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Drivers of migration flows in the European Union: Earnings or unemployment?

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Abstract. *In this article, we analyse the drivers of international migration in the European Union (EU) using data from 23 EU countries in Bayesian model averaging and quantile regression. Our findings reveal that the association between differences in earnings and migration is twice as strong as that of unemployment and a robust feature in the data. Nevertheless, we find that economic factors play a secondary role, with cultural proximity and the "friends and relatives" effect taking precedence. Our results indicate a limited role for labour mobility as an adjustment mechanism within the EU.*

Keywords: *migration flows, earnings, unemployment, Bayesian model averaging, quantile regression, EU.*

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1. Introduction

The theory of optimum currency areas (OCAs) proposed by Mundell (1961) explores alternative adjustment mechanisms for countries attempting to establish a monetary union. With a common central bank and a common monetary policy, the adjustment to asymmetric shocks must be transferred to other mechanisms or policy measures. However, compared with capital flow mobility, human capital mobility is stickier by far. A lower degree of labour mobility can have a decisive impact on a monetary union. In fact, Mundell (1961) advocated for labour mobility within the monetary union as an adjustment mechanism that could substitute monetary policy independence and a flexible exchange rate. Labour mobility is often referred to as one of the factors that makes the United States an OCA (Eichengreen 1992).

However, the mere presence of labour migration might not be sufficient. If migration is driven by differences in earnings, a steady flow of workers to countries with the highest wages is expected. However, this type of migration will not serve as an adjustment mechanism after an asymmetric shock. Krugman (1993) warns that this sort of migration, after an idiosyncratic shock, can lead to long-term economic depression in the affected region. In Mundell's (1961) model, workers who lose jobs because of a negative shock in one part of the OCA travel to parts that have been affected by a positive shock. Therefore, for it to serve as an adjustment mechanism in a monetary union, labour migration should be driven by the level of unemployment rather than the relative difference in real wages.

When determining OCA status, a comparison of the European Union (EU) and the United States should be approached with caution. The US states share the same language, currency and similar cultural, political and institutional values. In contrast, the enlargement of the EU introduces risks for the process of European integration itself. Shocks within EU countries can reveal several weaknesses in the community's institutional arrangements. The absence of full labour mobility across the Eurozone constrains the constituent economies' ability to overcome adverse shocks (Jager and Hafner 2013). Moreover, while fiscal federalism is a reality in the United States, in the EU there are no relevant fiscal transfers between regions through the "federal government" (the overall budget of the EU institutions is a small fraction of the EU's GDP). This is a determinant in the lack of OCA success in this region (Eichengreen 1992).

Currently, 20 of the 27 EU countries have joined the Eurozone, with more planning to join eventually. Assessing the main economic determinants of labour flows could, therefore, expand our knowledge about the potential role of migration flows in responding to asymmetric shocks in these countries. This could contribute to the debate on the costs of joining the Eurozone and consequently provide a basis for better-informed economic policy. It is widely acknowledged that the EU is not in fact an OCA in the strict sense of the term (Afonso and Furceri 2008). Still, it can be argued that the institutional architecture of the EU is quite close to the one defined by Mundell (1961), especially considering that the Eurozone countries are closer to OCA status, as predicted by Frankel and Rose's (1998) endogeneity of OCA criteria hypothesis.

This motivated us to investigate the drivers of international migration flows in the EU. We focus on the economic motives that lead people to leave their own country for another, studying the "push" and "pull" factors acting on the labour force within the EU. We examine data from 23 countries over the period 1995–2019, using Bayesian model averaging and quantile regression to assess the relative importance of differences in unemployment and earnings between countries in explaining international migration flows. We find that the impact of differences in earnings on migration is twice as strong as that of differences in unemployment. Hence, the "price" effect, proxied by differences in earnings, is more relevant for migration decisions than the "quantity" effect stemming from the differences in unemployment rates.

Furthermore, the connection between migration flows and differences in earnings proves to be a robust feature in the data, while the association with differences in unemployment is not. However, we find that economic considerations are of secondary importance compared to cultural proximity and the "friends and relatives" effect. Accordingly, our results indicate that labour mobility currently has a limited role as an adjustment mechanism in the EU. In this light, current and potential Member States should consider establishing a complementary mechanism such as fiscal federalism, which, combined with labour mobility, may play a major role in establishing a better institutional design for an OCA.[1]

The remainder of this article is organized as follows. The second section provides a review of the literature. The third section presents the methodology and data employed in our analysis. The fourth section discusses the empirical results from our study and the fifth section provides a summary of our findings and some conclusions.

2. Related literature

Migration movements across regions are part of a dynamic process that drives and explains the evolution of human societies and the development of economies. Historically, and beyond the traditional economic factors used to explain migration flows, other essential factors stimulate people to move from one region to another. Examples of massive migration flows abound. However, only in the last century have governments imposed legal barriers to immigration, not emigration. The main reason behind this decision can be attributed to the impact of immigrants on the labour markets of destination countries (Altonji and Card 1991; Borjas 1995 and 2003; Borjas, Freeman and Katz 1996; Card 2001, 2005 and 2009). Governments base their policies on the acceptance of foreign citizens on different criteria. Chiswick and Miller (2014) find that criteria related to cultural values and education are particularly important. Accordingly, individuals from culturally close countries or citizens with higher levels of educational attainment have better chances of entry.

Understanding the reasons for labour movements is essential in examining not only the factors that (dis)incentivize people from moving from one place to another but also in assessing the impacts of this process. While preserving the autonomy of each State, the European project is moving towards greater integration in which individual economies are willing to concede sovereignty to European authorities. The EU case is of particular interest given that, in contrast to federal countries, there are many differences among the EU Members. Gros (1996) concludes that external shocks had little effect on unemployment levels in most EU countries before 1994. The gap between international and interregional labour mobility is relatively small. In other words, the two types of flow are comparable.

Focusing on European countries in the second half of the twentieth century, Jennissen (2003) studies the “push” and “pull” factors at work in migration flows. The push factors are typically incentives that drive economic agents to move to a different country because of unfavourable conditions in their home country. Conversely, the pull factors are incentives that encourage economic agents to move owing to opportunities or favourable circumstances in other countries. The author finds that per capita GDP stimulates emigration decisions, and rising unemployment in the destination country is detrimental to the population’s incentives to leave their home country. Franc, Časni and Barišić (2019) conduct a panel data analysis of the EU economies during the enlargement process to determine the principal push and pull factors. Their results also support hypotheses positing per capita GDP and unemployment rates as major determinants of migration flows. The aggregate income and unemployment disparities are also essential for interregional migration (Etzo 2011). However, to the best of our knowledge, no research has thus far explored the relative roles of differences in unemployment and earnings on the size and direction of international migration flows. Accordingly, our study attempts to fill this gap in the literature.

In line with the human capital migration approach, Kahanec and Fabo (2013) concentrate on education and job skills when analysing migration induced by the EU enlargement to the east. Despite the classic push and pull macro- and microeconomic factors enumerated in the literature, the authors find a “brain circulation” – as opposed to a “brain drain” – process in

[1] See the discussion on the role of fiscal federalism and labour mobility for a more efficient OCA institutional arrangement in Obstfeld and Peri (1998), Perotti (2001), Evers (2015) and Baglioni, Boitani and Bordignon (2016).

migration outflows where young people decide to emigrate for shorter periods to improve their educational and job training and foster their future careers. These findings are also in line with the studies by Marsden (1992), Vandamme (2000) and Peixoto (2001), who share the idea that only high-skilled workers can truly move freely between European countries.

