

Mapping and modelling the main determinants of Migration Flows at the NUTS2 Level in European Union using Spatial Data Analysis Techniques

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Abstract. *Spatial data analysis approaches have grown in popularity in recent years as there has been an increased interest in studying migration at the regional level. We employed in our analysis the Nomenclature of Territorial Units for Statistics (NUTS) level, which offers a more thorough view of migratory patterns inside a nation as well as among EU countries. Using spatial data analytic tools, this research aims to investigate the key determinants of international migration at the NUTS2 level. Using data from the Eurostat database, we undertake an extensive analysis of migration movements in a sample of European Union countries. We apply spatial econometric models to examine the relationship between crude rate migration and other relevant variables as independent variables. Although the available data at the NUTS2 level of regional ranking are limited, we believe that we included the most comprehensive set of relevant variables in our analysis. Our study contributes to the existing literature on migration determinants by highlighting the importance of spatial analysis techniques in understanding migration factors at the NUTS2 level.*

Keywords: spatial analysis, spatial econometrics, spatial distribution, European Union, NUTS level, migration.

Please cite the article as follows: Prada, E-M and Cimpoeu, S, (2023), "Mapping and modelling the main determinants of Migration Flows at the NUTS2 Level in European Union using Spatial Data Analysis Techniques", *Management & Marketing*, Vol. 18, No. 4, pp. 594-607, DOI: 10.2478/mmcks-2023-0032.

Introduction

The migration phenomenon is an intricate and varied issue, with important ramifications for both the nations of origin and destination. Migration in European Union (EU) has become an increasingly salient challenge in the recent years, with the movement of people from different regions within the EU and from outside the EU (Kahanec et al., 2009; Boswell, 2018; Triandafyllidou, 2022). Also, migration is a dynamic phenomenon, constantly changing, that

is shaped by a wide range of factors that interact with each other (Mencutek, 2022). In this context, our paper addresses the determinants of migration from regional perspectives.

The main theories of migration identify the following migration factors: economic factors (such as job opportunities or a higher income); social factors (e.g. family reunification); political factors (wars or other political instabilities in a person's home country); environmental factors (such as climate change or natural disasters); demographic factors (age, gender or family status that influence the different need of a person when decide to relocate) (de Haas, 2011; Kurekova, 2011). These factors can be grouped in three different levels of analysis such as micro, mezzo, and macro (Faist, 2010; Faist, 2021).

Our focus for this research is a macro-level analysis to identify regional patters of migration factors. Examining regional data at NUTS2 level, we hope to identify the regional differences in terms of migration determinants.

Considering the continuously changing nature of migration and its diversity of factors, but keeping in mind the limits of macro-analysis, we employed the geographically weighted regression (GWR) method. GWR has various advantages such as: improved accuracy by considering spatial variation, better understanding of the spatial patters usually hard to be captured by traditional regression models, or identifying spatially specific patterns and relationships between variables (Charlton et al, 2009; Sheehan et al., 2013; de Bellefon & Floch, 2018; Goschin, 2018). The ultimate aim of this paper is to examine how GWR may be used to research the determinants of migration in the EU and we discuss about the insights that this method offers.

In our endeavour to address the stated objectives, our paper folds in four parts: literature review, methodology, data and variables, followed by the findings and conclusions.

Literature review

This study explores the relationship between migration rate and its main determinants, as stated by the leading migration scholars such as de Haas (2011) or Faist (2010, 2021).

The literature focusing on why people migrate is extensive and has been the subject of multiple theories. The reason for this plethora of existing theories is that migration is a very diverse and multifaceted phenomenon to be explained only by one theory (Arango, 2000).

Based on these theories, migration drivers can be analysed from a micro or macroeconomic perspective (for a review on the studies see Strey et al. (2018), Jennissen (2003). From a microeconomic perspective, individual-level drivers of the migration decision refer to: economic self-improvement, job opportunities in the destination country, expected earnings, improved social security, the existence of solid social networks in the host country (Fouarge & Ester, 2007). However, since the focus of our paper will be at macroeconomic level, we will approach more in depth this perspective.

