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Pay and Unemployment Determinants of Migration Flows in the European Union

Abstract

We analyze the migration drivers within the European Union countries. For a set of 23 EU countries over the 1995-2019 period, we use Bayesian Model Averaging and quantile regression to assess notably the relevance of unemployment and earnings. We find that the existence of a common border increases the number of net migrants by 172 people per 1000 inhabitants. In addition, 1000 PPP Euro increase in the difference in net annual salaries increases net migration by approximately 50 and 42 people per 1000 inhabitants in a working age of both countries under uniform and binomial-beta model prior, respectively. Moreover, one percentage point increase in the difference in the unemployment rate is associated with an increase in net immigration by approximately 6 and 3 persons by 1000 inhabitants in both countries. These results are also corroborated with the quantile regression results. Hence, human capital inside the EU is moving in search of higher cross-country earnings.

JEL-Codes: J610, J620, E240, F150, F220.

Keywords: migration flows, earnings, unemployment, Bayesian Model Averaging, quantile regression, EU.

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1. Introduction

The development of the theory of optimum currency areas (OCA) in Mundell (1961) was of extreme importance to understand that in a given geographic area sharing the same currency, the production factors, as labor and capital, can freely move within such area, mainly when there are asymmetric shocks within OCA. Contrarily to capital movements, labor mobility is stickier and, in that sense, the correction of the asymmetric shocks in what respects labor market gaps are, therefore, more difficult to correct. In that sense, the study of the causes that incentivize people to emigrate is crucial to better design policies aiming the correct of such heterogeneity across economies that compose an OCA.

According to this, we focus our analysis in the European Union since 1995 to understand what reasons explains migration flows. Despite European Union is not an OCA in the narrow sense of the definition, the institutional architecture of such organization can be consider quite close to what Mundell defines. Moreover, as all the euro area countries belong to the European Union, there is a closer parallelism between an OCA as the euro area and European Union. Analyzing also the countries that do not belong to the euro area but also to the European Union would also contribute to a better coordination between the euro area and the non-euro area countries that integrate into the European Union.

Furthermore, scholars tend to make a comparative analysis between an OCA as the United States and the European Union. However, the two cases are not entirely comparable since the United States share the same currency and the same cultural, political and institutional values. On the other hand, there is a perspective that the process of enlargement of the European Union can be a risk for the process of European Integration. In that sense, shocks within European Union countries can reveal several weaknesses of the institutional arrangement of this community of countries. In the meanwhile, the integration in the euro area for all the European Union economies can be the solution for the success of the integration process (Özdeşer, 2020). Alternatively, the absence of labor movements across the Economic and Monetary Union (EMU) severely constraint the capability of the economies to overcome adverse shocks (Jager and Hafner, 2013).

In sum, we decide to analyze the motives that lead people to exit from their own countries to another one, i.e., in this work we study the pull and push factors of labor force within European Union Countries. We analyze 23 countries over the 1995-2019 period. Our methodological approach. We find that the existence of a common border increases the number of net migrants by 172 people per 1000 inhabitants in working age in the given pair of countries. In addition, 1000 PPP Euro increase in the difference in net annual salaries increases net migration by approximately 50 and 42 people per 1000 inhabitants in a working age of both countries under uniform and binomial-beta model prior, respectively. Moreover, one percentage point increase in the difference in unemployment rate is associated with an increase in net immigration by approximately 6 and 3 persons by 1000 inhabitants in both countries.

Our paper is organized as follows. Section 2 provides the literature review. Section 3 presents the methodology and data employed in the analysis. Section 4 analyzes the empirical results reached in our study and, lastly, Section 5 summarizes the conclusions.

2. Related Literature

The existing literature analyze the push and pull economic determinants that influence the international movement of people. Contrarily to what would be expected according to the theory of OCA, Gros (1996) concludes the external shocks evidenced little effect on unemployment levels in the majority of European Union countries for the period prior to 1994. Moreover, and according to the author, what is important for the OCA theory is the gap between international and interregional labor mobility which is found to be very small.[1] In other words, both types of flows of people are comparable, being the real estate market the major explanation for the interregional mobility of people. Furthermore, and focusing the analysis on the Western European countries since the second half of the XX century, Jennissen (2003) and Simpson (2022) study some push and pull factors for determining the causes that lead people to migrate, reaching to the results of per capita GDP has a stimulating effect on emigration decisions while, on the other hand, the rise of unemployment in the destination country is detrimental for the incentives of population to leave their home country.