Hadler (2006) claims that push and pull factors fail to explain cross-country migration flows and that the push-and-pull models are only valid in explaining people's movements within countries, not across countries. This conclusion supports the idea that, according to the existing OCA theory, the EU fails to fulfil OCA criteria because some barriers between its Member States are still evident. However, when comparing the European core–periphery dualism, immigration is found to be an effective tool for all EU countries in reducing short-term unemployment rates (Esposito, Collignon and Scicchitano 2020). Such results serve as evidence that the EU exhibits some features of an OCA. Accordingly, cross-country migration can be an adjustment mechanism for countries facing adverse shocks (Beck 2021a; Beck and Nzimande 2023).

Cultural factors are frequently analysed in the context of international migration. Most studies assess whether the host and home countries share some past interdependencies, such as a colonial relationship. Hooghe et al. (2008) analyse European countries between 1980 and 2004 and find that cultural and economic variables are important in explaining these migration flows. Moreover, linguistic similarities between countries and a greater number of linguistic communities in host countries stimulate immigrant flows. Lower linguistic requirements for citizenship, together with policies that favour migrants' integration, are found to be essential in explaining migration flows within EU countries (Kim and Cohen 2010). Yet, as Aparicio-Fenoll and Kuehn (2016) suggest, would-be emigrants who have learned a foreign language as part of their education are five times more likely to choose a country where that language is spoken than one where it is not.

Gallardo-Sejas et al. (2006) develop a gravity model to determine the reasons behind intentions to move to European countries by analysing 139 countries of origin in the year 2000. They argue that, besides the importance of cultural proximity, host countries with better macroeconomic performance and more generous social benefits incentivize immigrant flows. Conversely, distance between countries is detrimental to international migration flows. Sardadvar and Rocha-Akis (2016) assess the migration flows between European regions. Apart from the main macro determinants of migration, they conclude that there is a spatial impact on migration decisions. Specifically, the closer the host region is to the region of origin, the stronger the push of macroeconomic factors. In addition, income inequality, corruption and crime levels are considered to be push factors as regards people's decisions to leave their home country (Davies and Wooton 1992; Poprawe 2015).

Network effects have been proposed as another explanation for international migration flows. As documented in Boyd (1989) and Pedersen, Pytlikova and Smith (2008), network effects are statistically and economically significant in explaining why people move between countries. However, network effects can be offset to some degree by restrictive immigration policies, leading to selection effects. In these authors' view, such restrictive policies have a higher impact on the lowest income segments of the countries of origin. Beyond network effects, differences between countries' labour market conditions – namely in unemployment and earnings – health services and education systems are significant in explaining migration flows (Geis, Uebelmesser and Werding 2013). Landesmann, Leitner and Mara (2015) find that gaps in real wages and productivity levels are crucial in determining the incentives for people to leave their home country. However, the relationship that is identified in the literature between wage gaps and migration flows is affected by the fact that researchers have been considering a static perspective. As Dustmann (2003) points out, in a dynamic framework analysis, the optimal migration duration may decrease if the wage differential increases. The quality of fiscal institutions, the welfare state and the institutional quality of the public sector also have been found to affect immigration (e.g. Ashby 2007; Ariu, Docquier and Squicciarini 2016).

To the best of our knowledge, previous studies have not compared the relative strength of determinants of migration flows with a view to assessing the potential of labour mobility as an adjustment mechanism. Our research thus concentrates on two main economic factors in labour mobility – earnings and unemployment – while accounting for other factors that have been established in the literature.

3. Data and methodology

3.1. Data

Our sample consists of 23 EU Member States: Austria, Belgium, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden and the United Kingdom.[2] The data used for our estimations on the examined determinants of migration flows cover the 2000–19 period, while data on the dependent variable, net migration flows, covers the 1995–2019 period, as we include the lagged dependent variable in our estimations.[3]

To measure the degree of labour migration, we utilize the newly available data set on international bilateral immigration flows prepared by Abel and Cohen (2022). The data set reports the data over 5-year periods and consequently all the variables used in the estimations are adjusted to this format – that is, all the regressors considered are constructed over 5-year period intervals. The data reported in the data set pertain only to EU citizens and exclude refugees and other non-citizens. We scaled the net migration flows using the sum of the working-age population in each pair of countries using data from Eurostat.[4] Consequently, the net migration per 1,000 inhabitants of working age (15–64) between any pair of countries is calculated as:

$$MIGR_{ijt} = \frac{\left|NetMIGR_{ijt}\right|}{\frac{1}{5}\sum_{z=0}^{4}\left(Pop_{it+z} + Pop_{jt+z}\right)} \tag{1}$$

where $|NetMIGR_{ijt}|$ is net migration between countries i and j at time t = 1995, 2000, ... , 2015, denoting the first year of the 5-year period in question. Pop_{it+z} and Pop_{jt+z} represent the working-age populations in country i and j, respectively, and z = 0, 1, ... , 4.[5]

The first explanatory variable that we consider is lagged migration ($MIGRlag \equiv MIGR_{ijt-1}$), which can be used as a proxy for well-established formal and informal migration channels: immigrants already living in each country are able to facilitate inflows of their relatives, friends and acquaintances by helping them find housing, jobs and introducing them to the new culture. As an alternative proxy for the "friends and relatives" effect (Boyd 1989), we used the stock values. However, since the database did not include the data on stock variables, we constructed a variable that reflects the accumulation of migration flows between two countries over the examined period. The variable is defined as:

$$CumMIG_{ijM} = \sum_{m=1}^{M} MIGR_{ijm} \tag{2}$$

[2] Before the withdrawal of the United Kingdom from the European Union in 2020.

[3] The detailed description of the variables and the sources of the data can be found in table A1 in the appendix.

[4] The scaling is introduced to avoid problems associated with relatively large countries dominating the results. However, we estimated the specification without scaling. The results are shown in table SB5 in supplementary online Appendix B, while discussion of these results can be found in subsection 4.1.

[5] The percentiles of the distribution of MIGR in six consecutive periods for the examined countries are presented in supplementary online Appendix A.

where M = 1,2,3,4 is a time index. In other words, we summarize all available past migrations to account for the "friends and relatives" effect.

In line with previous research, our evaluation of net migration flows between EU countries investigates both push and pull factors, analysing the disparities in the intensity of these factors within each pair of countries. For instance, low real wages or high unemployment serve as push factors that encourage economic agents in one country to migrate and seek employment abroad. Conversely, high wages and low unemployment rates can be considered to be pull factors that attract workers from abroad. To assess the net push-and-pull effect for a given pair of countries, we construct independent variables as the absolute values of the differences between push or pull factors in the examined pair of countries.

The two drivers of labour migration that we are most interested in for this research are the pair-wise country differences in earnings and unemployment. We calculate the difference in the level of earnings as:

$$EARN_{ijt} = \frac{1}{5}\sum_{z=0}^{4}\left|NetEARN_{it+z} - NetEARN_{jt+z}\right| \tag{3}$$

where $NetEARN_{it+z}$ and $NetEARN_{jt+z}$ are average after-tax earnings expressed in purchasing power parity (PPP) euros in country i and j, respectively, at time t = 2000, 2005, 2010, 2015, and z = 0, 1, … , 4.

