

***TEMPORARY IMMIGRATION AND REGIONAL INCOME
INEQUALITIES IN TIMES OF COVID-19. A SPATIAL PANEL DATA
ANALYSIS***

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Abstract

Confronted with ageing and depopulation, Romania needs to identify the main factors that attract immigrant population. This paper tackles the matter of regional income disparities as a key factor for temporary immigration in Romania. The quantitative approach includes a spatial panel data analysis based on a dataset retrieved from the Romanian National Institute of Statistics and our data consists of 378 observations on 42 counties in Romania over a time span of nine years starting with the year 2012. Our findings suggest that temporary immigration in Romania is shaped by location, but does not follow the labour market characteristics. Higher salaries and job opportunities are not the main factors of attraction to temporary immigration and it does not seem to be influenced by regional disparities.

Keywords: regional inequalities, temporary migration, income inequalities, spatial panel data models

JEL Classification: C21; C23; C33; E24; F22

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1. Introduction

Migration is a multifaceted phenomenon and takes numerous forms depending on a multitude of criteria. For example, taking into consideration the movement duration, we can distinguish two types of migration: permanent and temporary (Dustman, 2000). Dustman (2000) considers that a temporary migrant is any migrant that returns to its origin country, even after spending many years abroad.

The temporary nature of migration has become more and more prevailing nowadays, due to the ease of traveling from one place to another. Historically, people preferred to migrate to places where living conditions were favourable for a lifestyle suitable to their desires (Hagen-Zanker, 2008). Also, they had the tendency to settle in particular place until it was no longer appropriate for them (Manning, 2012). Thus, migration inclined to be more permanent than temporary.

The concept of the temporary migrant is differently defined by the stakeholders. In our case, we used the temporary migration available on the website of the Romanian National Institute of Statistics. According to the definition, a *temporary migrant* is a person who left their country (immigrant)/or came from another country (emigration) for a minimum period of twelve months.

In this paper, we tackle the matter of regional income inequalities as a possible incentive for temporary immigration in Romania. In our case, when we refer to temporary migration we are talking about those people who have migrated for a minimum period of twelve months.

Even though Romania is well known as an emigration country (Sandu and De Jong, 1996; Roman et al., 2010; Simionescu, 2016; Goschin, 2018; Davidescu et al., 2019), we chose immigration considering the context of recent events. The migrant crisis in Europe in 2015 left its mark on European countries, as the number of refugees and third-country nationals experienced a significant increase in all countries (Akgündüz, 2015). Romania was also part of this event, being one of the entry points to the more developed western European countries (Bejan et al., 2017; Manafi and Roman, 2022). In this respect, Bejan et al. (2017) remarked that “Romania is not yet perceived as a desirable country for immigration”. But recent data contradicts this aspect, as Manafi and Roman (2022) observed, Romania recorded an increase in the number of immigrants in 2018 compared to 2015. Interestingly enough, even though for most EU countries the number of asylum seekers peaked in 2015 or 2016, for Romania this peak was observed in 2017 (Manafi and Roman, 2022), caused by the Syrian refugee crisis.

Our paper is divided into three main sections: first, the introduction provides the background and the aim of our study; the second section is a short literature review of the research on the immigration topic, and the last section present the methodology and the conclusions of our paper.

The purpose of our research is to observe if the counties in Romania with incomes higher than the national average income are a point of attraction for temporary immigrants paying attention to the effects of county closeness. Our study is among the first that tackles this topic in Romania, in the context of an aging population and massive migration abroad, attracting immigrants as human capital, may be the key to future economic development and sustainability of the pension funds system.

2. Literature review

The main reasons why people migrate were organized in the so-called push and pull factors of migration. These main driving factors of migration cover various fields such as economic, social and political (Urbański, 2022). Thinking of these factors, we can consider that inequalities and migration coexisted at least in recent decades. For example, people were being pushed from their origin place by poverty (– push factor) to another place to improve their living standards or for higher wages (– pull factor) (Stark, 2005; Parkins, 2010; Urbański, 2022). Stark (2005) studied the behavioural linkage between migration and income inequalities. In his study, he measured income inequalities by using the Gini coefficient. Stark (2005) argued that “the income distribution at destination becoming more equal while the origin income distribution remaining as unequal as before will not dampen the relative deprivation inducement to migrate of low-income members of the origin population”.