On the other hand, and comparing the European core-periphery dualism, immigration is found as an effective tool to reduce the short-run unemployment rates for all the European Union countries (Esposito et al., 2020). This result is of extreme importance in the sense that it helps to conclude that the European Union shares important features of an OCA. Therefore, immigration between countries can be an adjustment tool for countries facing adverse shocks within these economies (Beck, 2021).

Cultural factors are indeed also one of the main variables under study to assess if there is a real incentive of migration flows between countries that share common cultural values or

[1] It has been argued that the EU is not an OCA, both from the labour mobility aspect and due to the limited degree of smoothing of asymmetric shocks. Indeed, Afonso and Furceri (2008) report that for the period 1998-2005 the amount of shock to GDP unsmoothed in the EU would be 69 percent. Hence the magnitude of the smoothing was much smaller than in the case of the US (see, Asdrubali et al, 1996).

if they share some ancient interdependency as the colonial relationship. For instance, Hooge et al. (2008) face these social variables to economic variables to disentangle the factors that really lead people to migrate. Their analysis covers the European countries during the years of 1980 and 2004 founding that both cultural and economic variables are both important to explain these flows. Moreover, similarities in linguistic, higher proportion of linguistic communities at the host countries stimulate immigrant flows at the same time that lower linguistic requirement to have the citizenship and migrant integration policies are some of the important conclusions presented in Adserà and Pytliková (2015) and Beverelli (2021).

Yet, in Gallardo-Sejas et al. (2006), where the authors develop a gravity model to determine the reasons why people intends to move to European countries by analyzing 139 origin countries in the year 2000 found that besides the importance of similarities in shared cultural values, host countries with better macroeconomic performances, and higher social benefits incentive immigrant flows. On the opposite side, distance between countries are found to be detrimental for international migration flows.

Additionally, network effects have been advanced as another explanation for international migration flows. As documented in Pedersen et al. (2008) network effects are extremely important to explain why people tend to move between countries. However, the network effects can be offset to some degree because of some restriction policies to immigration, originating some selection effects. That is, in the opinion of these scholars, these policies can disincentive the migration of from lowest income in the departing countries. Beyond the network effects, and while labor market conditions, i.e., unemployment and earnings differences between countries, as well as better conditions of health and education, are significant to explain migration flows (Geis et al., 2013), also real wages and productivity levels gaps are crucial for determine the incentive of people to leave their home country (Landesmann et al., 2015).

Most of all, economic determinants are found to be decisive to explain emigration from origin countries. Specifically, income gaps between departing and incoming country are crucial to explain such movements. Yet, distance between countries appears to have a negative effect while younger countries seems to register a positive effect on emigration. However, and by corroborating previous results in the literature, immigration policies, like the imposition of immigrant quotas, can hampers economic pull factors as income differences between economies (Mayda, 2010; Miller, 2012; Ortega and Peri, 2013).

3. Data and methodology

3.1. Data

Due to the data limitations our sample consists of 23 European Union countries: Austria, Belgium, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, and the UK. The data in the estimations cover the 2000-2019 period for the examined determinants of migration flows, while data on the dependent variable covers 1995-2019 period, as we include the lagged dependent variable in our estimations. The detailed description of the variables and the sources of the data can be found in appendix A.

To measure the degree of labor migration we utilize the newly available dataset on international bilateral inflation flows prepared by Abel and Cohen (2022)[2]. The database reports the data over five-year periods, and consequently all the variables used in the estimations are adjusted to this format. We scaled the net migration flows using the sum of the population of working age in each pair of countries using data from the Eurostat. Consequently, the net migration per 1000 inhabitants of working age (15-64) between any pair of countries is calculated as:

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

where, $\left|NetMIGR_{ijt}\right|$ is net migration between countries i and j, at time $t = 1995, 2000, \ldots, 2015$ denoting the first year of the considered five-year period, Pop_{it+k} and Pop_{jt+k} are populations of working age in country i and j respectively, and $k = 0, 1, \ldots 4$. The moments of the distribution of $MIGR$ in six consecutive periods for the examined countries are depicted table 1.

Table 1. Percentiles of the distribution of net migration per 1000 inhabitants (of both countries) in working age (15-64) in the examined country pairs.