Similarly, the difference in the level of the unemployment rate is calculated as:

$$UNEMP_{ijt} = \frac{1}{5}\sum_{z=0}^{4}\left|UN_{it+z} - UN_{jt+z}\right| \tag{4}$$

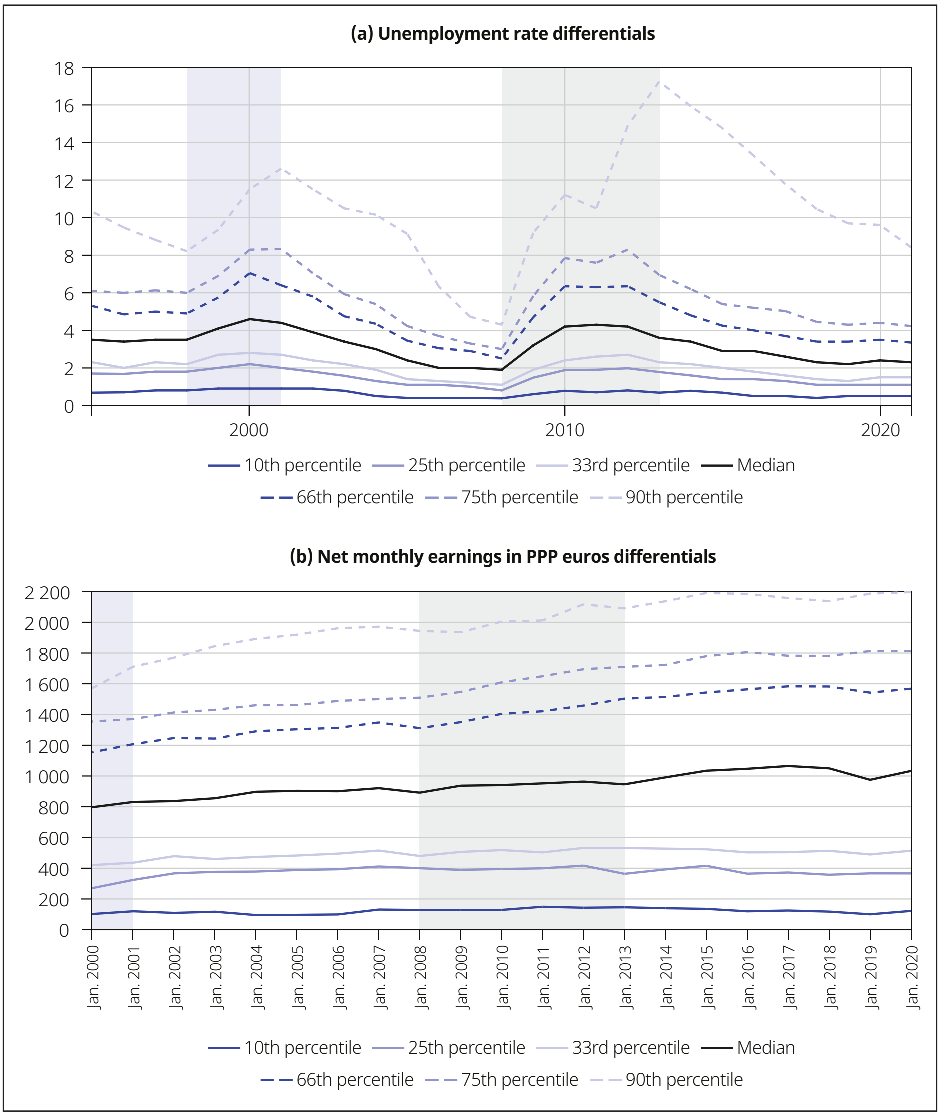
where UN_{it+z} and UN_{jt+z} are the unemployment rates in country i and j, respectively. The data on net earnings and unemployment rates are annual and come from Eurostat.

The percentiles and median of the distribution of the differences in unemployment rates and in net earnings are depicted in figure 1. The unemployment rate differentials demonstrate an upward trend during periods of economic expansion (e.g. the dot-com bubble) and recession (e.g. the dot-com bubble burst, global financial crisis and sovereign debt crisis). During tranquil periods, they exhibit a tendency towards unemployment rate convergence. The net earnings differentials, in contrast, do not display any convergence pattern. The percentiles below the median remain relatively stable, while those above the median manifest a slow evolution towards greater disparity. Unlike unemployment rates, tendencies in the behaviour of net earnings differentials remain roughly stable during times of crisis, expansion or tranquillity.

We control for several economic, social and institutional, and cultural factors that can potentially contribute to net migration. A detailed description of these variables and the source of the data can be found in table A1 in the appendix. As regards economic factors, we control for difference in income tax (*Tax*) and average social benefits per person (*Social*) between two countries. In this regard, Warin and Svaton (2008) provide an interesting investigation into "welfare migration". We also examine the impact of the size of government through the variable *GOV*. The role of government size on international migration flows is advocated by Clemente, Pueyo and Sanz (2008), while that of the quality of government institutions is supported by Ariu, Docquier and Squicciarini (2016). The human capital variable, *HC*, uses the measure provided by Barro and Lee (2013), based on schooling attainment. Following research on the impact of income inequality on migration flows by Davies and Wooton (1992), we account for the differences in income distribution using the variable *Gini*.

Moving to social and institutional factors, we first account for the differences in safety and crime through the *Crime* and *Corruption* variables. Lage de Sousa (2014) reports that crime rate is an effective impediment of migration flows and Poprawe (2015) indicates

Figure 1. Unemployment rate and net earnings differentials



Note: The lilac shaded area denotes the dot-com bubble period, and the grey shaded area denotes the period of the global financial and sovereign debt crises.
Source: Our own compilation based on Eurostat data.

that corruption encourages emigration and discourages immigration. We also control for differences in fertility rates through the *FER* variable. To the best of our knowledge, we are the first to examine the association between fertility rate and migration flows.

The last group of factors that we consider are related to the differences in culture. The first four variables could be seen as proxies for transportation costs; however, they are widely considered as proxies for cultural distance between countries. The dummy variables *B* and *MB*, controlling for countries sharing a common border and a maritime border, respectively, are complementary given that countries with shared land and sea borders often have a common history. The dummy variable *MA* controls for access to the ocean or sea, while *LNDGEO* is the natural logarithm of the distance between the capitals of a given pair of countries. Gravity variables are the most widely used type of regressors in the literature on international migration flows (Ashby 2007; Kim and Cohen 2010; Etzo 2011).

The variable on the difference in the average annual temperature between two countries (*Temp*) could be considered a proxy for quality of life, as living in warmer European countries is associated with additional benefits (nicer weather), and those countries are major tourism destinations. On the other hand, especially in the European context, the difference in temperature can also serve as a proxy for cultural similarity. The impact of temperature on migration flows has been widely researched given its bearing on the global warming debate (Minehan and Wesselbaum 2023).

Lastly, *OLDEU* is a dummy variable for membership of the EU before 2004. *L* is a dummy variable that controls for common official languages. *TRANS* is a binary variable that controls for post-communist countries.