One of the most important theories on the determinants of migration is the neo-classical theory of migration (Hicks, 1932). Within this theory, the decision to migrate is driven by a desire to maximize the net income, thus is based on the differences in earnings between receiving and sending economies. Later, Sjaastad (1962) added a socio-economic dimension to the migration decision, arguing that people would accept the initial cost associated with the migration process to gain skills and knowledge that would increase the productivity in the long-run. It is also worth mentioning the alternative to the neo-classical

theory offered by Harris and Todaro (1970) who claim that migration depends in fact on the expected difference in earnings and not on the actual difference. Thus, these findings argue a reaction of the migration process to the differences in earnings between sending and receiving countries. Based on this, we expect that income and earnings play an important role in the decision to migration. Consequently, we can formulate our first research hypothesis as follows:

H1. Income level is a significant predictor for migration and it has a positive effect on the net migration rate in the host region.

As main economic determinants, income differentials are usually studied together with unemployment rate, both indicators being crucial in analysing the status of the economy. Hence essential elements of the migration process.

The dual labour market theory (Piore, 1979) argues that one of the potential explanations for the demand of foreign market would be the labour shortages especially on the secondary segment. As postulated in the neo-classical theory, migrants will mainly move from regions with labour surplus (high unemployment) to labour-scarce regions (low unemployment rates) for better job prospects. More explicitly, unemployment is a strong supply-push factor in the host economy (Jennissen, 2003). Therefore, the second hypothesis can be stated as:

H2. Unemployment rate is a significant factor for migration and has a negative impact on the net migration rate.

A narrow string of the literature on migration pointed out that there are differences between regional labour markets with respect to their effect on migration (Rijnks, 2020). These differences refer to various socio-economic characteristics. For examples, while students move towards university cities, graduates would prefer larger and dynamic urban centres, whereas persons belonging to the so-called „counter urbanisation groups“ would prefer to move to rural areas (Rijnks, 2020). What is more, there are also differences between and within urban and rural areas regarding the people they attract. Starting from this, we formulate our third research hypothesis, namely:

H3. There is significant regional variation in the determinants of net migration at EU27 level

The existence of spatial variation implies that applying the standard regression models (for instance OLS), will average out the differences existing between factors influencing migration among regions (Rijnks, 2020). This would lead to an incorrect identification of migration drivers.

The changing nature of the migration phenomenon makes it difficult for global statistical models, such as linear regressions, to capture patterns that otherwise can be observed by considering the spatial variation. In this context, we applied a geographically weighted regression model to address the local variation of the migration phenomenon. Unlike the general OLS, a Geographically Weighted Regression (GWR) assumes that the effect of explanatory variables is not constant across regions. Accordingly, the GWR model estimates local coefficients for each area or region. Though GWR as a statistical instrument has various advantages, was scarcely applied in migration analysis (see Goschin, 2018; Rijnks, 2020). Based on this, we formulate our last research hypothesis:

H4. GWR offers a better insight for migration analysis than classical OLS regression.

Considering that existing studies primarily focused on a global analysis on determinants of migration, with little paid attention to regional differences and spatial variation, our paper enriches the current literature by examining data at a more granular level, such as the NUTS2 regional level. This approach allows us to gain a more nuanced understanding of the factors driving migration in different regions.

Methodology – The Geographically Weighted Regression (GWR)

To address our research questions, we have chosen for the Geographically Weighted Regression (GWR), a statistical technique employed in spatial data analysis to model spatial variation. Unlike traditional regression models, GWR offers insights of spatially varying relationships by estimating separate regression coefficients for each location in the dataset. This allows us to examine geographical data to find patterns and associations that might not be obvious using conventional regression approaches (Goschin, 2018).

Depending on how the response variable is measured we identify three different types of GWR models (de Bellefon & Floch, 2018). Specifically, we used the continuous GWR model (also known as Gaussian). This model requires the dependent variable to be continuous and ideally its distribution has to be normal. One way to respond to non-normally distributed dependent variables is to recode them into binary variables, but in this case the estimated model will be binary GWR.