Some authors raised the question if migration cause income inequalities (Orrenius and Zavodny, 2018, p 2; Uprety, 2020). Orrenius and Zavodny (2018) analysed a series of research papers that study the way migration influence the income and wage inequalities in the sending countries. They found that the Mexican migrants to U.S.A. “have played a large role in lowering global inequality by moving millions of low-income Mexican families further away from poverty and closer to the global middle class”. Uprety (2018) taking into account the concept of causality, showed that for 110 developing countries there was “evidence that the emigration of high-skilled individuals from developing countries increases income inequality within the countries in the short-run while low-skilled emigration appears to have no significant impact on inequality”.

Income inequalities in Romania seem to be an old and perpetual problem (Zamfir et al., 2010; Oancea et al., 2017; Goschin, 2018). In 2020, Romania had the lowest median equivalised net income (7724 PPS) in European Union. Even though Romania is one of the poorest countries in Europe, it is a country deeply characterized by income inequality. Crețu (2016) remarked that “the top 10% of the people in Romania gain 6 times more than the poorest Romanians, being the largest difference in the European Union”. In this respect and bear in mind that migration decision is usually based on improving living standards (Hagen-Zanker, 2008; Manning, 2012) we considered that income inequalities between counties may influence

temporary migration in Romania. For example, Török and Benedek (2018) studied the income distribution of local public administration (cities and communes) in 2013 as a proxy for household income, since in Romania nor GPD per capita or household income is not calculated for the NUTS-5 level. Their findings confirmed the income inequalities between cities and communes in Romania.

Romanian immigration was a scarcely studied topic, and regained an increased interest, especially starting with the refugee crisis of 2015. Most authors tackled the social aspects of immigration in Romania (Anghel and Cosciug, 2018; Cosciug, 2018; Oltean and Găvrus, 2018; Mészáros, 2019). Therefore, regarding what was discussed above, we can consider a quantitative approach to analyse temporary immigration in Romania in relation to income inequalities.

3. Method and Data

Our study focuses on regional disparities in Romanian and employs a spatial panel data analysis with different types of contiguity. We used spatial econometrics to describe spatial dependences on temporary immigration data, and how it was influenced by unemployment, regional income disparities and Covid-19 crisis in Romania. To determine that a model with spatial specification better fits our data than an OLS model, we test the hypothesis if the spatial spill over occurs or not in our data set. One way to test the spatial dependence hypothesis is using the Moran's I coefficient (Anselin and Rey, 1991), which measures the global spatial autocorrelation of our data set. Neighboring counties tend to have resemblance in features, and Moran's I test allows us establish how strong are similarities between one region and the other regions surrounding it. The Moran's I test lies between +1 (identical characteristics, among neighbouring counties) and -1 (total dissimilarity), the null value corresponds to no spatial autocorrelation (Anselin and Rey, 1991):

$$Moran's\ I = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{(\sum_{i=1}^n \sum_{j=1}^n w_{ij}) \sum_{i=1}^n (x_i - \bar{x})^2} \quad (1)$$

Where: x_i and x_j are the variables in the county i and j respectively, $\bar{x}$ represents the average and w_{ij} stands for spatial weights matrixes (distance matrices and contiguity matrices).

After the spatial dependence hypothesis test, following the literature, the spatial investigation starts with the General Nesting Spatial (GNS) (Anselin et al, 2008; Elhorst, 2010, 2014; Goschin, 2021) model as expressed in the equation below:

$$Y_{it} = \rho \sum_j W_{ij} Y_{jt} + \sum_k X_{itk} \beta_k + \sum_k \sum_j W_{ij} X_{itk} \theta_k + \mu_i + \gamma_t + \varepsilon_{it} \quad (2)$$

Where: $\varepsilon_{it} = \lambda \sum_j W_{ij} \varepsilon_{jt} + v_{it}$, and in which Y_{it} stands for temporary migration in county i and time X_{itk} are our explanatory variables; W stands for different types of matrices that we used in our model, ρ is the lagged in space response parameter for the dependent variable;

$W_{ij}X_{itk}$ stands for the space lagged explanatory k variable, and $W_{ij}Y_{it}$ is the space lag for temporary migration. The terms μ_i and γ_t stand for space and time fixed and random effects, respectively, while β and θ represent response parameters of the exogenous explanatory variables, and λ is the coefficient for spatial autocorrelation. Finally, ε_{it} represents the spatial errors, and v_{it} are the uncorrelated spatially errors.

The General Nesting Spatial Model described above in equation (2), can be particularized to several more restrictive models (Elhorst, 2010; LeSage, 2014). The Table 1 shows the most common spatial regression models.