3.2. Estimation strategy

We adopt Bayesian model averaging (BMA) as a method of evaluating the robustness of the examined determinants of international migration in Europe. In particular, BMA is based on an estimation[6] of all possible models that can be assigned based on the set of determinants under consideration. BMA utilizes Bayes' theorem to provide inferences based on the entire model space, thus accounting for model uncertainty. As demonstrated in the literature (Kass and Raftery 1995; Raftery 1995), methodology based on model averaging outperforms approaches based on the evaluation of multiple model specifications estimated with OLS. The latter fails to adequately account for model uncertainty.

Our baseline regression can be expressed as follows:

$$y_{ijt} = \gamma + \alpha y_{ijt-1} + \beta x_{ijt} + \upsilon_{ijt} \tag{5}$$

where y_{ijt} is the net migration flow between countries i and j over the period t, defined in equation (1), x_{ijt} is a matrix of potential bilateral migration determinants, β is a parameter vector, γ is a constant, and υ_{ijt} is a random disturbance to net migration. All the variables were standardized before estimation to facilitate comparisons of the relative strength of influence among the examined regressors.

The model setup in equation (5) allows for the use of BMA. Given 19 potential regressors (including lagged net migration), indexed by $k = 1, \ldots, 19$, it is possible to estimate $2^K = 2^{19} = 524{,}288$ models. Once estimated, each model is assigned a posterior model probability (PMP) given by Bayes' rule:

$$PMP_m = \frac{L\left(data \mid M_m\right) * P\left(M_m\right)}{\sum_{m=1}^{2^K} L\left(data \mid M_m\right) * P\left(M_m\right)} \tag{6}$$

where $L(data \mid M_m)$ is the value of the likelihood function for model m (M_m) and $P(M_m)$ is the prior probability of model m. Using the PMPs as weights allows for the calculation of the posterior mean (PM) and posterior standard deviation (PSD) of the coefficient β_k. The posterior PM of the coefficient β_k is then given by:

$$PM_k = \sum_{m=1}^{2^K} PMP_m * \hat{\beta}_{km} \tag{7}$$

where $\hat{\beta}_{km}$ is the value of the coefficient β_k estimated for the model m and k indexes the regressor. In addition, the PSD is equal to:

$$PSD_k = \sqrt{\sum_{m=1}^{2^K} PMP_m * V\left(\beta_k \mid data, M_m\right) + \sum_{m=1}^{2^K} PMP_m * \left[\hat{\beta}_{km} - PM_k\right]^2} \tag{8}$$

[6] Estimated with ordinary least squares (OLS), as well as with other estimators described later in the text.

where $V(\beta_k | data, M_m)$ denotes the conditional variance of the parameter in model M_m.

Assuming that each model M_m has a binary vector φ ascribed to it, where 0 signifies exclusion and 1 indicates the inclusion of a variable k in the model, the posterior inclusion probability is calculated as:

$$PIP_k = \sum_{m=1}^{2^K} 1(\varphi_k = 1 | data, M_m) * PMP_m \tag{9}$$

The posterior probability of a positive sign of the coefficient in the model, $P(+)$, is calculated as follows:

$$P(+) = \begin{cases} \sum_{j=1}^{2^K} P(M_j | y) * CDF(t_{ij} | M_j), \text{if } sign[E(\beta_i | y)] = 1 \\ 1 - \sum_{j=1}^{2^K} P(M_j | y) * CDF(t_{ij} | M_j), \text{if } sign[E(\beta_i | y)] = -1 \end{cases} \tag{10}$$

where *CDF* denotes the cumulative distribution function and $t_{ij} \equiv (\hat{\beta}_i / \widehat{SD}_i | M_j)$.

The application of BMA requires the specification of the model prior, and it is common to use a *g*-prior on the parameter space. The "benchmark" rule (Fernández, Ley and Steel 2001) dictates the choice of the unit information prior (UIP) (Kass and Wasserman 1995) on coefficients. The combination of UIP with the uniform model prior (equal probabilities of all considered models) is advocated by Eicher, Papageorgiou and Raftery (2011), while Ley and Steel (2009) recommend a binomial-beta model prior (equal probabilities on all considered model sizes). Accordingly, in all the estimations presented here, UIP was combined with uniform and binomial-beta priors on model space.

The robustness of the variables is assessed with the posterior inclusion probability and the absolute value of the ratio of PM to PSD of a given regressor. Raftery (1995) classifies a variable as weak, positive, strong and very strong when the posterior inclusion probability (PIP) is between 0.5 and 0.75, between 0.75 and 0.95, between 0.95 and 0.99, and above 0.99, respectively. He considers a variable robust if this ratio is higher than 1, indicating that the inclusion of the variable improves the power of the model. Masanjala and Papageorgiou (2008) advocate a critical value of 1.3 relating to a 90 per cent confidence interval in the frequentist approach, while Sala-i-Martin, Doppelhofer and Miller (2004) advise using a critical value of 2 corresponding to a 95 per cent confidence interval.

Lastly, we resort to a quantile regression by estimating equation (4) and including all the variables as explanatory factors of migration flows. The main contribution of this approach is derived from the assessment of bilateral migration flows and the above-mentioned variables outside the mean values of the data, at the same time allowing the analysis of possible non-linear relations between the set of explanatory factors and our variable of interest. Therefore, the main goal of this methodology is to disclose heterogeneous impacts of push and pull factors over migration flows. Hence, we split our sample into quantiles, from the lowest (lowest relative migration flows) to the highest quantiles (highest relative migration flows). Quantile regression has the important advantage of distinguishing which determinants are associated with different magnitudes of relative migration flows. Therefore, using this approach, we can assess not only the statistical but also the economic significance of the results. Lastly, it is important to highlight that the country-pair, as well as period composition, of each quantile changes. The period composition of quantiles is presented in table A2 in the appendix and we can see that the time composition of quantiles is relatively stable, while the country-pair composition of quantiles is characterized by far greater variability.[7]

[7] The results for the country-pair composition are not reported in the interest of brevity. They are available upon request from the authors.

4. Empirical results

4.1. BMA results

Table 1. BMA statistics under uniform and binomial-beta model priors (standardized PMs and PSDs)