Percentile	Min	5th	10th	25th	33rd	50th	66th	75th	90th	95th	Max
1990-1994	0.00005	0.00059	0.00178	0.00580	0.01253	0.03020	0.07701	0.13313	0.56932	1.52391	8.42161
1995-1999	0.00007	0.00053	0.00133	0.00485	0.00926	0.02264	0.09013	0.15088	0.56453	1.60135	21.79887
2000-2004	0.00000	0.00045	0.00110	0.00628	0.01067	0.03884	0.09262	0.16622	0.80376	2.52815	31.51318
2005-2009	0.00002	0.00092	0.00144	0.00779	0.01373	0.04381	0.09614	0.18847	0.72667	2.04273	12.68762
2010-2014	0.00001	0.00064	0.00178	0.00970	0.01797	0.06873	0.16753	0.27903	1.09142	2.44986	18.31758
2015-2019	0.00010	0.00125	0.00381	0.00945	0.01702	0.05664	0.13772	0.24600	1.06381	2.01134	8.38275

Source: Authors calculations based on Abel and Cohen (2022) and the Eurostat.

[2] The dataset used in this paper is an extension of the dataset described in detail in Abel and Cohen (2019)[2].

The first explanatory variable that we consider is lagged migration ($MIGRlag \equiv MIGR_{ijt-1}$). Lagged migration can be used as a proxy for well-established formal and informal migration channels, especially that immigrants already living in a given country are able to facilitate inflows of their relatives, friends, and acquaintances by helping them finding housing, jobs, and introducing them into the new culture.

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

$$EARN_{ijt} = \frac{1}{5}\sum_{k=0}^{4}\left|NetEARN_{it+k} - NetEARN_{jt+k}\right| \tag{2}$$

where, $NetEARN_{it+k}$ and $NetEARN_{jt+k}$ are average after-tax earnings expressed in purchasing power parity Euros in country i and j respectively, at time $t = 2000, 2005, 2010, 2015$, and $k = 0, 1, \dots 4$.

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

$$UNEMP_{ijt} = \frac{1}{5}\sum_{k=0}^{4}\left|UN_{it+k} - UN_{jt+k}\right| \tag{3}$$

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

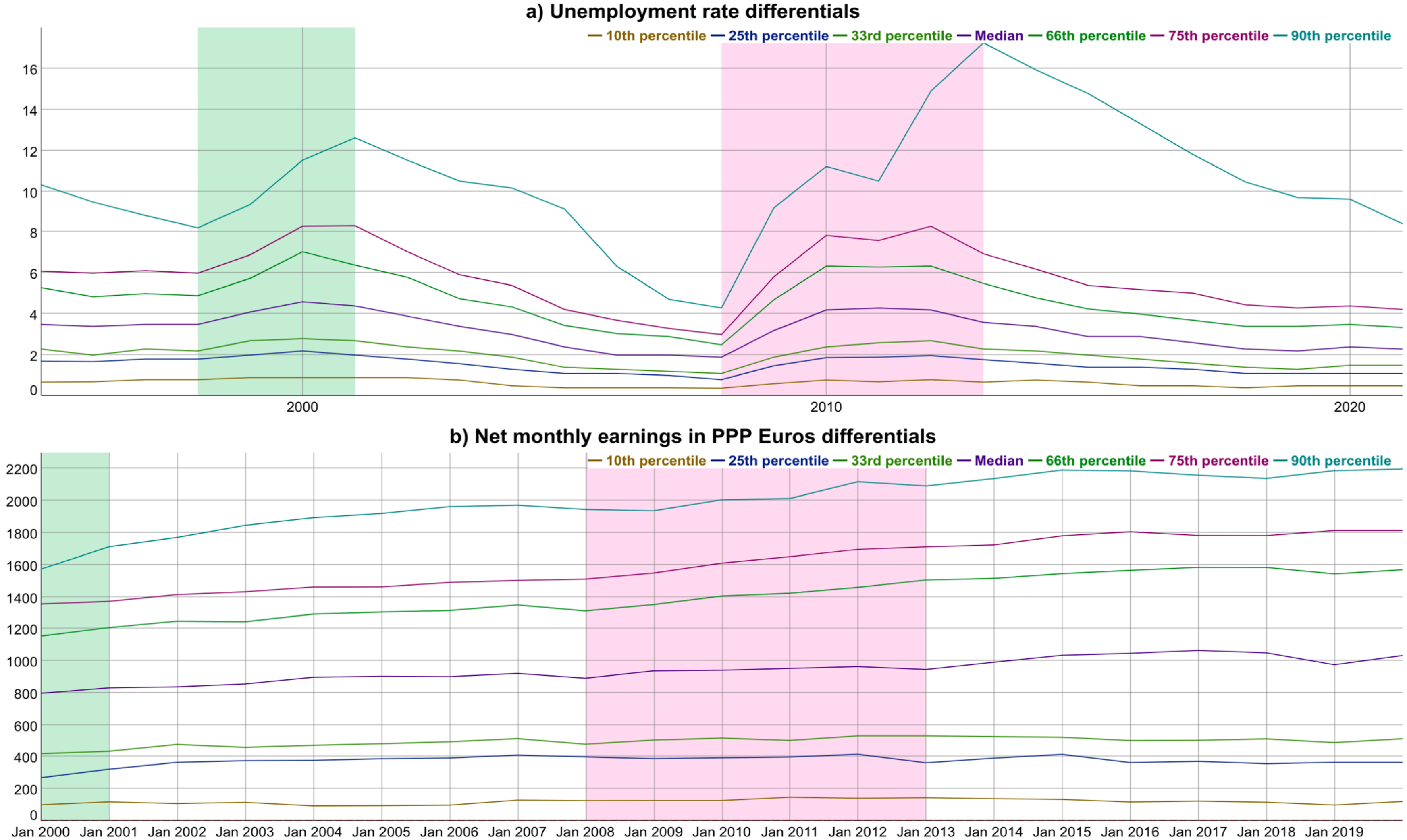
The moments of the distribution of the differences in the unemployment rates and in net earnings are depicted in Figure 1. The unemployment rate differentials demonstrate the tendency of increasing during the periods of economic expansions (e.g., dot-com bubble) and recessions (e.g., dot-com bubble burst, Global Financial Crisis, and Sovereign Debt crisis), while during the tranquility periods they exhibit the tendency towards unemployment rate convergence. The net earnings differentials, on the other hand, do not display any pattern of convergence. The moments below the median remain relatively stable, while those above median manifest slow evolution towards larger disparities. In contrast with the unemployment rates, the tendencies in the behavior of net earnings differentials remain roughly similar in the times of crises, expansion, or tranquility.

