeted, context-specific policy interventions. While economic development is essential for reducing migration pressures, policymakers must also consider the broader social, political, and institutional factors that influence migration decisions. Future research should continue to explore these complexities, particularly by integrating micro-level data and addressing the governance challenges that shape migration trends.

Authors' contributions

Dr. Duraković was responsible for study design and revisions, while Prof. Kršo oversaw data collection and preparation. Both authors collaboratively drafted and revised the manuscript. We have jointly read and approved the final version.

Competing interests

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

Informed consent

Obtained.

Ethics approval

The Publication Ethics Committee of the Redfame Publishing.

The journal's policies adhere to the Core Practices established by the Committee on Publication Ethics (COPE).

Provenance and peer review

Not commissioned; externally double-blind peer reviewed.

Data availability statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Data sharing statement

No additional data are available.

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Appendix 1. - Stata outputs

VIF (testing for multicollinearity)

```
    Variable |       VIF       1/VIF
-------------+----------------------
         rol |     20.72    0.048273
          ge |     14.89    0.067142
        corr |     12.96    0.077179
          ps |      3.84    0.260307
         vaa |      3.71    0.269748
       gdppc |      3.25    0.307846
      europe |      2.61    0.382545
         edu |      2.60    0.384877
          eu |      2.43    0.410823
          ap |      2.30    0.434266
    conflict |      1.59    0.628769
         unr |      1.30    0.767838
        gdpg |      1.10    0.912040
-------------+----------------------
    Mean VIF |      5.64
```