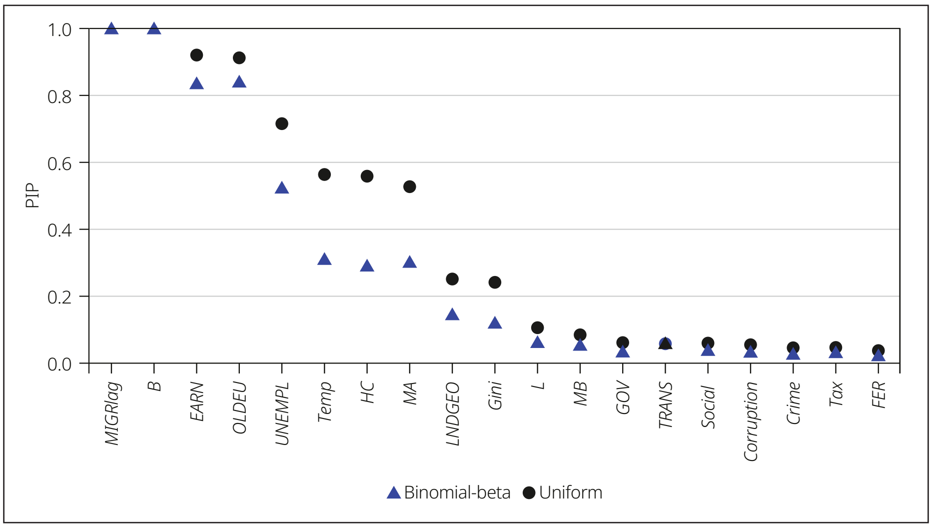
Model prior	Uniform					Binomial-beta				
Statistic	PIP	PM	PSD	PM/PSD	P(+)	PIP	PM	PSD	PM/PSD	P(+)
MIGRlag	**1.000**	**0.366**	**0.031**	**11.647**	**1.000**	**1.000**	**0.377**	**0.032**	**11.680**	**1.000**
B	**0.999**	**0.180**	**0.037**	**4.815**	**1.000**	**0.998**	**0.185**	**0.036**	**5.109**	**1.000**
EARN	**0.924**	**0.115**	**0.046**	**2.494**	**1.000**	**0.842**	**0.105**	**0.055**	**1.916**	**1.000**
OLDEU	**0.916**	**0.115**	**0.048**	**2.396**	**1.000**	**0.843**	**0.107**	**0.056**	**1.920**	**1.000**
UNEMPL	**0.712**	**0.059**	**0.044**	**1.330**	**1.000**	**0.521**	**0.043**	**0.046**	**0.936**	**1.000**
Temp	0.563	−0.054	0.054	−0.990	0.000	0.310	−0.028	0.046	−0.606	0.000
HC	0.559	0.048	0.049	0.979	1.000	0.295	0.024	0.041	0.584	1.000
MA	0.524	−0.040	0.043	−0.921	0.000	0.309	−0.023	0.038	−0.606	0.000
LNDGEO	0.253	−0.023	0.045	−0.513	0.000	0.152	−0.013	0.035	−0.377	0.000
Gini	0.240	−0.017	0.034	−0.493	0.000	0.117	−0.008	0.025	−0.321	0.000
L	0.100	0.005	0.019	0.278	1.000	0.058	0.003	0.015	0.210	1.000
MB	0.081	0.004	0.018	0.227	0.984	0.049	0.003	0.014	0.182	0.994
Social	0.063	0.002	0.011	0.188	1.000	0.039	0.001	0.010	0.154	1.000
TRANS	0.061	−0.002	0.016	−0.127	0.425	0.058	−0.003	0.018	−0.176	0.237
GOV	0.061	−0.002	0.013	−0.187	0.006	0.033	−0.001	0.010	−0.139	0.006
Corruption	0.053	0.002	0.014	0.112	0.691	0.037	0.001	0.012	0.113	0.714
Tax	0.044	0.001	0.007	0.125	0.997	0.025	0.001	0.006	0.106	0.999
Crime	0.042	0.001	0.009	0.098	0.896	0.021	0.000	0.006	0.052	0.821
FER	0.033	0.000	0.006	−0.045	0.154	0.018	0.000	0.004	−0.027	0.178

Notes: PIP = posterior inclusion probability; PM = posterior mean; PSD = posterior standard deviation; P(+) = posterior probability of a positive sign of the coefficient in the model. Variables classified as robust according to at least one criterion under both model priors are in bold.
Source: Our own calculations – see appendix table A1 for data sources of variables.

The results of the BMA under uniform and binomial-beta model priors are presented in table 1. Figure 2 depicts the comparison of PIPs between the results obtained with uniform and binomial-beta models priors. We have identified five variables that are classified as robust according to at least one criterion under both model prior specifications. All the PMs and PSDs are standardized to facilitate comparison of the relative strength among the examined determinants.[8]

[8] The non-standardized values of PM and PSD can be found in table SB1 in supplementary online Appendix B. We also examined the possibility of a nonlinear relationship using natural logarithms of all the time-variant variables. The results are presented in table SB2, where all the time-variant variables are fragile, however. This shows that, in this case, the relationship is best approximated by a linear model.

Figure 2. Posterior inclusion probabilities obtained with uniform and binomial-beta model priors



Source: Our own calculations – see appendix table A1 for data sources of variables.

The lagged migration (*MIGRlag*) variable is characterized by the highest PIP and the highest PM to PSD ratio. It also has the highest PMs for uniform and binomial priors, 0.366 and 0.377, respectively, roughly twice the size of the second variable, the border dummy. This effect is relatively strong and demonstrates that past immigration lays the foundation for future migration by facilitating better conditions for the arrival of family, friends and acquaintances. As mentioned above, current immigrants can help them find housing and jobs and introduce them to the new culture and legislation of the hosting country.

Table 2 reports the results obtained using an alternative measure of past migration – cumulated bilateral migration over the examined period, defined in equation (2). In this case, we find that the variable *CumMIG* ("friends and relatives") is even stronger, as PMs rise to 0.466 and 0.477 for uniform and binomial-beta priors, respectively, with virtually the same PSDs. This increase in the association between past and current migration demonstrates that the so-called "friends and relatives" effect increases with time as more immigrants integrate into the host country's culture or create networks and institutions that facilitate the arrival of new immigrants. Interestingly, the increase in the association between past and current migration was accompanied by a drop in the correlation between migration and unemployment differentials. As a result, *UNEMPL* is fragile in this case. This outcome further illustrates our assertion about the dominant role of differences in earnings over differences in unemployment.

As table 1 illustrates, the variable with the second highest PIP and PM to PSD ratio is the border dummy, *B*. This outcome reveals that the cultural ties connecting neighbouring countries are strong enough to outweigh the economic incentives expressed in differences in earnings or unemployment rates. The last cultural variable classified as robust is the dummy variable for EU membership prior to 2004, *OLDEU*. It is ranked above the differences in unemployment, but below differences in earnings. The results thus show that cultural factors dominate economic considerations in terms of the strength of their association with migration flows.

Regarding our main variables of interest, the first economic variable on the list of robust determinants of migration is the absolute value of the difference in net salary expressed in PPP, while differences in the unemployment rate rank as the last variable classified as robust. Their comparison shows that the effect of the difference in earnings is more than twice as strong as the effect of unemployment differences. The standardized PMs for *EARN* are 0.115 and 0.105, while for *UNEMPL* they are 0.059 and 0.043, under uniform and binomial-beta model priors, respectively. The relative strength of differences in earnings

Table 2. BMA statistics under uniform and binomial-beta model priors – specification with cumulative measure of past migration (standardized PM and PSD)