We control for several economic, social, and cultural factors that can potentially contribute to net migration. We use nine economic variables. The variable Tax represents the absolute value of the difference in the income tax rate between two countries, averaged over the five-year period. $Social$ denotes the absolute value in the average in social benefits per person between two countries, averaged over the five-year period. The data on Tax and $Social$ is taken from the Eurostat.

We also examine the impact of the size of the government through the variable GOV, calculated as the absolute value of the difference in the government spending share of GDP between two countries, averaged over the five-year period. The variable HC is calculated as the absolute value of the difference in the level of human capital between two examined countries, averaged over the five-year period. We use the Barro and Lee (2013) measure of human capital based on schooling attainment. The data on GOV and HC come from the PWT database (Feenstra *et al*. 2015). We account for the differences in income distribution using the variable $Gini$, defined as the absolute value of the difference in the Gini coefficient between two countries, averaged over the five-year period. The data on the Gini coefficients comes from Frederick (2020).

Moving to social and institutional, we first account for the differences in safety and crime. The variable $Crime$ is defined as the absolute value of the difference in the number of intentional homicides per 1000 inhabitants, averaged over the five-year period. The data on the number of homicides comes from the World Bank database. Next, we control for the difference in the level of corruption using the absolute of the difference in the value of control of corruption measure from the Worldwide Governance Indicator database prepared by the World Bank. The variable $Corruption$ is defined as a five-year average of those absolute values. FER is calculated as the absolute value of the difference in the fertility rate in each pair of countries, averaged over the five-year period. The data on fertility rate comes from the World Bank database.

Figure 1. Unemployment rate and net earnings differentials



Note: The green shaded area denotes the period dot.com bubble, and the pink shaded area denotes the period of Global Financial and Sovereign Debt Crisis.

The last group of factors that we consider are related to the differences in culture. The first four variables could be considered proxies for transportation costs; however, they are widely considered as proxies for cultural distance between the countries. B is a dummy variable that takes the value of 1 if the two countries share a common border and 0 otherwise. MB is a dummy variables that takes the value of 1 if the two countries share a common marine border and 0 otherwise. MA is a dummy variable that takes the value of 1 if both countries have access to the ocean or the sea and 0 otherwise. $LNDGEO$ is a natural logarithm of the distance between the capital of a given pair of countries (the shortest route on Google Maps).

The variable $Temp$ is calculated as the absolute value of the difference in the average annual temperature between two countries, averaged over the five-year period. The data on average annual temperature is taken from the World Bank. On the one hand, the variable could be considered a proxy for the quality of life, as living in warmer European countries is associated with additional befits (nicer whether) and those countries are the major tourism destinations. On the other hand, especially in the European context, the difference in temperature can serve as a proxy for cultural similarity.

$OLDEU$ is a dummy variable that takes the value of 1 if the two countries were members of the European Union before 2004 and 0 otherwise. L is a dummy variable that takes the value of 1 if the two countries share at least one official language and 0 otherwise. $TRANS$ is a binary variable taking the value of 1 if both countries are transition countries (classification according to IMF), in other words they are post-communist countries, and 0 otherwise.