OLS estimation (low income base category for income category)

```
. reg emig unr gdppc edu ap gdpg europe eu ps conflict ib1.income_category

      Source |       SS           df       MS      Number of obs   =     2,701
-------------+----------------------------------   F(12, 2688)     =     70.32
       Model |  810.358608         12  67.529884   Prob > F        =    0.0000
    Residual |  2581.40147      2,688  .960342808   R-squared       =    0.2389
-------------+----------------------------------   Adj R-squared   =    0.2355
       Total |  3391.76007      2,700  1.25620744   Root MSE        =    .97997

--------------------------------------------------------------------------------
        emig |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+------------------------------------------------------------------
         unr |   .0126759   .0037771     3.36   0.001     .0052696    .0200823
       gdppc |  -.0000183   1.77e-06   -10.34   0.000    -.0000218   -.0000148
         edu |   .0095245   .0011056     8.61   0.000     .0073566    .0116925
          ap |    .009391   .0016283     5.77   0.000     .0061981    .0125838
        gdpg |  -.0423268   .0041231   -10.27   0.000    -.0504116   -.0342419
      europe |   .3585847   .0643098     5.58   0.000     .2324831    .4846863
          eu |  -.1348442   .0729093    -1.85   0.064    -.2778081    .0081197
          ps |   .0158496   .0324139     0.49   0.625     -.047709    .0794083
    conflict |  -.0919341   .0664615    -1.38   0.167    -.2222549    .0383868
             |
income_category |
           2 |  -.0764098   .0673535    -1.13   0.257    -.2084797    .0556601
           3 |  -.4483035   .0847769    -5.29   0.000    -.6145381   -.2820689
           4 |  -.6990381   .1153611    -6.06   0.000    -.9252436   -.4728326
             |
       _cons |  -.3820449   .1487415    -2.57   0.010    -.6737042   -.0903855
--------------------------------------------------------------------------------


. *Diagnostic tests after OLS
```

```
. estat imtest

Cameron & Trivedi's decomposition of IM-test

---------------------------------------------------
            Source |     chi2     df      p
-------------------+-------------------------------
 Heteroskedasticity |    731.33     78   0.0000
          Skewness |    116.61     12   0.0000
          Kurtosis |      4.31      1   0.0378
-------------------+-------------------------------
             Total |    852.25     91   0.0000
---------------------------------------------------


. estat hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
        Ho: Constant variance
        Variables: fitted values of emig


        chi2(1)      =   3696.43
        Prob > chi2  =    0.0000

. estat ovtest

Ramsey RESET test using powers of the fitted values of emig
      Ho:  model has no omitted variables
            F(3, 2685) =    140.63
              Prob > F =      0.0000

. predict resid1, residuals
(3,389 missing values generated)


. kdensity resid1, normal
```

```
. xi: reg emig unr gdppc edu ap gdpg europe eu ps conflict ib1.income_category i.year
i.year          _Iyear_1990-2022   (naturally coded; _Iyear_1990 omitted)
note: _Iyear_1991 omitted because of collinearity
note: _Iyear_1992 omitted because of collinearity
note: _Iyear_1993 omitted because of collinearity
note: _Iyear_1994 omitted because of collinearity
note: _Iyear_1995 omitted because of collinearity
note: _Iyear_1997 omitted because of collinearity
note: _Iyear_1999 omitted because of collinearity
note: _Iyear_2001 omitted because of collinearity
note: _Iyear_2021 omitted because of collinearity
note: _Iyear_2022 omitted because of collinearity
      Source |       SS           df       MS      Number of obs   =     2,701
-------------+---------------------------------   F(34, 2666)     =     25.76
       Model | 838.624224         34  24.6654184   Prob > F        =    0.0000
    Residual | 2553.13585      2,666   .95766536   R-squared       =    0.2473
-------------+---------------------------------   Adj R-squared   =    0.2377
       Total | 3391.76007      2,700  1.25620744   Root MSE        =     .9786
```

```
--------------------------------------------------------------------------------
        emig |    Coef.   Std. Err.     t    P>|t|     [95% Conf. Interval]
-------------+------------------------------------------------------------------
         unr |  .0122448    .003822    3.20   0.001     .0047505    .0197392
       gdppc |  -.0000189  1.79e-06  -10.54   0.000    -.0000224   -.0000153
         edu |  .0092901   .0011411    8.14   0.000     .0070527    .0115275
          ap |  .0089703   .0016334    5.49   0.000     .0057675    .0121731
        gdpg |  -.0491088  .0047237  -10.40   0.000    -.0583713   -.0398464
      europe |  .3660399   .0646984    5.66   0.000     .2391758    .4929039
          eu |  -.1383644  .0728698   -1.90   0.058    -.2812515    .0045226
          ps |  .0289195   .0333443    0.87   0.386    -.0364638    .0943027
    conflict |  -.0694556  .0671505   -1.03   0.301     -.201128    .0622168
             |
income_category |
           2 |  -.093713   .0681585   -1.37   0.169    -.2273619    .0399358
           3 |  -.481338   .0858946   -5.60   0.000    -.6497648   -.3129112
           4 |  -.7281532  .1156463   -6.30   0.000    -.9549187   -.5013878
             |
 _Iyear_1991 |        0   (omitted)
 _Iyear_1992 |        0   (omitted)
 _Iyear_1993 |        0   (omitted)
 _Iyear_1994 |        0   (omitted)
 _Iyear_1995 |        0   (omitted)
 _Iyear_1996 |  -.1382299  .1443338   -0.96   0.338    -.4212474    .1447876
 _Iyear_1997 |        0   (omitted)
 _Iyear_1998 |  -.3000538   .151633   -1.98   0.048    -.5973841   -.0027236
 _Iyear_1999 |        0   (omitted)
 _Iyear_2000 |  -.2712934  .1402548   -1.93   0.053    -.5463125    .0037258
 _Iyear_2001 |        0   (omitted)
 _Iyear_2002 |  -.3736452  .1373904   -2.72   0.007    -.6430477   -.1042428
 _Iyear_2003 |  -.2868907  .1351836   -2.12   0.034     -.551966   -.0218154
 _Iyear_2004 |  -.1143137  .1348385   -0.85   0.397    -.3787123    .1500848
 _Iyear_2005 |  -.3155858  .1351397   -2.34   0.020     -.580575   -.0505966
 _Iyear_2006 |  -.3948061  .1350232   -2.92   0.003    -.6595669   -.1300453
 _Iyear_2007 |  -.2238934  .1350638   -1.66   0.097    -.4887338     .040947
 _Iyear_2008 |  -.1627445  .1346248   -1.21   0.227    -.4267241    .1012351
 _Iyear_2009 |  -.3856078  .1367636   -2.82   0.005    -.6537812   -.1174343
 _Iyear_2010 |   -.138532  .1318945   -1.05   0.294     -.397158    .1200939
 _Iyear_2011 |  -.1462895  .1313599   -1.11   0.266    -.4038671     .111288
 _Iyear_2012 |  -.1366983  .1318124   -1.04   0.300    -.3951633    .1217666
 _Iyear_2013 |   -.245719  .1320803   -1.86   0.063    -.5047093    .0132713
 _Iyear_2014 |  -.2278071  .1322851   -1.72   0.085    -.4871989    .0315847
 _Iyear_2015 |  -.3672437  .1307762   -2.81   0.005    -.6236766   -.1108107
 _Iyear_2016 |  -.2841313  .1316671   -2.16   0.031    -.5423113   -.0259513
 _Iyear_2017 |  -.2769934  .1313699   -2.11   0.035    -.5345906   -.0193963
 _Iyear_2018 |  -.2182535  .1315437   -1.66   0.097    -.4761915    .0396846
 _Iyear_2019 |  -.1859774  .1324785   -1.40   0.160    -.4457484    .0737936
 _Iyear_2020 |  -.4690701  .1416418   -3.31   0.001     -.746809   -.1913312
 _Iyear_2021 |        0   (omitted)
 _Iyear_2022 |        0   (omitted)
       _cons |  -.0483068   .187833   -0.26   0.797      -.41662    .3200063
--------------------------------------------------------------------------------


. estat hettest
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
       Ho: Constant variance
       Variables: fitted values of emig


       chi2(1)    = 3965.94
       Prob > chi2 =  0.0000


. estat ovtest

Ramsey RESET test using powers of the fitted values of emig
     Ho:  model has no omitted variables
           F(3, 2663) =   187.21
             Prob > F =      0.0000




. xi: xtreg emig unr gdppc edu ap gdpg europe eu ps conflict ib1.income_category i.year, fe
i.year         _Iyear_1990-2022   (naturally coded; _Iyear_1990 omitted)
note: europe omitted because of collinearity
note: eu omitted because of collinearity
note: _Iyear_1991 omitted because of collinearity
note: _Iyear_1992 omitted because of collinearity
note: _Iyear_1993 omitted because of collinearity
note: _Iyear_1994 omitted because of collinearity
note: _Iyear_1995 omitted because of collinearity
note: _Iyear_1997 omitted because of collinearity
note: _Iyear_1999 omitted because of collinearity
note: _Iyear_2001 omitted because of collinearity
note: _Iyear_2021 omitted because of collinearity
note: _Iyear_2022 omitted because of collinearity


Fixed-effects (within) regression              Number of obs    =    2,701
Group variable: countryno                      Number of groups =      170

R-sq:                                  Obs per group:
    within  = 0.0710                             min =        2
    between = 0.2423                             avg =     15.9
    overall = 0.1642                             max =       23

                                       F(32,2499)     =      5.97
corr(u_i, Xb) = -0.4754                    Prob > F       =     0.0000


------------------------------------------------------------------------------
       emig |    Coef.   Std. Err.     t    P>|t|    [95% Conf. Interval]
------------+-----------------------------------------------------------------
        unr | .0077829   .0083281    0.93   0.350   -.0085478   .0241136
      gdppc | -.0000182   3.32e-06  -5.49   0.000   -.0000247  -.0000117
        edu | .0031524   .0023202    1.36   0.174   -.0013973   .0077021
         ap | .0123196    .004214    2.92   0.003    .0040563    .020583
       gdpg | -.0335805  .0045262   -7.42   0.000   -.0424559  -.0247051
     europe |        0  (omitted)
         eu |        0  (omitted)
         ps | -.0982252  .0570591   -1.72   0.085   -.2101132   .0136627
   conflict | .1375893   .0837478    1.64   0.101    -.026633   .3018116
            |
```

```
income_category |
              2 |  -.3291572   .0871088   -3.78   0.000     -.49997   -.1583444
              3 |  -.6209859   .1261761   -4.92   0.000    -.8684063   -.3735655
              4 |  -.9232987   .1696045   -5.44   0.000    -1.255878    -.590719
                |
   _Iyear_1991 |          0  (omitted)
   _Iyear_1992 |          0  (omitted)
   _Iyear_1993 |          0  (omitted)
   _Iyear_1994 |          0  (omitted)
   _Iyear_1995 |          0  (omitted)
   _Iyear_1996 |  -.3703491    .158981   -2.33   0.020    -.6820972    -.058601
   _Iyear_1997 |          0  (omitted)
   _Iyear_1998 |  -.4894046   .1615314   -3.03   0.002    -.8061538   -.1726554
   _Iyear_1999 |          0  (omitted)
   _Iyear_2000 |  -.4885144   .1491699   -3.27   0.001    -.7810237    -.196005
   _Iyear_2001 |          0  (omitted)
   _Iyear_2002 |  -.4941417   .1421924   -3.48   0.001    -.7729688   -.2153146
   _Iyear_2003 |  -.4506978   .1374858   -3.28   0.001    -.7202955       -.1811
   _Iyear_2004 |  -.3163356   .1328342   -2.38   0.017    -.5768121   -.0558591
   _Iyear_2005 |  -.4751799   .1305302   -3.64   0.000    -.7311383   -.2192215
   _Iyear_2006 |  -.5521627   .1276942   -4.32   0.000    -.8025601   -.3017653
   _Iyear_2007 |     -.3657   .1254327   -2.92   0.004    -.6116627   -.1197374
   _Iyear_2008 |  -.2758122   .1234513   -2.23   0.026    -.5178895   -.0337349
   _Iyear_2009 |  -.4249045     .12558   -3.38   0.001     -.671156    -.178653
   _Iyear_2010 |  -.2609317   .1203213   -2.17   0.030    -.4968714    -.024992
   _Iyear_2011 |   -.220683   .1189208   -1.86   0.064    -.4538765    .0125105
   _Iyear_2012 |  -.1857992   .1187166   -1.57   0.118    -.4185921    .0469937
   _Iyear_2013 |  -.2787389   .1183095   -2.36   0.019    -.5107337   -.0467441
   _Iyear_2014 |  -.2644137   .1181887   -2.24   0.025    -.4961715   -.0326558
   _Iyear_2015 |  -.4015829    .117049   -3.43   0.001    -.6311059   -.1720598
   _Iyear_2016 |  -.3286805   .1175726   -2.80   0.005    -.5592303   -.0981307
   _Iyear_2017 |  -.2839469   .1166206   -2.43   0.015    -.5126297    -.055264
   _Iyear_2018 |  -.2274122    .116461   -1.95   0.051     -.455782    .0009577
   _Iyear_2019 |  -.1931526   .1174833   -1.64   0.100    -.4235271     .037222
   _Iyear_2020 |  -.3742352   .1265565   -2.96   0.003    -.6224016   -.1260688
   _Iyear_2021 |          0  (omitted)
   _Iyear_2022 |          0  (omitted)
          _cons |   .2580949   .3245546    0.80   0.427    -.3783286    .8945185
----------------+----------------------------------------------------------------
        sigma_u |  .75182877
        sigma_e |  .85308132
            rho |  .43716088   (fraction of variance due to u_i)
--------------------------------------------------------------------------------
F test that all u_i=0: F(169, 2499) = 6.25             Prob > F = 0.0000

. predict residfe1, residuals
(3,389 missing values generated)


. xtserial emig residfe1


Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,     151) =     32.707
           Prob > F =      0.0000


. *GMM
```

```
. xtabond2 emig L.emig unr gdppc edu ap gdpg europe eu ps conflict ib1.income_category, gmm(L.emig,
laglimits(1 1)) gmm(ap unr gd
> pg , laglimits (2 2)) iv(gdppc edu europe eu ps conflict ib1.income_category) robust
Favoring speed over space. To switch, type or click on mata: mata set matafavor space, perm.
Warning: Number of instruments may be large relative to number of observations.
Warning: Two-step estimated covariance matrix of moments is singular.
  Using a generalized inverse to calculate robust weighting matrix for Hansen test.
  Difference-in-Sargan/Hansen statistics may be negative.


Dynamic panel-data estimation, one-step system GMM
------------------------------------------------------------------------------
Group variable: countryno                  Number of obs      =      2692
Time variable : year                       Number of groups   =       170
Number of instruments = 178                Obs per group: min =         2
Wald chi2(14) =   658.56                                  avg =     15.84
Prob > chi2  =    0.000                                   max =        23
------------------------------------------------------------------------------
                 |              Robust
           emig |    Coef.   Std. Err.     z    P>|z|    [95% Conf. Interval]
-----------------+------------------------------------------------------------
           emig |
            L1. |  .633145    .092241    6.86   0.000    .4523559    .813934
                |
            unr |  .0012594   .0155868    0.08   0.936   -.0292903    .031809
          gdppc | -7.40e-06   3.07e-06   -2.41   0.016   -.0000134   -1.39e-06
            edu |  .0025216   .0014571    1.73   0.084   -.0003343   .0053775
             ap |  .0066331   .0060581    1.09   0.274   -.0052404   .0185067
           gdpg | -.0271469   .0111876   -2.43   0.015   -.0490743  -.0052196
         europe |  .1730331   .1030666    1.68   0.093   -.0289736   .3750398
             eu | -.0977694    .079608   -1.23   0.219   -.2537982   .0582595
             ps |  .0520142   .0325399    1.60   0.110   -.0117628   .1157912
       conflict |  .1119852   .0935114    1.20   0.231   -.0712938   .2952642
                |
income_category |
              1 |        0   (empty)
              2 |  .0484176   .1209223    0.40   0.689   -.1885857   .2854209
              3 | -.0625649   .1746278   -0.36   0.720   -.4048292   .2796994
              4 | -.1226092   .2046417   -0.60   0.549   -.5236995    .278481
                |
          _cons | -.3158106     .45642   -0.69   0.489   -1.210377   .5787561
------------------------------------------------------------------------------
Instruments for first differences equation
  Standard
    D.(gdppc edu europe eu ps conflict 1b.income_category 2.income_category
    3.income_category 4.income_category)
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L2.(ap unr gdpg)
    L.L.emig
Instruments for levels equation
  Standard
    gdppc edu europe eu ps conflict 1b.income_category 2.income_category
    3.income_category 4.income_category
    _cons
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    DL.(ap unr gdpg)
    D.L.emig
```

```
-------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -2.11  Pr > z =  0.035
Arellano-Bond test for AR(2) in first differences: z =   0.05  Pr > z =  0.958
-------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(163) = 844.79  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(163) = 163.74  Prob > chi2 =  0.469
  (Robust, but weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:
  GMM instruments for levels
    Hansen test excluding group:    chi2(71)  = 110.05  Prob > chi2 =  0.002
    Difference (null H = exogenous): chi2(92)  =  53.69  Prob > chi2 =  1.000
  gmm(L.emig, lag(1 1))
    Hansen test excluding group:    chi2(121) = 135.65  Prob > chi2 =  0.171
    Difference (null H = exogenous): chi2(42)  =  28.09  Prob > chi2 =  0.951
  gmm(ap unr gdpg, lag(2 2))
    Hansen test excluding group:    chi2(37)  =  48.06  Prob > chi2 =  0.105
    Difference (null H = exogenous): chi2(126) = 115.68  Prob > chi2 =  0.735
  iv(gdppc edu europe eu ps conflict 1b.income_category 2.income_category 3.income_category
4.income_category)
    Hansen test excluding group:    chi2(154) = 162.77  Prob > chi2 =  0.299
    Difference (null H = exogenous): chi2(9)   =   0.97  Prob > chi2 =  1.000
```