Model prior	**Uniform**					**Binomial-beta**				
Statistic	PIP	PM	PSD	PM/PSD	P(+)	PIP	PM	PSD	PM/PSD	P(+)
CumMIG	**1.000**	**0.466**	**0.031**	**15.036**	**1.000**	**1.000**	**0.477**	**0.032**	**14.818**	**1.000**
EARN	**0.844**	**0.101**	**0.053**	**1.900**	**1.000**	**0.597**	**0.070**	**0.063**	**1.108**	**1.000**
OLDEU	**0.824**	**0.092**	**0.052**	**1.771**	**1.000**	**0.581**	**0.065**	**0.061**	**1.073**	**1.000**
B	**0.822**	**0.104**	**0.060**	**1.740**	**1.000**	**0.819**	**0.108**	**0.060**	**1.807**	**1.000**
HC	0.687	0.059	0.047	1.257	1.000	0.330	0.027	0.042	0.640	1.000
LNDGEO	0.473	−0.051	0.062	−0.829	0.000	0.249	−0.028	0.053	−0.525	0.000
UNEMPL	0.254	0.015	0.029	0.515	1.000	0.108	0.006	0.020	0.312	1.000
L	0.206	0.013	0.030	0.444	1.000	0.127	0.010	0.028	0.342	1.000
Temp	0.184	−0.012	0.030	−0.412	0.000	0.066	−0.004	0.018	−0.232	0.000
Gini	0.152	−0.008	0.023	−0.363	0.000	0.053	−0.003	0.014	−0.203	0.000
TRANS	0.112	−0.007	0.025	−0.282	0.064	0.159	−0.013	0.032	−0.394	0.013
MA	0.109	−0.005	0.017	−0.293	0.000	0.040	−0.002	0.010	−0.173	0.000
Social	0.103	0.005	0.017	0.280	1.000	0.055	0.003	0.014	0.207	1.000
Corruption	0.085	0.004	0.019	0.232	0.972	0.054	0.003	0.016	0.200	0.989
Tax	0.062	0.002	0.010	0.192	1.000	0.028	0.001	0.007	0.134	1.000
GOV	0.052	−0.002	0.010	−0.162	0.008	0.021	−0.001	0.007	−0.105	0.010
MB	0.047	0.001	0.009	0.126	0.909	0.019	0.000	0.006	0.085	0.938
Crime	0.038	0.000	0.007	0.033	0.735	0.015	0.000	0.005	−0.017	0.546
FER	0.036	0.000	0.006	−0.044	0.209	0.014	0.000	0.004	−0.018	0.341

Notes: PIP = posterior inclusion probability; PM = posterior mean; PSD = posterior standard deviation; P(+) = posterior probability of a positive sign of the coefficient in the model. Variables classified as robust according to at least one criterion under both model priors are in bold.
Source: Our own calculations – see appendix table A1 for data sources of variables.

against differences in the unemployment rate is further substantiated by the fact that *EARN* passes the robustness checks that we describe in the supplementary online appendix, while *UNEMPL* fails to do so on several occasions. Still, the results on the impact of unemployment and salary differences on migration are corroborated by average values for net migration for the period.[9]

Three more variables turned out to be weakly robust under the uniform model prior; however, they were found to be fragile under the binomial-beta model prior. The first of these is the difference in human capital (*HC*), whose positive PM indicates that workers flow from the countries with low human capital to the countries with high human capital. The last two robust variables are proxies for cultural similarity: access to the ocean or sea (*MA*) and difference in the average temperature (*Temp*). The case of *Temp* is especially interesting, as it shows that the difference in temperature is a better proxy for cultural

[9] Table SB3 in supplementary online Appendix B shows that the countries characterized by the highest mean salaries and the lowest mean unemployment are the net recipients of migrants. The two exceptions are the Netherlands and Sweden, the only explanation – within the realm of identified determinants of migration flows – being that they both border on only two countries, suggesting greater cultural distance from the rest of the sample.

similarity than a common language in the European context. Moreover, a negative PM on *Temp* shows that there is no evidence for people migrating from colder to warmer countries. The remaining variables turned out to be weaker regardless of the considered robustness criterion. However, the fragility of some variables can be considered an interesting result in its own right. Differences in average tax rates (*Tax*), the level of social benefits (*Social*), the government spending share of GDP (*GOV*) and the Gini coefficient (*Gini*) are fragile. This result holds even if we drop net earnings from the considered set of regressors.[10] Therefore, the results demonstrate that intra-EU migration is not characterized by the "migration to welfare states" phenomenon. Similarly, differences in the prevalence of crime and corruption do not correlate with migration flows.

We conducted several robustness checks on the BMA results, which are presented and discussed in section B.1 of supplementary online appendix B. These confirm the findings reported in this article.

4.2. Quantile regression results

The results of the quantile regression estimation are presented in table 3.[11] The first quantile represents the smallest net migration flows, while the ninth quantile is associated with the highest migration flows. As expected, the point estimates in quantile regression are always higher than their respective PMs. In the case of quantile regression, we do not account for model uncertainty, so the estimated coefficients are biased upward in comparison. Accordingly, point estimates in quantile regression should be interpreted as upper limits of the association. For this reason, in the case of quantile regression, we interpret the results from a qualitative rather than from a quantitative perspective.

Our findings indicate that past migration is the best predictor of current migration across all quantiles. The strength of the association between the two increases from the first and the ninth quantile, from 0.542 to 0.875. The value of the point estimate increases successively from quantile to quantile. This finding further highlights the influence of the "friends and relatives" effect, where higher past migration flows contribute to increased flows in the future. The effect is non-linear and the data show that migrants gravitate more strongly towards places where their fellow citizens are already established in vast numbers. We found that differences in unemployment rates and earnings affect nearly all quantiles. We can see that the results for *EARN* in table 3 are mainly driven by lower quantiles, where the association between migration and differences in earnings is the strongest.

The values of the point estimates for earnings, as depicted in figure 3, are above the values of those for unemployment in all quantiles except the ninth, and here the coefficients are not statistically significant. This outcome corroborates the results obtained under the BMA framework regarding the relative importance of earnings and unemployment differences in driving the net migration flows. It also strongly reinforces the role of past immigration in facilitating future immigration. Relatively, the size of the impact of differences in earnings and unemployment diminishes as the size of the flow increases, while the so-called "friends and relatives" effect takes over.

The quantile regression results for the variables associated with physical distance and cultural proximity are more diverse. The geographical distance between the countries, *LNDGEO*, has a negative effect on migration in the first six and in the eighth quantiles. As expected, the greater the distance between the two countries, the smaller the size of

[10] See table SB4 in supplementary online Appendix B.

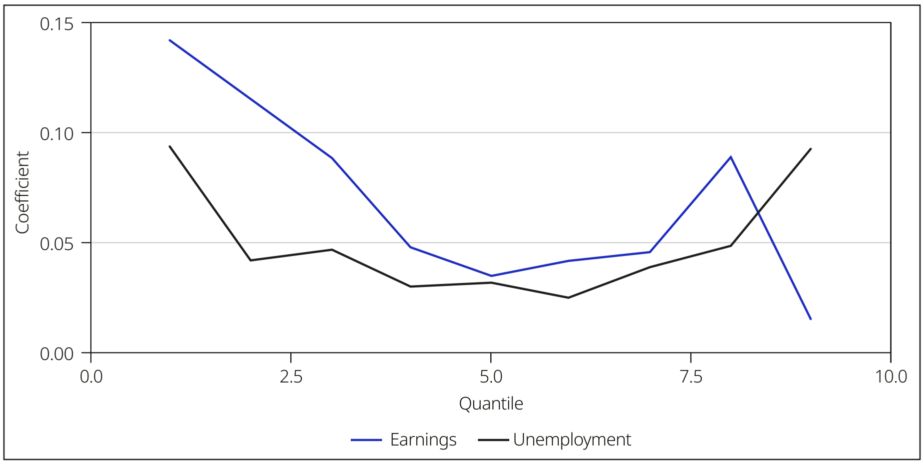
[11] We carried out robustness checks by running quantile regressions with the quantile fixed in the first period. The results are reported in section B.2 of supplementary online Appendix B. The estimation results provide even stronger evidence of the prevalence of the differences in earnings over the differences in unemployment in prompting international migration flows.