3.2. Estimation strategy

The baseline regression can be expressed as follows:

$$y_{ijt} = \gamma + \alpha y_{ijt-1} + \beta x_{ijt} + \upsilon_{ijt} \tag{4}$$

where y_{ijt} is a net migration flow between country *i* and *j* over the period *t*, 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 of the examined regressors.

With the model setup in equation (4) it is possible to use Bayesian Model Averaging (BMA). Given nineteen potential regressors (including lagged net migration), indexed by $k = 1, \dots, 19$, it is possible to estimate $2^K = 2^{19} = 524288$ models. Once estimated, each model is assigned a posterior model probability (PMP) given by the Bayes rule:

$$PMP_m = \frac{L(data|M_m) * P(M_m)}{\sum_{m=1}^{2^K} L(data|M_m) * P(M_m)}, \tag{5}$$

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

$$PM_k = \sum_{m=1}^{2^K} PMP_m * \hat{\beta}_{km}, \tag{6}$$

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 posterior standard deviation (PSD) is equal to:

$$PSD_k = \sqrt{\sum_{m=1}^{2^K} PMP_m * V(\beta_k|data, M_m) + \sum_{m=1}^{2^K} PMP_m * \left[\hat{\beta}_{km} - PM_k\right]^2}, \tag{7}$$

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, while 1 inclusion of a variable k in the model, the posterior inclusion probability is calculated as:

$$PIP_k = \sum_{m=1}^{2^K} 1(\varphi_k = 1|data, M_m) * PMP_m. \tag{8}$$

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

$$P(+) = \begin{cases} \sum_{j=1}^{2^K} P(M_j|y) * CDF(t_{ij}|M_j), & if\ \ sign[E(\beta_i|y)] = 1 \\ 1 - \sum_{j=1}^{2^K} P(M_j|y) * CDF(t_{ij}|M_j), & if\ sign[E(\beta_i|y)] = -1 \end{cases} \tag{9}$$

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

The application of BMA requires the specification of the model prior, and it is common to use g prior on parameter space. The Benchmark rule (Fernández *et al*. 2001) dictates the choice of 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 et al. (2011), while Ley and Steel (2009) recommend binomial-beta model prior (equal probabilities on all considered model sizes). Therefore, 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 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. Raftery (1995) 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% confidence interval in the frequentist approach, while Sala-I-Martin *et al*. (2004) advise 2 corresponding to a 95% 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 relies on the assessment of the bilateral migration flows and the abovementioned variables outside the mean values of the data, permitting, at the same time, the analysis of possible nonlinear 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 deciles, from the lowest (highest share of immigration) to the highest quantiles (lowest shares of immigration). Moreover, it is also worth mentioning that we treat our panel data for both time and fixed effects, then our quantile regressions consider those fixed effects.

4. Empirical results

The results of the Bayesian model averaging under uniform and binomial-beta model prior are depicted in Table 2. We have identified five variables that are classified as robust according to at least one criterion in the case of both model prior specifications. All the posterior means (PM) and posterior standard deviations (PSD) are standardized to facilitate comparison of the relative strength of the examined determinants. The not standardized values of posterior mean and posterior standard deviation are in Appendix B.

The lagged migration (*MIGRlag*) is the variable that is characterized by the highest posterior inclusion probability and the highest posterior mean to posterior standard deviation ratio. It also has the highest posterior mean, 0.366 and 0.377, for uniform and binomial prior respectively, roughly twice the size of the second variable, the border dummy. For instance, an increase in the net migration by 1000 people per one thousand inhabitants in the productive age of a given pair of countries increases migration in the next period by 376 to 387 people per one thousand inhabitants. This effect is relatively strong and demonstrates that past immigration lies foundation for the future migration by facilitating better conditions for the arrival of the family, friends, and acquaintances. The current immigrants can help them find housing, jobs, and introducing them into the new culture and legislature of the hosting country.

The variable with the second highest posterior inclusion probability and posterior mean to posterior standard deviation ratio is the border dummy, *B*. Not surprisingly the existence of the common border increases the number of net migrants by 172 and 177 people per 1000 inhabitants in working age in the given pair of countries. This outcome reveals that the cultural ties connecting the neighboring countries are strong enough to dominate the economic incentives expressed in differences in earnings or unemployment rates. The other cultural variable classified as robust is *OLDEU* – dummy variable taking value of 1 for both countries being members of the European Union before 2004. We find that old European Union members are characterized by higher net migration flows by 73 and 68 people per 1000 inhabitants in productive age in the given pair of countries in comparison with country pairs containing at least one country that joined the EU in 2004 or after.