The GWR approach is easy to implement, with the hypothesis testing procedure being similar to that of traditional models, but with the advantage of revealing significant spatial regularities that are not captured by standard methods. In this sense, spatial variations in regression coefficients are determined using a weighting matrix in the estimation process. As mentioned before, for each location or area in the dataset a varying sample is established, each generating its own set of regression coefficients. These local regression coefficients indicate the sample heterogeneity, since they evaluate the variation in the effects of the explanatory variables across space (Vinuela et al., 2015).

Accordingly, the GWR model considers how the relationship between the variables employed are shaped around a geographical location of the j th case, denoted as Y_j ¹, and the GWR equation is described as (Charlton et al, 2009; de Bellefon & Floch, 2018):

$$y_j(Y_j) = \sum_{i=0}^k X_{ij}\beta_i(Y_j) + \varepsilon_j \text{ (eq. 1)}$$

Where:

y_j – dependent (response) variable;

X_{ij} – independent variables;

β_i – regression coefficients;

ε_j – residuals.

Thus, the estimator will take the following form: $\hat{\beta}_i(Y_j) = (X^T W(Y_j) X)^{-1} X^T W(Y_j) y$, and the $W(Y_j)$ is a squared matrix of geographical weights on the main diagonal and 0 in its off-diagonal elements. For each area (region) a separate regression model is estimated, with

¹ Y_j – is a vector of coordinates.

the sample composed of the areas (regions) within a certain distance or bandwidth. The weights are determined based on the linear distance between the observations and emphasize the spatial effects for neighbouring regions in the specified bandwidth (Vinuela et al., 2015).

There are multiple options for determining the weighting scheme and the number of regions (neighbours) included in each local sample (see Nakaya et al., 2012 for a full review). In this paper, the adaptive bi-square specification is chosen for the spatial weights matrix. This ensures that each regression model will have enough data points (areas), by widening the bandwidth to an optimum value. Our choice is also in line with other studies in the literature (Goschin, 2018; Rjinks, 2020). The bi-square model implies that after a certain threshold (the bandwidth), the spatial weight of the data points will be zero. The optimal bandwidth is found by running models with varying bandwidths (in our case from 46 to 241 regions) and choosing the one with the lowest Akaike Information Criterion (AICc) score – in our model the optimal bandwidth is found for 67 nearest neighbours.

The spatial weights for the adaptive bi-square specification are calculated as follows: (Nakaya et al, 2012):

$$w_{ij} = \begin{cases} (1 - \frac{d_{ij}^2}{\theta_{i(k)}})^2, & d_{ij}^2 < \theta_{i(k)} \\ 0, & d_{ij}^2 > \theta_{i(k)} \end{cases}$$

Where:

w_{ij} is the weight value of observation for the region j when estimating the coefficient in region i ;

d_{ij}^2 is the Euclidean distance between regions i and j ;

$\theta_{i(k)}$ is an adaptive bandwidth size defined for the k -th nearest neighbour.

There are several advantages of using a GWR model. First of all, GWR calculates a distinct variance for each coordinate point, making it a local rather than a global model. This is in contrast to conventional regression models, which presume that the relationship between variables is constant across space (Sheehan, 2013; Goschin, 2018). Secondly, by accounting for spatially shifting interactions between variables, GWR can increase model accuracy, revealing patterns and linkages that may not be obvious in classic regression analysis (Goschin, 2018). With respect to disadvantages and limitations of the method, we could mention: less efficiently estimated coefficients in small samples; computationally intensive method; robustness of results that depend on bandwidth selection and possible sample overlaps (Vinuela et al., 2015).

The approach we follow is the one usually applied for this type of models (Goschin, 2018). First, we determine the spatial autocorrelation index, Moran's I , for all variables included in analysis. If the spatial autocorrelation is confirmed, we proceed with estimating the GWR model. Second, we estimate the global OLS model, without considering the potential spatial variability. Third, we estimate the local regression models after selecting beforehand the parameters of the GWR as mentioned earlier; we then compare the performance of the GWR model with that of the global regression model. Lastly, we discuss and analyse the spatial variability of the locally estimated regression models.