Table no. 1: Types of spatial regression models

Type of models	Restrictions	Spatial effects interactions
Spatial Autoregressive model with autoregressive errors (SAC)	$\theta = 0$	WY, Wu
Spatial Durbin Model (SDM)	$\lambda = 0$	WY, WX
Spatial Autoregressive model (SAR)	$\theta = 0$ and $\lambda = 0$	WY
Spatial Error Model (SEM)	$\theta = 0$ and $\rho = 0$	Wu

Source: Elhorst, J. P. (2010)

We also applied Exploratory Spatial Data Analysis (ESDA) techniques to visualize and examine temporary immigration in Romania over time.

Our explanatory variables were selected based on the results of previous studies (Orrenius and Zavodny, 2018; Upreti, 2020; Hagen-Zanker, 2008; Manning, 2012). All of the variables were selected for a time span of 9 years, starting with the year 2012. The data were retrieved from the Tempo Online database available online on Romanian National Institute of Statistics website, and are displayed in Table 2.

Table no. 2: The variables

Variable name	Description	Role
Temporary Immigration	According to the National Institute of Statistics, this variable includes the people who emigrated to Romania regardless of citizenship for at least 12 months. This variable captures both pendular migration and the refugee, asylum seekers, or any type of third-country nationals	Dependent variable
Unemployment	This variable is the unemployment rate which is computed as the number of unemployed people divided by the total labour force	Independent variable
Regional average wage	This variable is the average wage of the county concerned Denoted as W_r	Independent variable
National average wage	This variable is the national average wage of Romania Denoted as W_t	Independent variable
COVID	1 = year 2020, otherwise 0	Dummy variable

Source: National Institute of Statistics

We used two different statistical software to obtain our results. For the ESDA techniques we used GeoDa, and all the spatial regression models were estimated using Stata.

4. Results and discussions

We aim in our study to point out the spatial concentration of temporary immigration in Romania and to determine the influences of wage disparities, unemployment and Covid-19 travel restrictions on this phenomenon. Previous studies confirmed the spatial autocorrelation in immigration among and within EU regions (Barthel and Neumayer, 2015; Viñuela, 2022). Also, some patterns can be identified by applying ESDA techniques. In Figure 1, we presented nine standard deviation maps for temporary migration for each year on our dataset.

Our results show that there are preferences for certain counties regarding temporary immigration. Bucharest is the outlier for all nine years included in the analysis.

Another aspect to point out is that the refugees' crisis in Romania made its presence starting with the year 2017. The results must be viewed with some caution, since temporary migration, according to the definition, does not only include refugees or third-country nationals. We consider that year 2020 is different from all the others due to COVID-19 pandemics. In Romania, the lockdown was imposed on March 16th, 2020* which among other measures, it limited the movement of people.

Spatial concentration of immigration in Romania is determined mainly by two types of destinations: Moldovan counties (especially preferred by immigrants from the Republic of Moldova (Culic, 2008)) and areas with rapid economic development (Bucharest, Cluj, Constanta, Prahova, Timiș), in some cases especially because of the industry (Dolj, Arges). This polarization means that one third of the Romanian's counties receive more than 59% of the total number of immigrants, according to data from INS.

Spatial dependence in our variables were confirmed, by performing the Moran's I test in Stata, using different types of spatial contiguity matrices: distance matrices (distance matrix-Wd, inverse distance matrix-Wid, inverse squared distance matrix-Wid2) and contiguity matrices (first-WC1 and first and second order neighbours-WC2), with the results on Appendix 1.

* Decree on the establishment of the emergency situation on the territory of Romania (Decret nr. 195 din 16 martie 2020 privind instituirea stării de urgență pe teritoriul României), 16 March 2020. Official translation in English is available at: <https://rm.coe.int/09000016809cee30>