Regarding our main variables of interest, the first economic variable of the list of robust determinants is the absolute value of the difference in net salary expressed in PPP. A 1000 PPP Euro increase in the difference in net annual salaries increases net migration by approximately 50 and 42 people per 1000 inhabitants in a working age of both countries under uniform and binomial-beta model prior, respectively. In addition, the absolute value of the difference in the unemployment rate is also statistically significant. A one percentage point increase in the difference in the unemployment rate is associated with an increase in net immigration by approximately 6 and 3 persons by 1000 inhabitants in both countries. The comparison between the effects of these two economic determinants of migration shows that the effect of the difference in earnings is more than twice as strong as the unemployment differences. The standardized posterior mean on EARN is 0.115 and 0.105, while for UNEMPL is 0.059 and 0.043, under uniform and binomial-beta model prior respectively. The results on the impact of unemployment and salary differences on migration are corroborated by Table 3. There we can see that the countries characterized by highest mean salaries and the lowest mean unemployment are the net recipients of migrants, with the exception of Netherlands and Sweden.

Table 2. BMA statistics under uniform and binomial-beta model prior
(Standardized PM and PSD)

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

Note: variables classified as robust according to at least one criterion under both model priors are in bold.

Three more variables turned out to be weekly robust under the uniform model prior, however, fragile under binomial-beta model prior. The first of them, is the difference in human capital (HC). The positive posterior mean of this variable indicates that workers flow from the countries with low human capital to the countries with high human capital or from countries with high human capital to countries with low human capital.

The remaining two variables are proxies for the cultural similarity, the access to the ocean or the see (MA) and the 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 similarity than common language in the European context. Moreover, a negative posterior mean on Temp, shows that there is no evidence for people migrating from colder to warmer countries. The remaining examined variables turned out to be fragile regardless of the considered robustness criterion.

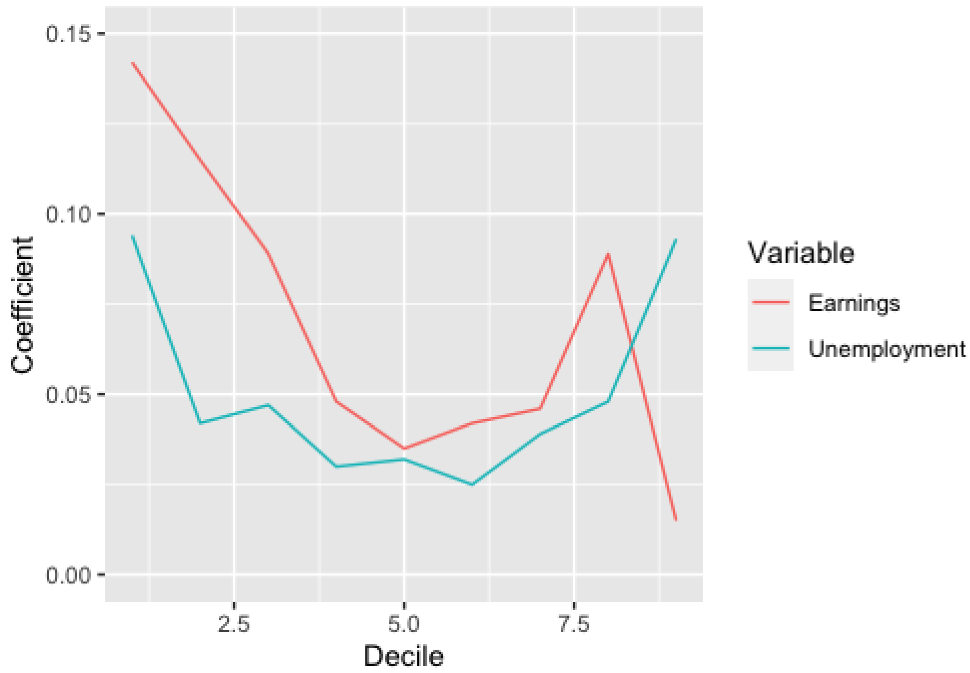
Table 3. Average net salary, unemployment rate and net migration per 1000 of inhabitants of working age over the 2000-2019 period.