Data and variables

The variables employed in the analysis are in line with the research questions formulated in the second section of the paper. The extent of the migratory phenomenon is proxied by the Crude Rate of Net Migration, having the role of dependent variable in the regression models. The explanatory variables considered are: Compensation of employees (a proxy for Income level) – to address research hypothesis H1 and Unemployment rate - to address research hypothesis H2.

To address research hypotheses H3 and H4 and thus account for spatial variability in our model, we used NUTS 2 level data for the EU27 countries, thus for a total of 241 regions (only one region – Åland in Finland – was excluded from analysis due to missing data), at 2020. The choice of the variables was thus limited by data availability at NUTS level. All variables were retrieved from the Eurostat database. Next, we will briefly describe the variable used and provide Eurostat data sources for each of them.

Crude rate of net migration provides a general overview of the migration phenomenon in EU being a demographic measure computed as the difference between the immigration to an area and the emigration from that area, per 1000 inhabitants (Lieberson, 1980). Data source: https://ec.europa.eu/eurostat/databrowser/view/DEMO_R_GIND3_custom_5092853/default/table.

*Unemployment rate*² calculated as percentage of total population measures the percentage of the labour force that is currently without employment, but actively seeking and available for work. It is calculated as the number of unemployed people divided by the total number of people in the labour force, which includes both employed and unemployed individuals, within age group of 15 and 75 years. Data source: https://ec.europa.eu/eurostat/databrowser/view/LFST_R_LFU3RT_custom_5092896/default/table.

*Compensation of employee*³ is the total payment that an employer makes to an employee for services performed within a specific accounting period, whether it be in monetary or non-monetary form. The three primary elements that make up employee compensation are cash-based wages and salaries, non-cash-based wages and salaries, and social contributions made by employers. We will further name this variable as “Salary”. The data source is: https://ec.europa.eu/eurostat/databrowser/view/nama_10r_2lp10/default/table?lang=en.

The GWR models were estimated using GWR4 semiparametric tool software, while the maps and the spatial autocorrelation coefficients were obtained using GeoDa software.

Findings and Discussion

As mentioned in the methodology section, first of all, we will determine the spatial autocorrelation index, Moran’s I, for all variables included in the analysis (Table 1). It should be noted that the inference for Moran’s I is determined based on a permutation procedure. This implies recalculating the statistic multiple times to obtain a reference distribution. Then, the computed statistic is compared to the reference distribution and the pseudo p-value or pseudo significance level is computed (see Anselin, 2005 for a detailed description of the procedure).

² We refer to the long term unemployment rate as defined by the eurostat glossary. Available at: <https://data.europa.eu/data/datasets/usksjnmphs6zcmqzwpsg?locale=en>

³The definition of compensation of employee is available at: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Compensation_of_employees

The spatial autocorrelation indexes are highly statistically significant and have positive values for all variables, indicating a general tendency towards clustering. As expected, the variable chosen as a proxy for salaries has the highest degree of spatial autocorrelation, considering the significant spill over effect of the earnings variable. Thus, adjacent neighbours (NUTS2 regions) are expected to have similar values of wages, having in mind also the national context.

Table 1. Moran's I spatial autocorrelation index

Variable	Moran's I	Pseudo p-value	Z-value
Crude rate of net migration	0.3058	0.001	6.3261
Salary	0.8811	0.001	18.2004
Unemployment Rate	0.6769	0.001	14.2518

Source: Authors' own processing.

Figure 1 depicts the crude rate of net migration by NUTS2 regions, at EU27 level for 2020. The intervals illustrated on the map are constructed using the quartiles and outliers are defined at a distance of 1.5 Inter Quartile Range from the lower and upper quartile, respectively.

The spatial correlation is confirmed by regions with high or low values of crude rate of net migration clustered together. For instance, Italy shows a high concentration of regions with very low levels for net migration. On one hand, Central and Eastern Europe still exhibit negative value of net migration (Romania, Czech Republic, Poland, Slovakia), a consequence of the East to West migratory flows that started in Europe following the fall of communism, a situation that is still ongoing (Black et al., 2010).