Table 3. Estimation results of the quantile regressions (standardized coefficients)

Quantile	1st	2nd	3rd	4th	5th	6th	7th	8th	9th
MIGRlag	0.542***	0.602***	0.635***	0.691***	0.716***	0.736***	0.759***	0.785***	0.875***
	(0.083)	(0.082)	(0.070)	(0.071)	(0.064)	(0.067)	(0.059)	(0.067)	(0.109)
UNEMPL	0.094**	0.042**	0.047***	0.030***	0.032***	0.025**	0.039**	0.048*	0.093
	(0.043)	(0.018)	(0.011)	(0.010)	(0.010)	(0.011)	(0.015)	(0.026)	(0.069)
EARN	0.142	0.115***	0.089***	0.048**	0.035**	0.042**	0.046**	0.089**	0.015
	(0.100)	(0.038)	(0.023)	(0.020)	(0.015)	(0.020)	(0.020)	(0.037)	(0.116)
Tax	−0.033	−0.034	−0.020	−0.018*	−0.005	−0.004	−0.007	0.008	0.038
	(0.041)	(0.024)	(0.015)	(0.010)	(0.006)	(0.007)	(0.011)	(0.014)	(0.037)
Social	0.067	0.025	0.002	−0.005	−0.008	0.003	0.005	0.008	−0.037
	(0.058)	(0.030)	(0.016)	(0.014)	(0.010)	(0.010)	(0.015)	(0.016)	(0.045)
TRANS	0.012	0.031	0.010	−0.004	−0.007	−0.005	−0.008	0.004	−0.105
	(0.065)	(0.033)	(0.023)	(0.015)	(0.012)	(0.013)	(0.016)	(0.028)	(0.066)
OLDEU	0.039	0.039	0.012	−0.002	0.005	0.017	0.032	0.044	0.006
	(0.060)	(0.036)	(0.031)	(0.024)	(0.016)	(0.018)	(0.025)	(0.035)	(0.090)
MB	0.095	0.029	0.037*	0.036**	0.031**	0.029**	0.040*	0.077**	0.177***
	(0.067)	(0.032)	(0.022)	(0.016)	(0.013)	(0.014)	(0.022)	(0.031)	(0.066)
B	0.001	0.030	0.030	0.019	0.025	0.021	0.033*	0.050*	0.065
	(0.053)	(0.037)	(0.028)	(0.024)	(0.021)	(0.019)	(0.019)	(0.028)	(0.095)
LNDGEO	−0.103**	−0.072**	−0.088***	−0.051**	−0.041**	−0.032**	−0.029	−0.050**	−0.078
	(0.048)	(0.030)	(0.024)	(0.020)	(0.016)	(0.016)	(0.019)	(0.022)	(0.050)
L	0.133***	0.031	0.017	0.023	0.016	0.028	0.037*	0.055	0.113**
	(0.046)	(0.029)	(0.027)	(0.026)	(0.021)	(0.019)	(0.022)	(0.033)	(0.055)
MA	−0.110***	−0.019	−0.011	0.004	0.008	0.009	0.008	0.017	0.023
	(0.040)	(0.013)	(0.012)	(0.011)	(0.008)	(0.008)	(0.008)	(0.016)	(0.046)
Temp	0.029	−0.011	−0.002	0.001	−0.004	−0.013	−0.026*	−0.008	−0.057
	(0.060)	(0.019)	(0.019)	(0.017)	(0.012)	(0.014)	(0.014)	(0.023)	(0.049)
HC	0.109***	0.093***	0.071***	0.044***	0.036***	0.036***	0.051***	0.071***	0.090**
	(0.034)	(0.022)	(0.021)	(0.016)	(0.012)	(0.012)	(0.012)	(0.020)	(0.040)
GOV	0.003	−0.026	−0.044***	−0.039***	−0.035***	−0.035***	−0.045***	−0.075***	−0.162***
	(0.052)	(0.017)	(0.016)	(0.011)	(0.012)	(0.009)	(0.014)	(0.024)	(0.057)
Gini	0.000	−0.029	−0.038**	−0.030**	−0.021	−0.019	−0.018	−0.047**	−0.110**
	(0.067)	(0.022)	(0.016)	(0.014)	(0.014)	(0.013)	(0.014)	(0.021)	(0.045)
FER	−0.004	0.010	−0.009	−0.010	−0.012	−0.013	−0.024	−0.053	−0.154**
	(0.057)	(0.027)	(0.018)	(0.010)	(0.011)	(0.016)	(0.019)	(0.035)	(0.065)
Corrup-tion	−0.043	−0.051**	−0.030*	−0.013	−0.005	−0.005	0.010	0.026	0.153*
	(0.063)	(0.024)	(0.015)	(0.014)	(0.012)	(0.016)	(0.023)	(0.045)	(0.084)
Crime	0.004	0.035*	0.015	0.012	0.016**	0.017*	0.032***	0.043*	0.121**
	(0.055)	(0.021)	(0.020)	(0.014)	(0.008)	(0.009)	(0.010)	(0.023)	(0.052)

*, ** and *** indicate statistical significance at the 90, 95 and 99 per cent levels, respectively.
Note: Standard errors are in parentheses.
Source: Our own calculations – see appendix table A1 for data sources of variables.

Figure 3. Point estimates on unemployment and earnings differentials over the migration distribution (standardized coefficients)



Source: Our own calculations – see appendix table A1 for data sources of variables.

the migration flows, indicating the importance of transportation costs, as well as cultural distance proxied by spatial distance. However, transportation cost does not seem to be a major factor for the largest migration flows. Sharing a common marine border, *MB*, is associated with higher bilateral migration in the top seven quantiles. The presence of a common border, *B*, is significant in the seventh and eighth quantiles, while a common language is significant in the first, seventh and ninth quantiles. The difference in average temperature, *Temp*, and access to the sea, *MA*, are significant in only one quantile. These results demonstrate that unlike past migration and economic considerations, cultural factors tend to be more quantile-specific.

Consistent with the results for the entire sample, we find that past migration is the most important predictor of future migration. Moreover, the strength of the "friends and relatives" effect increases with the magnitude of the relative migration flows. On the one hand, lower quantiles are dominated by economic considerations, including differences in earnings, differences in available job opportunities, as well as travel costs. On the other hand, cultural factors play a greater role in the higher quantiles, where we see that sharing a common border and having a common language are associated with the highest net migration flows, which can even override the purely economic drivers.

Contrary to the results across the entire distribution, the difference in human capital is positively associated with migration in all quantiles. This result demonstrates that variations in the skill level of the population are a good predictor of international migration flows. This outcome is particularly surprising, as differences in human capital are classified as fragile. However, this may be explained by the concept of complementarity of regressors from the jointness literature (Ley and Steel 2007; Doppelhofer and Weeks 2009; Hofmarcher et al. 2018). *HC* exhibits a complementary relationship with other robust determinants of international migration, such that differences in human capital are statistically significant when included with them. This is reflected by the fact that *HC* is robust under the uniform model prior. The binomial-beta model prior places greater probability mass on smaller models where the association of international migration with *HC* is not significant. Another possible explanation for the lack of robustness of *HC* in the main results is that the data suggest that the relationship is not well modelled by a linear approximation. The quantile regression results indicate that *HC* has a u-shaped impact across the quantiles, in terms of the estimated magnitude of the effect, the highest degree of association with international migration flows observed in the lowest and highest quantiles.