Country	Net salary	Unemployment rate	Net migration per 1000 people
Luxembourg	**35,342.18**	**5.01**	**2.49**
UK	**32,559.47**	**5.69**	**0.12**
Ireland	**31,003.66**	**8.26**	**0.70**
Denmark	**30,880.70**	**5.71**	**0.10**
Netherlands	*30,312.31*	*5.76*	*-0.29*
Sweden	*28,370.05*	*7.16*	*-0.07*
Finland	**26,291.12**	**8.25**	**0.15**
Austria	**26,106.57**	**5.37**	**0.45**
Germany	**25,374.79**	**6.32**	**0.31**
Belgium	**24,453.54**	**7.62**	**0.24**
France	*24,319.92*	*8.97*	*-0.24*
Italy	**19,195.03**	**9.47**	**0.03**
Spain	**18,516.97**	**16.01**	**0.00**
Greece	*15,832.33*	*16.22*	*-0.56*
Portugal	*12,030.63*	*10.15*	*-0.12*
Slovenia	*10,397.39*	*6.78*	*-0.15*
Estonia	**8,284.49**	**8.63**	**0.29**
Czechia	**7,914.51**	**5.80**	**0.20**
Slovakia	*7,159.32*	*12.66*	*-0.10*
Poland	*6,875.57*	*10.91*	*-0.33*
Hungary	*5,961.82*	*6.88*	*-0.17*
Lithuania	*5,470.63*	*10.33*	*-1.47*
Latvia	*5,153.08*	*11.15*	*-0.58*
Average “Recipient”	***23826.92***	**7.68**	***0.42***
Average “Donor”	*13316.46*	*9.40*	*-0.32*

Note: Countries with positive net-flows, “Recipients”, are in bold, while countries with negative net-flows, “Donors”, are in italic.
Source: Authors calculation based on Eurostat and Abel and Cohen (2022)

Regarding our quantile regression estimations, we found that differences in unemployment rates and earnings affect almost all the quantiles. The values of the point estimates for earnings, depicted in Figure 2, are above the values of those of unemployment in all deciles except the 9th decile, however, in the 9th decile the coefficients are not statistically significant. This outcome corroborates the results obtained within the BMA framework regarding the relative importance of earnings and unemployment differences in driving the net migration flows. The main driver of migration over all quantiles is past migration. It is statistically significant in all quantiles, and it is characterized by the highest value of the coefficient, and increases from the 1st to the 9th decile by 61%. This outcome strongly reinforces the role of past immigration in facilitating future immigration, Nevertheless, the size of the impact is declining with the increasing size of the flow.

Figure 2. Point estimates on unemployment and earnings differentials over the migration distribution



On the other hand, the results from quantile regression are different for the variables associated with physical distance and cultural proximity. The geographical distance between the countries, *LNDGEO*, has negative effect on migration in the first eight quantiles. Sharing common marine border, *MB*, is associated with higher bilateral migration for seven deciles. However, other cultural proximity variables (B, L, MA, and Temp) are statistically significant only in one or two quantiles.

Contrarily to the results over the entire distribution, the differences in human capital have positive impacts on migration in all deciles. The difference in government share of GDP is negatively associated with international net migration flows. This outcome indicates that "migration to welfare states" is not supported by the data. This notion is further reinforced by the results for the difference in the degree of income distribution (*Gini*). The point estimates on this variable are negative and statistically significant only in four quantiles. Finally, the estimated coefficients on differences in crime rates are negative and statistically significant in six deciles demonstrating that European citizens prefer living in safer countries.

Table 4. Estimation results of the quantile regressions

Decile	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)
Corruption	-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)
Observations	1014	1014	1014	1014	1014	1014	1014	1014	1014

Standard errors are in parentheses; */**/*** denotes coefficient statistically significant at 0.9/0.09/0.99 level. All models were estimated with country-pair and time fixed effects estimator

5. Conclusion

In this paper we have studied the pull and push factors of labor force within European Union Countries. We analyze 23 countries over the 1995-2019 period. Our methodological approach. We find that the existence of a common border increases the number of net migrants by 172 people per 1000 inhabitants in working age in the given pair of countries.

In addition, 1000 PPP Euro increase in the difference in net annual salaries increases net migration by approximately 50 and 42 people per 1000 inhabitants in a working age of both countries under uniform and binomial-beta model prior, respectively. Moreover, one percentage point increase in the difference in unemployment rate is associated with an increase in net immigration by approximately 6 and 3 persons by 1000 inhabitants in both countries.

Moreover, the values of the point estimates for earnings, are above the values of those of the unemployment rate differences in all deciles except the 9th decile (where it is not statistically significant). This outcome corroborates the results obtained within the BMA framework regarding the relative importance of earnings and unemployment differences in driving the net migration flows in the EU countries in the period under analysis.