Without Quatar and Syria

```
. *OLS regression (with low income countries as a base category for income groups)
. reg emig unr gdppc edu ap gdpg europe eu ps conflict ib1.income_category

      Source |       SS           df       MS      Number of obs   =     2,666
-------------+----------------------------------   F(12, 2653)     =     55.59
       Model |  361.139072         12  30.0949227   Prob > F        =    0.0000
    Residual |   1436.2209      2,653  .541357295   R-squared       =    0.2009
-------------+----------------------------------   Adj R-squared   =    0.1973
       Total |  1797.35998      2,665  .674431511   Root MSE        =    .73577


-------------------------------------------------------------------------------
        emig |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+-----------------------------------------------------------------
         unr |   .0122185   .0028399     4.30   0.000     .0066498    .0177872
       gdppc |  -.0000106   1.38e-06    -7.71   0.000    -.0000133   -7.92e-06
         edu |   .0042519   .0008578     4.96   0.000     .0025699     .005934
          ap |   .0025034    .001272     1.97   0.049     9.28e-06    .0049976
        gdpg |  -.0168538   .0032048    -5.26   0.000     -.023138   -.0105696
      europe |   .2878059   .0484451     5.94   0.000     .1928119    .3827998
          eu |  -.1462553     .05481    -2.67   0.008    -.2537299   -.0387806
          ps |   .0216213   .0244909     0.88   0.377    -.0264018    .0696444
    conflict |  -.1210962   .0500045    -2.42   0.016    -.2191481   -.0230444
             |
income_category |
           2 |   -.091033   .0509183    -1.79   0.074    -.1908766    .0088106
           3 |  -.4264293   .0644923    -6.61   0.000    -.5528896    -.299969
           4 |  -.6817073   .0874104    -7.80   0.000    -.8531068   -.5103078
             |
       _cons |   .0817487   .1157391     0.71   0.480    -.1451994    .3086968
```
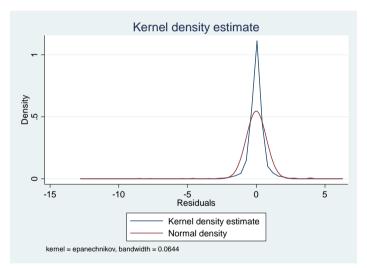
```
--------------------------------------------------------------------------------

.
. *Diagnostic tests after OLS
. estat imtest

Cameron & Trivedi's decomposition of IM-test

---------------------------------------------------
          Source |    chi2    df     p
--------------------+------------------------------
 Heteroskedasticity |  210.69    78   0.0000
         Skewness |   19.90    12   0.0689
         Kurtosis |    3.02     1   0.0820
--------------------+------------------------------
           Total |  233.62    91   0.0000
---------------------------------------------------

. estat hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
       Ho: Constant variance
       Variables: fitted values of emig

       chi2(1)    =    181.09
       Prob > chi2  =   0.0000

. estat ovtest

Ramsey RESET test using powers of the fitted values of emig
     Ho:  model has no omitted variables
           F(3, 2650) =      6.69
             Prob > F =     0.0002

. predict resid10, residuals
(3,371 missing values generated)

. kdensity resid10, normal
```

```
. xi: reg emig unr gdppc edu ap gdpg europe eu ps conflict ib1.income_category i.year
i.year          _Iyear_1990-2022   (naturally coded; _Iyear_1990 omitted)
note: _Iyear_1991 omitted because of collinearity
note: _Iyear_1992 omitted because of collinearity
note: _Iyear_1993 omitted because of collinearity
note: _Iyear_1994 omitted because of collinearity
note: _Iyear_1995 omitted because of collinearity
note: _Iyear_1997 omitted because of collinearity
note: _Iyear_1999 omitted because of collinearity
note: _Iyear_2001 omitted because of collinearity
note: _Iyear_2021 omitted because of collinearity
note: _Iyear_2022 omitted because of collinearity

     Source |     SS        df       MS     Number of obs  =    2,666
```

```
------------+------------------------------  F(34, 2631)    =    20.18
      Model | 371.762384      34 10.9341878  Prob > F       =   0.0000
   Residual | 1425.59759   2,631 .541846291  R-squared      =   0.2068
------------+------------------------------  Adj R-squared  =   0.1966
      Total | 1797.35998   2,665 .674431511  Root MSE       =    .7361


-------------------------------------------------------------------------------
        emig |     Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+-----------------------------------------------------------------
         unr |  .0126199   .0028794     4.38   0.000     .0069738    .0182661
       gdppc |  -.000011   1.39e-06    -7.87   0.000    -.0000137   -8.25e-06
         edu |  .0042025   .0008862     4.74   0.000     .0024648    .0059402
          ap |  .0023629   .0012792     1.85   0.065    -.0001453    .0048712
        gdpg | -.0187086   .0037095    -5.04   0.000    -.0259825   -.0114347
      europe |  .2901992    .048819     5.94   0.000     .1944717    .3859267
          eu | -.1464566   .0548849    -2.67   0.008    -.2540786   -.0388346
          ps |  .0312824   .0252264     1.24   0.215    -.0181831     .080748
    conflict | -.1087573   .0506265    -2.15   0.032     -.208029   -.0094856
             |
income_category |
           2 | -.1030962   .0516673    -2.00   0.046    -.2044089   -.0017835
           3 | -.4505436   .0655695    -6.87   0.000    -.5791167   -.3219705
           4 | -.7019434   .0878776    -7.99   0.000    -.8742596   -.5296273
             |
 _Iyear_1991 |         0  (omitted)
 _Iyear_1992 |         0  (omitted)
 _Iyear_1993 |         0  (omitted)
 _Iyear_1994 |         0  (omitted)
 _Iyear_1995 |         0  (omitted)
 _Iyear_1996 | -.0383702   .1088645    -0.35   0.725    -.2518389    .1750984
 _Iyear_1997 |         0  (omitted)
 _Iyear_1998 |  -.151469   .1144008    -1.32   0.186    -.3757937    .0728557
 _Iyear_1999 |         0  (omitted)
 _Iyear_2000 | -.1679266   .1057942    -1.59   0.113    -.3753749    .0395217
 _Iyear_2001 |         0  (omitted)
 _Iyear_2002 | -.2129865   .1041348    -2.05   0.041    -.4171809   -.0087922
 _Iyear_2003 | -.1848967   .1023759    -1.81   0.071    -.3856422    .0158487
 _Iyear_2004 | -.0774013    .102106    -0.76   0.448    -.2776174    .1228148
 _Iyear_2005 | -.1515216   .1023802    -1.48   0.139    -.3522754    .0492323
 _Iyear_2006 | -.1932474   .1022808    -1.89   0.059    -.3938064    .0073117
 _Iyear_2007 | -.0440248    .102316    -0.43   0.667    -.2446527    .1566032
 _Iyear_2008 | -.0179926   .1020423    -0.18   0.860    -.2180838    .1820987
 _Iyear_2009 | -.1212625   .1039498    -1.17   0.243    -.3250941    .0825691
 _Iyear_2010 | -.0599164   .0999012    -0.60   0.549    -.2558092    .1359764
 _Iyear_2011 | -.0420286   .0994935    -0.42   0.673    -.2371221    .1530648
 _Iyear_2012 | -.0280413   .0997463    -0.28   0.779    -.2236305    .1675478
 _Iyear_2013 | -.1683662    .099952    -1.68   0.092    -.3643587    .0276263
 _Iyear_2014 | -.1243577   .1001754    -1.24   0.215    -.3207882    .0720727
 _Iyear_2015 | -.2113601    .099048    -2.13   0.033      -.40558   -.0171402
 _Iyear_2016 | -.1144652    .099706    -1.15   0.251    -.3099754     .081045
 _Iyear_2017 | -.1641899   .0993065    -1.65   0.098    -.3589167    .0305369
 _Iyear_2018 | -.1089423    .099465    -1.10   0.273    -.3039798    .0860953
 _Iyear_2019 | -.0658818   .1001844    -0.66   0.511     -.26233    .1305665
 _Iyear_2020 | -.1583123   .1077033    -1.47   0.142     -.369504    .0528795
 _Iyear_2021 |         0  (omitted)
 _Iyear_2022 |         0  (omitted)
```

```
        _cons |  .2269553  .1451981   1.56   0.118  -.0577586   .5116692
-------------------------------------------------------------------------------
```

```
.
. *Diagnostic tests after OLS
. estat hettest
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
        Ho: Constant variance
        Variables: fitted values of emig
```

```
        chi2(1)     =   231.12
        Prob > chi2 =   0.0000
```

```
. estat ovtest
```

```
Ramsey RESET test using powers of the fitted values of emig
      Ho:  model has no omitted variables
            F(3, 2628) =      6.88
              Prob > F =      0.0001
```

```
. predict resid11, residuals
(3,371 missing values generated)
```

```
. kdensity resid11, normal
```



```
. *Fixed effects estimation
. xi: xtreg emig unr gdppc edu ap gdpg europe eu ps conflict ib1.income_category i.year, fe
i.year          _Iyear_1990-2022  (naturally coded; _Iyear_1990 omitted)
note: europe omitted because of collinearity
note: eu omitted because of collinearity
note: _Iyear_1991 omitted because of collinearity
note: _Iyear_1992 omitted because of collinearity
note: _Iyear_1993 omitted because of collinearity
note: _Iyear_1994 omitted because of collinearity
note: _Iyear_1995 omitted because of collinearity
note: _Iyear_1997 omitted because of collinearity
note: _Iyear_1999 omitted because of collinearity
note: _Iyear_2001 omitted because of collinearity
note: _Iyear_2021 omitted because of collinearity