On the other hand, regions in Spain, Germany, Austria, France register positive values of the migratory flow, suggesting these countries remain the preferred emigration destinations. However, Figure 1 indicates that the migration phenomenon exhibits significant variations at regional level and it is not uniformly distributed at country level.

In France, there is a clear divide between East and West sending and receiving regions. Even in Romania, although most regions record a negative net migration, Bucharest-Ilfov region has a positive migratory balance in 2020.

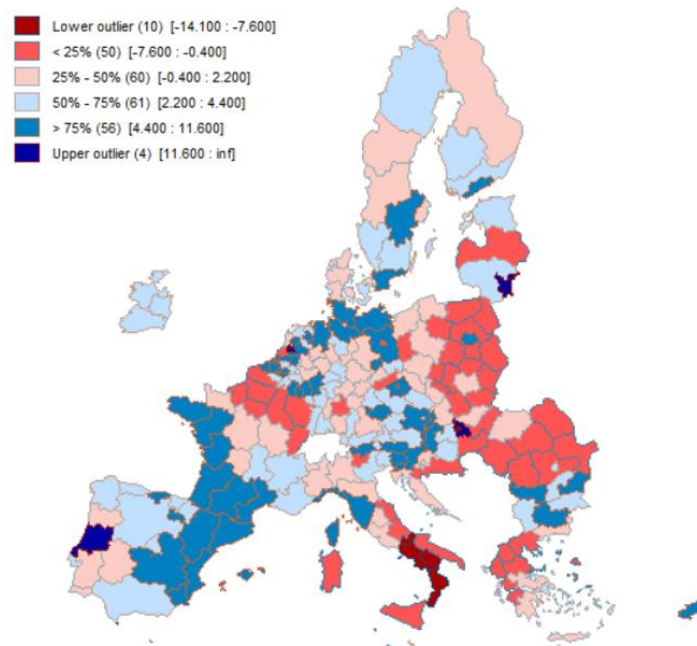


Figure 1. Crude Rate of net Migration by EU27 NUTS2 regions, 2020 (quartile intervals)

Source: Authors' own processing .

These findings show that a country level approach of the problem would be inaccurate, justifying the estimation of a geographically weighted regression model.

Considering that the dependent variable (crude rate of net migration) is a continuous one, we opt for a Gaussian model and use an adaptive bi-square geographic kernel, as justified in the methodology.

The optimal bandwidth is selected using the golden section search, based on the Akaike Criterion (corrected for small sample bias). We also run the geographical variability test for the coefficients of the independent variables.

Following the methodological approach, the second step is to estimate the global regression model. The results of this model (the traditional OLS model with fixed coefficients among regions) show that both independent variables have statistically significant coefficients at a 5% level of significance (Table 2). Moreover, the signs of the coefficients are the ones expected from economic theory – negative for the Unemployment rate (push factor for migration) and positive for the Salary (pull factor for migration). However, the reported adjusted R-square is rather small at only 0.11 (Table 2).

Table 2. Results of the OLS global model

Variable	Estimate	Standard Error	t-statistic
Intercept	-11.1477	5.7405	-1.9419
Unemployment rate	-0.2925	0.0561	-5.2059
Ln(Salary)	1.4781	0.5524	2.6756
AICc	1402.53		
R-Square	0.1288		
Adjusted R-Square	0.1178		

Source: Authors' own processing.

Thirdly, we obtain the results for the GWR model, synthesized in Tables 3, 4 and 5 and compare the performance of the global model with that of the GWR model. Findings show a significant improvement compared to the global regression model, both in terms of R-square and Akaike criterion. The R-square increases from approximately 0.13 for the global model to 0.45 in case of the GWR model. Other diagnostic indicators, for instance AICc of the GWR model (1342.83) is clearly smaller than that of the global regression model (1402.53).

Table 4 presents the results of the ANOVA test that compares the residuals of the global OLS regression model to the GWR Model. The F test is highly statistically significant (p-value <0.0001), confirming that the residuals associated with the GWR model are significantly lower than those of the global OLS model. Additionally, the geographical variability test for each coefficient (Table 5) reports the difference between the GWR model and a model in which only the respective coefficient is fixed while the others vary as per the GWR model. Since the difference of criterion (Akaike Information Criterion) is negative for each variable, the GWR model is better than the one having each coefficient (in turn) fixed, thus we conclude that all the coefficients of the model vary significantly over space. Thus, all diagnostics tests confirm the choice of the GWR model as a better fit than the global OLS regression model.