Our results offer some possible policy implications. The “price” effect, proxied by the differences in earnings is then more relevant for migration decisions, than necessarily the “quantity” effect, linked to the differences in the unemployment rates. Therefore, if the unemployment rates are not too different across countries, the main economic driver for migrations within the EU is linked to salaries, which will attract labour forces from other countries. Indeed, if we recall Table 3, countries with higher average net salaries seem to go hand-in-hand with higher net migration inflows. In other words, human capital inside the EU is moving in search of higher earnings.

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Appendix A

Table A. Description of the examined variables

Shorthand	Description	Source
MIGR	The absolute value of the net migration flows scaled by the sum of 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 population of a given pair of countries lagged by one period (5 years)	Abel and Cohen (2022)
EARN	The absolute value of the difference in net earnings expressed in PPP, averaged over the five year period	Eurostat
UNEMPL	The absolute value of the difference in unemployment rates, averaged over the five year period	Eurostat
Tax	The absolute value of the difference in mean income tax, averaged over the five year period	Eurostat
Social	The absolute value of the difference in mean social benefits per person, averaged over the five year period	Eurostat
GOV	The absolute value of the difference in government spending share of GDP, averaged over the five year period	PWT
HC	The absolute value of the difference in the human capital index (Barro and Lee 2013), averaged over the five year period	PWT
Crime	The absolute value of the difference in the number of intentional homicides per 1000 inhabitants, averaged over the five-year period	World Bank
Corruption	The absolute of the difference in the value of control of corruption measure from the Worldwide Governance Indicator, averaged over the five-year period	World Bank
FER	The absolute value of the difference in the fertility rate in each pair of countries, averaged over the five-year period	World Bank
Temp	The absolute value of the difference in mean annual temperature, averaged over the five year period	World Bank
Gini	The absolute value of the difference in the Gini coefficient between two countries, averaged over the five-year period	Frederick (2020)
TRANS	A binary variable taking the value of one 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	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	-

Appendix B

Table B. BMA statistics under uniform and binomial-beta model prior (not standardized PM and PSD)

Model prior	*Uniform*				*Binomial-beta*			
Statistic	*PIP*	*PM*	*PSD*	*P(+)*	*PIP*	*PM*	*PSD*	*P(+)*
MigLAG	**1.000**	**0.3755725**	**0.0322754**	**1.000**	**1.000**	**0.3870318**	**0.0331924**	**1.000**
B	**0.999**	**0.1724157**	**0.0358659**	**1.000**	**0.998**	**0.1771481**	**0.0343089**	**1.000**
Earn	**0.924**	**0.0000042**	**0.0000017**	**1.000**	**0.842**	**0.0000038**	**0.0000020**	**1.000**
OLDEU	**0.916**	**0.0734890**	**0.0305800**	**1.000**	**0.843**	**0.0675566**	**0.0355768**	**1.000**
Unempl	**0.712**	**0.0048812**	**0.0036558**	**1.000**	**0.521**	**0.0035526**	**0.0037830**	**1.000**
Temp	0.563	-0.0062355	0.0062491	0.000	0.310	-0.0032044	0.0052951	0.000
HC	0.559	0.0561786	0.0569985	1.000	0.295	0.0277204	0.0480026	1.000
MA	0.524	-0.0264638	0.0284689	0.000	0.309	-0.0147588	0.0247367	0.000
LNDGEO	0.253	-0.0105463	0.0204881	0.000	0.152	-0.0057335	0.0157437	0.000
Gini	0.240	-0.0017498	0.0035021	0.000	0.117	-0.0008269	0.0025502	0.000
L	0.100	0.0078340	0.0278041	1.000	0.058	0.0046860	0.0220479	1.000
MB	0.081	0.0034023	0.0149518	0.984	0.049	0.0024154	0.0126145	0.994
Social	0.063	0.0000003	0.0000018	1.000	0.039	0.0000002	0.0000016	1.000
TRANS	0.061	-0.0019756	0.0155183	0.425	0.058	-0.0032109	0.0177309	0.237
GOV	0.061	-0.0196242	0.1037506	0.006	0.033	-0.0111917	0.0786776	0.006
Corruption	0.053	0.0008375	0.0071910	0.691	0.037	0.0006823	0.0060799	0.714
Tax	0.044	0.0000561	0.0004533	0.997	0.025	0.0000421	0.0003857	0.999
Crime	0.042	0.0001422	0.0014324	0.896	0.021	0.0000620	0.0010155	0.821
FER	0.033	-0.0004565	0.0103694	0.154	0.018	-0.0001952	0.0079039	0.178

Note: variables classified as robust according to at least one criterion under both model priors are in bold.