```

```
note: _Iyear_2022 omitted because of collinearity

Fixed-effects (within) regression              Number of obs    =     2,666
Group variable: countryno                      Number of groups =       168

R-sq:                                          Obs per group:
    within  = 0.0396                                        min =         2
    between = 0.1958                                        avg =      15.9
    overall = 0.1415                                        max =        23

                                               F(32,2466)     =      3.18
corr(u_i, Xb)  = -0.2459                         Prob > F     =    0.0000


------------------------------------------------------------------------------
        emig |     Coef.   Std. Err.     t    P>|t|    [95% Conf. Interval]
-------------+----------------------------------------------------------------
         unr |   .0221563   .0062667    3.54   0.000    .0098678    .0344449
       gdppc |  -8.08e-06   2.63e-06   -3.08   0.002   -.0000132   -2.93e-06
         edu |     .00234   .0017441    1.34   0.180   -.0010801    .0057601
          ap |   .0122991   .0031774    3.87   0.000    .0060684    .0185298
        gdpg |  -.0098434   .0035104   -2.80   0.005    -.016727   -.0029599
      europe |         0  (omitted)
          eu |         0  (omitted)
          ps |   .0125464   .0434689    0.29   0.773    -.072693    .0977857
    conflict |   .0871087   .0629195    1.38   0.166   -.0362718    .2104892
             |
income_category |
           2 |  -.1524678   .0660708   -2.31   0.021   -.2820278   -.0229078
           3 |  -.2445233   .0972158   -2.52   0.012   -.4351564   -.0538903
           4 |   -.484347   .1297557   -3.73   0.000   -.7387883   -.2299057
             |
 _Iyear_1991 |         0  (omitted)
 _Iyear_1992 |         0  (omitted)
 _Iyear_1993 |         0  (omitted)
 _Iyear_1994 |         0  (omitted)
 _Iyear_1995 |         0  (omitted)
 _Iyear_1996 |    -.09165   .1195908   -0.77   0.444   -.3261588    .1428588
 _Iyear_1997 |         0  (omitted)
 _Iyear_1998 |  -.1568542   .1216206   -1.29   0.197   -.3953433    .0816349
 _Iyear_1999 |         0  (omitted)
 _Iyear_2000 |  -.2037125   .1123092   -1.81   0.070   -.4239425    .0165176
 _Iyear_2001 |         0  (omitted)
 _Iyear_2002 |   -.190396   .1074056   -1.77   0.076   -.4010105    .0202186
 _Iyear_2003 |  -.1961719   .1037019   -1.89   0.059   -.3995237    .0071799
 _Iyear_2004 |   -.138678   .1000831   -1.39   0.166   -.3349337    .0575777
 _Iyear_2005 |  -.1813276   .0984339   -1.84   0.066   -.3743492     .011694
 _Iyear_2006 |  -.2149104    .096203   -2.23   0.026   -.4035573   -.0262635
 _Iyear_2007 |  -.0660041   .0944383   -0.70   0.485   -.2511906    .1191824
 _Iyear_2008 |  -.0320229   .0930365   -0.34   0.731   -.2144607    .1504149
 _Iyear_2009 |  -.1059403   .0950159   -1.11   0.265   -.2922596    .0803789
 _Iyear_2010 |  -.1125207   .0905892   -1.24   0.214   -.2901594     .065118
 _Iyear_2011 |  -.0658466   .0895034   -0.74   0.462   -.2413562    .1096629
 _Iyear_2012 |  -.0388158   .0892901   -0.43   0.664    -.213907    .1362754
 _Iyear_2013 |  -.1715584    .088946   -1.93   0.054    -.345975    .0028581
 _Iyear_2014 |  -.1303713   .0889481   -1.47   0.143   -.3047919    .0440493
 _Iyear_2015 |  -.2017613   .0881528   -2.29   0.022   -.3746225   -.0289001
```

```
  _Iyear_2016 |  -.1138971   .0885153   -1.29   0.198   -.2874691    .0596748
  _Iyear_2017 |  -.1341727   .0876472   -1.53   0.126   -.3060423    .0376969
  _Iyear_2018 |  -.0948745    .087533   -1.08   0.279   -.2665203    .0767712
  _Iyear_2019 |  -.0443657   .0883438   -0.50   0.616   -.2176013    .1288699
  _Iyear_2020 |  -.0960138   .0957759   -1.00   0.316   -.2838232    .0917956
  _Iyear_2021 |          0  (omitted)
  _Iyear_2022 |          0  (omitted)
        _cons |  -.4858799    .245701   -1.98   0.048   -.9676815   -.0040782
--------------+----------------------------------------------------------------
      sigma_u |  .54558849
      sigma_e |  .63746062
          rho |  .42280844   (fraction of variance due to u_i)
-------------------------------------------------------------------------------
F test that all u_i=0: F(167, 2466) = 6.53              Prob > F = 0.0000


. predict residfe10, residuals
(3,371 missing values generated)


. xtserial emig residfe1


Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
   F( 1,    149) =     42.118
         Prob > F =      0.0000


.
. *GMM
. xtabond2 emig L.emig unr gdppc edu ap gdpg europe eu ps conflict ib1.income_category, gmm(L.emig,
laglimits(1 1)) gmm(ap unr gd
> pg , laglimits (2 2)) iv(gdppc edu europe eu ps conflict ib1.income_category) robust
Favoring speed over space. To switch, type or click on mata: mata set matafavor space, perm.
Warning: Number of instruments may be large relative to number of observations.
Warning: Two-step estimated covariance matrix of moments is singular.
  Using a generalized inverse to calculate robust weighting matrix for Hansen test.
  Difference-in-Sargan/Hansen statistics may be negative.


Dynamic panel-data estimation, one-step system GMM
-------------------------------------------------------------------------------
Group variable: countryno              Number of obs      =      2657
Time variable : year                   Number of groups   =       168
Number of instruments = 178            Obs per group: min =         2
Wald chi2(14) =   569.82                               avg =     15.82
Prob > chi2   =    0.000                               max =        23
-------------------------------------------------------------------------------
             |              Robust
        emig |    Coef.   Std. Err.    z    P>|z|    [95% Conf. Interval]
-------------+-----------------------------------------------------------------
        emig |
         L1. |   .4482467   .1010149    4.44   0.000    .2502611    .6462323
             |
         unr |   .0146603   .0127985    1.15   0.252   -.0104242    .0397448
       gdppc |  -5.38e-06   2.09e-06   -2.57   0.010   -9.48e-06   -1.28e-06
         edu |   .0027821   .0012586    2.21   0.027    .0003153    .0052489
          ap |   .0064048   .0046344    1.38   0.167   -.0026784     .015488
        gdpg |  -.0087177     .00468   -1.86   0.062   -.0178904    .0004549
      europe |   .1515539   .1056654    1.43   0.151   -.0555464    .3586542
```

```
           eu |  -.112886    .085912    -1.31   0.189    -.2812704    .0554984
           ps |  .0577259   .0346101     1.67   0.095    -.0101087    .1255605
     conflict |  .0643177    .087335     0.74   0.461    -.1068557    .2354911
              |
income_category |
            1 |         0  (empty)
            2 |  .0002395   .0618731     0.00   0.997    -.1210295    .1215085
            3 |  -.1525784  .0904576    -1.69   0.092    -.3298721    .0247153
            4 |  -.2779184  .0979584    -2.84   0.005    -.4699133   -.0859235
              |
        _cons |  -.4083387  .4108861    -0.99   0.320    -1.213661    .3969833
-------------------------------------------------------------------------------
Instruments for first differences equation
  Standard
    D.(gdppc edu europe eu ps conflict 1b.income_category 2.income_category
    3.income_category 4.income_category)
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L2.(ap unr gdpg)
    L.L.emig
Instruments for levels equation
  Standard
    gdppc edu europe eu ps conflict 1b.income_category 2.income_category
    3.income_category 4.income_category
    _cons
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    DL.(ap unr gdpg)
    D.L.emig
-------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -1.97  Pr > z =  0.049
Arellano-Bond test for AR(2) in first differences: z =   0.37  Pr > z =  0.714
-------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(163) = 748.12  Prob > chi2 = 0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(163) = 159.01  Prob > chi2 = 0.574
  (Robust, but weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:
  GMM instruments for levels
    Hansen test excluding group:    chi2(71)  =  97.93  Prob > chi2 = 0.019
    Difference (null H = exogenous): chi2(92)  =  61.08  Prob > chi2 = 0.995
  gmm(L.emig, lag(1 1))
    Hansen test excluding group:    chi2(121) = 130.75  Prob > chi2 = 0.257
    Difference (null H = exogenous): chi2(42)  =  28.26  Prob > chi2 = 0.948
  gmm(ap unr gdpg, lag(2 2))
    Hansen test excluding group:    chi2(37)  =  51.61  Prob > chi2 = 0.056
    Difference (null H = exogenous): chi2(126) = 107.40  Prob > chi2 = 0.883
  iv(gdppc  edu  europe  eu  ps  conflict  1b.income_category  2.income_category  3.income_category
4.income_category)
    Hansen test excluding group:    chi2(154) = 158.88  Prob > chi2 = 0.377
    Difference (null H = exogenous): chi2(9)   =   0.13  Prob > chi2 = 1.000
```