Table 3. Results of the GWR model

Variable	Minimum	Lower Quartile	Mean	Upper Quartile	Maximum
Intercept	-101.0873	-45.5937	-16.4674	15.2997	163.1230
Unemployment rate	-1.2107	-0.7523	-0.4331	-0.1320	0.3683
Ln(Salary)	-15.8095	-0.8983	1.9940	4.9915	10.0159
AICc	1342.83				
R-Square	0.4538				
Adjusted R-Square	0.3629				

Source: Authors' own processing.

Table 4. GWR ANOVA table

Source	SS	Df	MS	F
Global Residuals	4594.743	238		
GWR Improvement	1713.914	31.236	54.870	
GWR Residuals	2880.829	206.764	13.933	3.938

Source: Authors' own processing.

Table 5. Geographical variability tests of local coefficients

Variable	F	DOF for F test	Difference of Criterion
Intercept	7.4291	6.569	-33.0475
Unemployment Rate	3.9341	7.259	-12.1594
Ln(Salary)	14.6534	7.016	-76.8567

Source: Authors' own processing.

Finally, we comment on the estimated coefficients for the variables included in the model, that vary significantly between regions. For the unemployment rate, the estimated coefficient varies from a minimum of -1.21 (for a region in Netherlands) to a maximum of

0.36 (in Latvia), having an average of -0.43. In 11% of the locally estimated models the coefficient is positive, however in none of these cases being statistically significant.

Moreover, the coefficient of unemployment rate is statistically significant (at a 5% level of significance) in 92 of the 241 locally estimated models. These are predominantly regions in countries with positive net migration rates such as: Belgium, western Germany, Spain, Portugal, northern France, Luxembourg, Netherlands.

In a significant part of Italy (central and southern regions), the relationship between unemployment (high levels) and net migration (negative value) is also strong, confirming that high unemployment in the country of origin acts as a push factor, but also (for the cases with positive net migration), that migrants typically move to countries with low unemployment rates (Simpson, 2022).

The coefficient of variable Salary varies also significantly among regions. This time, the opposed influences of the factor in different region is more evident, the coefficient being negative in about a third of the estimated models (but statistically significant in only 28.5% of these models, 22 of 77). These differences between the results of locally estimated models confirm the GWR method as a better choice to investigate the spatial variation of migration compared to the country-level OLS regression.

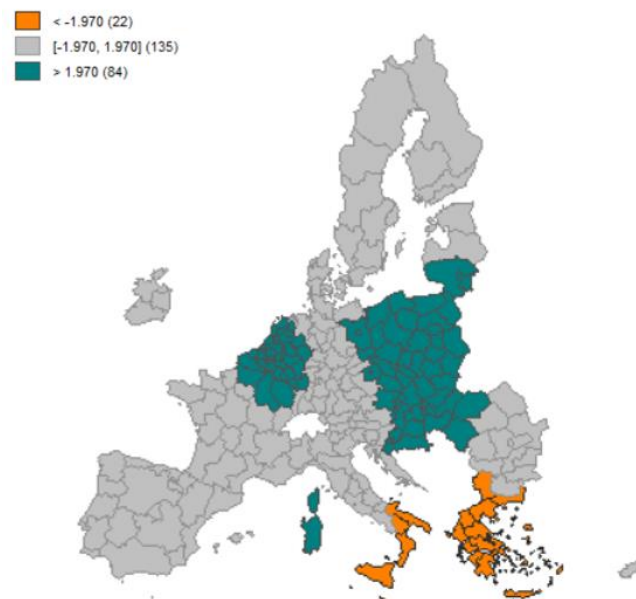


Figure 2. The t-statistics associated with the coefficients of variable Salary

Source: Authors' own processing.