The difference in the government spending share of GDP (*GOV*) is negatively associated with international net migration flows, indicating that “migration to welfare states” is not supported by the data. This notion is further reinforced by the results for the difference in income distribution (*Gini*). The point estimates for this variable are negative and statistically significant in only four quantiles. The difference in the level of corruption (*Corruption*) exhibits a negative slope in lower quantiles, and coefficients are statistically significant for just two quantiles. However, the estimated coefficient turns positive in the three highest quantiles, with a statistically significant point estimate in the ninth quantile. Therefore, the data do not provide any clear conclusion regarding the association between the level of corruption and the size of migration flows. Lastly, the estimated coefficients for differences in crime rates (*Crime*) are positive and statistically significant in six quantiles, suggesting that European citizens prefer living in safer countries. However, this effect is limited to relatively high migration flows.

5. Summary and conclusion

In this article, we have examined the determinants of labour migration within the EU using a data set covering 23 countries over the 1995–2019 period. Our methodological approach involves BMA and quantile regression, our main goal being to assess the relative importance of differences in unemployment and earnings. We find that cultural proximity and the “friends and relatives” effect take the first tier in terms of the strength of their association with international migration flows. Notably, past migration remains by far the strongest predictor of future migration.

Economic determinants constitute the second tier of relative importance. Our findings indicate that the association between differences in earnings and migration is twice as strong as that of unemployment. Furthermore, the connection between differences in earnings and migration flows proves to be a robust feature in the data, while the association with differences in unemployment is not. Using quantile regression, we find that the values of the point estimates for earnings exceed those for unemployment rate differences in all quantiles (except in the ninth). This outcome corroborates the results obtained with the BMA framework regarding the relative importance of earnings and unemployment differences in driving net migration flows in the selected EU countries over the period under analysis.

Combining these findings with the gradually increasing differences in earnings, depicted in panel (b) of figure 1, we get a less optimistic picture of the EU’s potential for adjustment to asymmetric shocks. This poses an especially pressing problem, given the amount of research documenting business cycle divergence within the EU over the past decade (Beck 2020, 2021b, 2021c and 2022; Degiannakis, Duffy and Filis 2014; Ferroni and Klaus 2015; Grigoraş and Stanciu 2016). Even the COVID-19 shock had only a temporary synchronizing effect (Beck 2023). Hence, an alternative adjustment mechanism in the presence of a common monetary policy is welcome. Our results underscore that labour force migration cannot effectively fulfil this role. Consequently, both EU officials and leaders of sovereign countries, including those within the Eurozone and potential new entrants, should consider alternative solutions. With leaders’ political will, fiscal federalism might be a complementary means of ensuring a better institutional design of the EU as an OCA. However, addressing this question requires a comprehensive analysis of labour mobility in US states and in EU countries, considering the role of fiscal transfers and fiscal integration in order to disentangle the role of fiscal federalism in OCA success.

When we consider our findings regarding economic determinants, it is important to recognize their secondary importance in comparison with cultural proximity and the “friends and family” effect, which constitute the first tier of determinants of international migration. In the second tier, differences in earnings dominate over differences in unemployment rates as an important favourable economic adjustment factor. The “price” effect, proxied by differences in earnings, is thus more relevant for migration decisions than the “quantity” effect linked to the differences in unemployment rates. Therefore, unless the unemployment rates are significantly different across countries, the primary economic driver of migration within the EU is connected to salaries. Indeed, countries with higher average net salaries tend to have higher net migration inflows. In other words, human capital within the EU seeks higher earnings through migration.

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Competing interests

The authors declare that they have no competing interests.

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Appendix

Table A1. Description of the examined variables

Shorthand	Description	Source
MIGR	The absolute value of the net migration flows scaled by the sum of the population of a given pair of countries	Abel and Cohen (2022)
MIGRlag	The absolute value of the net migration flows scaled by the sum of the population of a given pair of countries lagged by one period (5 years)	Abel and Cohen (2022)
CUMmig	The absolute value of the net migration flows scaled by the sum of the population of a given pair of countries cumulated over the last *m* 5-year periods	Abel and Cohen (2022)
EARN	The absolute value of the difference in net earnings expressed in PPP, averaged over the 5-year period	Eurostat
UNEMPL	The absolute value of the difference in unemployment rates, averaged over the 5-year period	Eurostat
Tax	The absolute value of the difference in mean income tax, averaged over the 5-year period	Eurostat
Social	The absolute value of the difference in mean social benefits per person, averaged over the 5-year period	Eurostat
GOV	The absolute value of the difference in government spending share of GDP, averaged over the 5-year period	PWT
HC	The absolute value of the difference in the human capital index (Barro and Lee 2013), averaged over the 5-year period	PWT
Crime	The absolute value of the difference in the number of intentional homicides per 1 000 inhabitants, averaged over the 5-year period	World Bank
Corruption	The absolute difference in the value of control of corruption measure from the Worldwide Governance Indicator, averaged over the 5-year period	World Bank
FER	The absolute value of the difference in the fertility rate between a pair of countries, averaged over the 5-year period	World Bank
Temp	The absolute value of the difference in mean annual temperature, averaged over the 5-year period	World Bank
Gini	The absolute value of the difference in the Gini coefficient between a pair of countries, averaged over the 5-year period	Solt (2020)
TRANS	A binary variable taking the value of 1 if both countries are transition countries (post-communist countries) and 0 otherwise	IMF
LNDGEO	A natural logarithm of the distance between the capital of a given pair of countries based on the shortest route	Google Maps
B	A dummy variable that takes the value of 1 if the two countries share a common border and 0 otherwise	Google Maps
MB	A dummy variable that takes the value of 1 if the two countries share a common marine border and 0 otherwise	Google Maps
MA	A dummy variable that takes the value of 1 if both countries have access to the ocean or the sea and 0 otherwise	Google Maps
L	A dummy variable that takes the value of 1 if the two countries share at least one official language and 0 otherwise	–
OLDEU	A dummy variable that takes the value of 1 if the two countries were members of the European Union before 2004 and 0 otherwise	–
lnPOPprod	A natural logarithm of a population product of two countries averaged over a 5-year period	PWT
MIPEX	A product of the values of the indices of rigidity of labour market migration policies averaged over the 2007–19 period	miplex.eu

Note: PPP = purchasing power parities.

Table A2. Period composition of quantiles used in the estimation of table 3 (percentages)

Period	1st quantile	2nd quantile	3rd quantile	4th quantile	5th quantile	6th quantile	7th quantile	8th quantile	9th quantile
1996–2000	34	27	25	26	24	28	28	19	20
2001–05	23	36	30	20	31	17	22	25	24
2006–10	25	19	20	27	22	27	20	32	30
2011–15	19	19	26	28	24	29	31	25	26

Note: The percentages in the table show a percentage share of observations from a given period in each quantile.
Source: Our own calculations.