VARIABLES	(OLS no income group and no time dummies) emig	(OLS no income group and with time dummies) emig	(OLS with income group and time dummies) emig	(FE no income group, no time dummies) emig	(FE no income group and with time dummies) emig	(FE with income group and time dummies) emig
unr	0.0107***	0.0109***	0.0122***	0.0126***	0.0247***	0.0222***
	(0.00281)	(0.00284)	(0.00284)	(0.00288)	(0.00611)	(0.00627)
gdppc	-1.64e-05***	-1.66e-05***	-1.06e-05***	-1.10e-05***	-7.41e-06***	-8.08e-06***

	(1)	(2)	(3)	(4)	(5)	(6)
	(1.08e-06)	(1.10e-06)	(1.38e-06)	(1.39e-06)	(2.58e-06)	(2.63e-06)
edu	0.00135*	0.00127	0.00425***	0.00420***	0.00155	0.00234
	(0.000808)	(0.000840)	(0.000858)	(0.000886)	(0.00170)	(0.00174)
ap	0.00566***	0.00569***	0.00250**	0.00236*	0.0126***	0.0123***
	(0.00112)	(0.00112)	(0.00127)	(0.00128)	(0.00313)	(0.00318)
gdpg	-0.0148***	-0.0162***	-0.0169***	-0.0187***	-0.00977***	-0.00984***
	(0.00324)	(0.00376)	(0.00320)	(0.00371)	(0.00351)	(0.00351)
europe	0.363***	0.365***	0.288***	0.290***		
	(0.0482)	(0.0486)	(0.0484)	(0.0488)		
eu	-0.277***	-0.279***	-0.146***	-0.146***		
	(0.0528)	(0.0530)	(0.0548)	(0.0549)		
ps	-0.0244	-0.0188	0.0216	0.0313	-0.00593	0.0125
	(0.0243)	(0.0250)	(0.0245)	(0.0252)	(0.0430)	(0.0435)
conflict	-0.147***	-0.138***	-0.121**	-0.109**	0.0768	0.0871
	(0.0507)	(0.0513)	(0.0500)	(0.0506)	(0.0630)	(0.0629)
o._Iyear_1991		-		-	-	-
o._Iyear_1992		-		-	-	-
o._Iyear_1993		-		-	-	-
o._Iyear_1994		-		-	-	-
o._Iyear_1995		-		-	-	-
_Iyear_1996		-0.0403		-0.0384	0.000403	-0.0917
		(0.110)		(0.109)	(0.116)	(0.120)
o._Iyear_1997		-		-	-	-
_Iyear_1998		-0.144		-0.151	-0.0558	-0.157
		(0.116)		(0.114)	(0.118)	(0.122)
o._Iyear_1999		-		-	-	-
_Iyear_2000		-0.152		-0.168	-0.110	-0.204*
		(0.107)		(0.106)	(0.108)	(0.112)
o._Iyear_2001		-		-	-	-
_Iyear_2002		-0.173		-0.213**	-0.0983	-0.190*
		(0.105)		(0.104)	(0.103)	(0.107)
_Iyear_2003		-0.164		-0.185*	-0.111	-0.196*
		(0.104)		(0.102)	(0.100)	(0.104)
_Iyear_2004		-0.0705		-0.0774	-0.0675	-0.139
		(0.103)		(0.102)	(0.0976)	(0.100)
_Iyear_2005		-0.137		-0.152	-0.113	-0.181*
		(0.104)		(0.102)	(0.0961)	(0.0984)
_Iyear_2006		-0.188*		-0.193*	-0.163*	-0.215**
		(0.104)		(0.102)	(0.0949)	(0.0962)
_Iyear_2007		-0.0545		-0.0440	-0.0289	-0.0660
		(0.104)		(0.102)	(0.0936)	(0.0944)
_Iyear_2008		-0.0281		-0.0180	-0.00607	-0.0320
		(0.104)		(0.102)	(0.0926)	(0.0930)
_Iyear_2009		-0.116		-0.121	-0.0696	-0.106
		(0.105)		(0.104)	(0.0944)	(0.0950)
_Iyear_2010		-0.0736		-0.0599	-0.0847	-0.113
		(0.101)		(0.0999)	(0.0902)	(0.0906)
_Iyear_2011		-0.0577		-0.0420	-0.0507	-0.0658
		(0.101)		(0.0995)	(0.0893)	(0.0895)
_Iyear_2012		-0.0347		-0.0280	-0.0244	-0.0388
		(0.101)		(0.0997)	(0.0893)	(0.0893)
_Iyear_2013		-0.184*		-0.168*	-0.163*	-0.172*
		(0.102)		(0.1000)	(0.0889)	(0.0889)
_Iyear_2014		-0.140		-0.124	-0.122	-0.130
		(0.102)		(0.100)	(0.0890)	(0.0889)
_Iyear_2015		-0.207**		-0.211**	-0.176**	-0.202**
		(0.101)		(0.0990)	(0.0880)	(0.0882)
_Iyear_2016		-0.109		-0.114	-0.0901	-0.114
		(0.101)		(0.0997)	(0.0884)	(0.0885)
_Iyear_2017		-0.161		-0.164*	-0.116	-0.134
		(0.101)		(0.0993)	(0.0876)	(0.0876)