As can be observed in Figure 2, significant and positive relationship between the salary level and net migration rate can be observed in a cluster of regions around: Poland, Czech Republic, Slovakia, Hungary northern Romania on one hand and Austria, Belgium, Netherlands, northern France and western Germany on the other hand. The findings confirm the neo-classical economic migration theory stating that the differences in earnings are the main cause of migratory labour flows (Massey et al., 1993). A significant negative impact of Salary on net migration is reported in southern Italy and parts of Greece, all regions with a negative net migration. The explanation could be that in these regions the reasons for

migrating are structurally different. For instance, in Greece the major outflow of migration was initiated by the global financial crisis in 2009 (“crisis-driven migration”). However, as highlighted by Pratsinakis (2022), this “new migration” is different than the previous waves, since most emigrants left Greece “due to a perception of a depressing lack of prospects in their home country and a deep-felt disappointment in the socioeconomic environment in Greece” (Pratsinakis, 2022, p. 41). Thus, the factors triggering migration are much more profound and surpass the classical economic factors.

The distribution for the coefficient of determination of the locally estimated regression model suggest that the regression models fit the data well (Figure 3). Almost half of the locally estimated regression models have a R^2 higher than 0.3. Moreover, less than 3% of the models have the R^2 lower than that of the global OLS regression model, confirming once more the choice of the model.

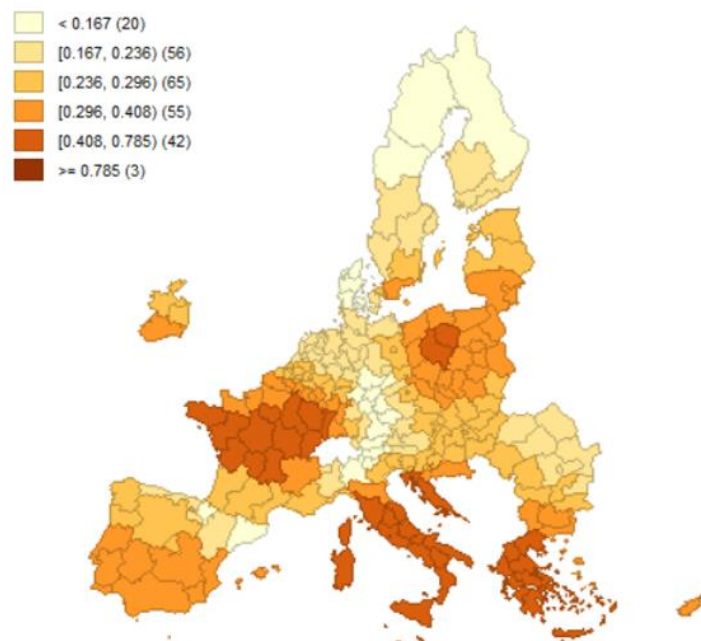


Figure 3. The coefficient of determination (R -Square) of the locally estimated models at NUTS2 EU27 level

Source: Authors' own processing.

To sum up, the findings reveal a significant regional variation in the determinants of the net migration rate for the EU27 countries. Generally, we can observe the classical East-West divide, with the salary variable having a strong influence as a pull factor for migration in western regions. The result is also in line with other findings from the literature (Simpson, 2022). However, there are differences within countries and regional patterns appear – for instance western Germany or northern France have a different behaviour. Moreover, the findings also revealed that migrants in certain regions from Italy or Greece are driven by more complex factors, thus outflows of migrants in these regions have to be addressed specifically. The regional estimates resulting from the GWR models can also be

used to shape local migration policies for a better management of the migration phenomenon.

Conclusion

Our study enriches the current literature on migration determinants by examining regional differences within EU countries using a geographically weighted regression model. Our findings suggest that economic factors play a crucial role in explaining the migration patterns across regions in the European Union. Specifically, salary levels have a strong influence on the net migration rate with regional pattern that varies within EU countries. Thus, the use of geographically weighted regression models allowed us to capture the spatial variation of the migration phenomenon and provide regional estimates that can inform local migration policies.

However, it is important to note that our study has several constraints, including the limited availability of data at the regional level and the exclusion of non-economic determinants of migration.

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