	(1)	(2)	(3)	(4)	(5)	(6)
_Iyear_2018		-0.109		-0.109	-0.0840	-0.0949
		(0.101)		(0.0995)	(0.0877)	(0.0875)
_Iyear_2019		-0.0756		-0.0659	-0.0324	-0.0444
		(0.102)		(0.100)	(0.0885)	(0.0883)
_Iyear_2020		-0.135		-0.158	-0.0785	-0.0960
		(0.109)		(0.108)	(0.0958)	(0.0958)
o._Iyear_2021		-		-	-	-
o._Iyear_2022		-		-	-	-
2.income_category			-0.0910*	-0.103**		-0.152**
			(0.0509)	(0.0517)		(0.0661)
3.income_category			-0.426***	-0.451***		-0.245**
			(0.0645)	(0.0656)		(0.0972)
4.income_category			-0.682***	-0.702***		-0.484***
			(0.0874)	(0.0879)		(0.130)
o.europe					-	-
o.eu					-	-
Constant	-0.230**	-0.111	0.0817	0.227	-0.780***	-0.486**
	(0.0928)	(0.125)	(0.116)	(0.145)	(0.218)	(0.246)
Observations	2,666	2,666	2,666	2,666	2,666	2,666
R-squared	0.175	0.180	0.201	0.207	0.034	0.040
Number of countries					168	168

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(GMM no income group and no time dummies) emig	(GMM no income group and yes time dummies) emig	(GMM with income group and no time dummies) emig	(GMM with income group and time dummies) emig
L.emig	0.450***	0.446***	0.448***	0.445***
	(0.103)	(0.104)	(0.101)	(0.100)
unr	0.0139	0.0190	0.0147	0.0146
	(0.0142)	(0.0165)	(0.0128)	(0.0122)
gdppc	-8.18e-06***	-8.08e-06***	-5.38e-06**	-5.46e-06***
	(2.31e-06)	(2.48e-06)	(2.09e-06)	(2.04e-06)
edu	0.00203	0.00198	0.00278**	0.00279**
	(0.00140)	(0.00136)	(0.00126)	(0.00126)
ap	0.00880**	0.00907**	0.00640	0.00632
	(0.00435)	(0.00406)	(0.00463)	(0.00455)
gdpg	-0.00789*	-0.00434	-0.00872*	-0.00855*
	(0.00445)	(0.00603)	(0.00468)	(0.00464)
europe	0.195*	0.180	0.152	0.152
	(0.117)	(0.122)	(0.106)	(0.103)
eu	-0.187*	-0.177*	-0.113	-0.111
	(0.0970)	(0.0989)	(0.0859)	(0.0847)
ps	0.0466	0.0530	0.0577*	0.0575*
	(0.0380)	(0.0399)	(0.0346)	(0.0342)
conflict	0.0575	0.0633	0.0643	0.0638
	(0.0887)	(0.0928)	(0.0873)	(0.0870)
_Iyear_1991		0		
		(0)		
_Iyear_1992		0		
		(0)		
_Iyear_1993		0		
		(0)		
_Iyear_1994		0		
		(0)		
_Iyear_1995		0		
		(0)		
_Iyear_1996		-0.618*		
		(0.368)		
_Iyear_1997		0		
		(0)		

_Iyear_1998		-0.709**		
		(0.358)		
_Iyear_1999		0		
		(0)		
_Iyear_2000		-0.745**		
		(0.367)		
_Iyear_2001		0		
		(0)		
_Iyear_2002		-0.701*		
		(0.372)		
_Iyear_2003		-0.718*		
		(0.372)		
_Iyear_2004		-0.661*		
		(0.366)		
_Iyear_2005		-0.677*		
		(0.365)		
_Iyear_2006		-0.732*		
		(0.402)		
_Iyear_2007		-0.596*		
		(0.332)		
_Iyear_2008		-0.590*		
		(0.345)		
_Iyear_2009		-0.620*		
		(0.344)		
_Iyear_2010		-0.686*		
		(0.354)		
_Iyear_2011		-0.628*		
		(0.355)		
_Iyear_2012		-0.625*		
		(0.358)		
_Iyear_2013		-0.718*		
		(0.410)		
_Iyear_2014		-0.645*		
		(0.363)		
_Iyear_2015		-0.722**		
		(0.344)		
_Iyear_2016		-0.624*		
		(0.347)		
_Iyear_2017		-0.703**		
		(0.341)		
_Iyear_2018		-0.647*		
		(0.337)		
_Iyear_2019		-0.601*		
		(0.338)		
_Iyear_2020		-0.608*		
		(0.366)		
_Iyear_2021		-0.643*		
		(0.341)		
_Iyear_2022		0		
		(0)		
2.income_category			0.000240	0.00149
			(0.0619)	(0.0601)
3.income_category			-0.153*	-0.150*
			(0.0905)	(0.0892)
4.income_category			-0.278***	-0.280***
			(0.0980)	(0.0981)
Constant	-0.595*	0	-0.408	-0.403
	(0.360)	(0)	(0.411)	(0.407)
Observations	2,657	2,657	2,657	2,657
Number of countryno	168	168	168	168