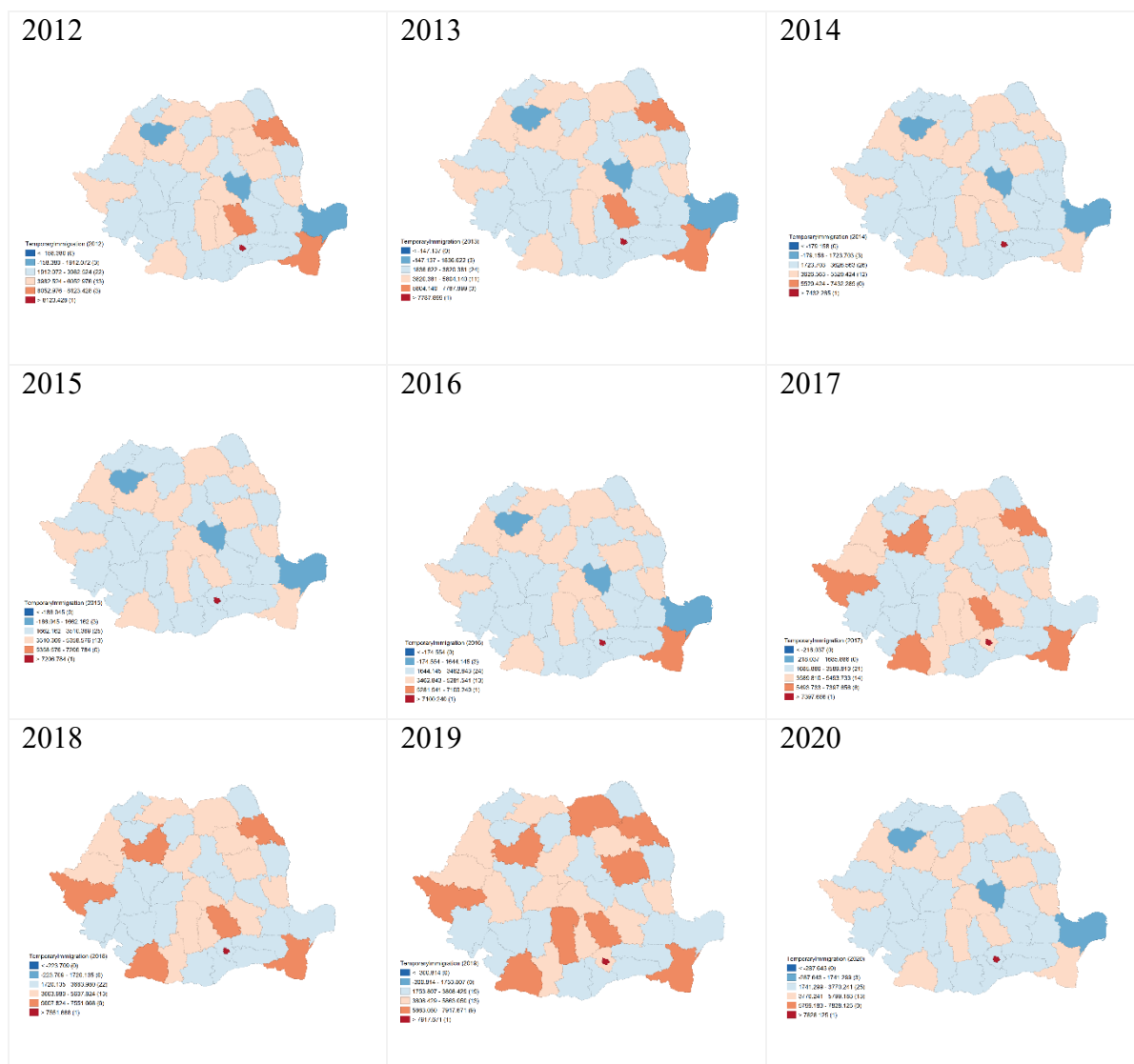


Figure no. 1: Spatial distribution of the temporary immigration in Romania over time
Source: own computation using GeoDa 1.2

Understanding the main determinants of regional attraction of the foreign population coming to Romania is essential to explain present spatial concentration patterns and to predict future migration flows, in the new socio-economic context among European countries, where immigrants are growing in number. Spatial econometrics comes in handy to determine those aspects with maximum precision. For model selection we took into account several statistics. Spatial investigation starts with Spatial Durbin Model (SDM) as recommended by LeSage and Pace (2009), Baltagi et al. (2003) and Elhorst (2011, 2013b). Next step is to use LR test to verify if $\theta = 0$ and $\lambda = 0$ (Table no. 3), so that SDM model can be reduced to the spatial autoregressive model (SAR) model, known also as spatial lag model (Elhorst 2014). In table no. 3 are the test results for SAR and in all of the cases we strongly reject the null hypothesis, with a p-value lower than one percent, SDM cannot be reduced to SAR.

Table no. 3: Test for SAR

WC1	WC2	Wd	Wid	Wid2
chi2(3) = 82.06 Prob > chi2 = 0.0000	chi2(3) = 3509.94 Prob > chi2 = 0.0000	chi2(2) = 3.5e+05 Prob > chi2 = 0.0000	chi2(3) = 93.57 Prob > chi2 = 0.0000	chi2(3) = 82.35 Prob > chi2 = 0.0000

Source: own computation on using Stata 16.1

If the SDM model cannot be simplified to SAR, then we impose the restriction $\theta = 0$ and $\rho = 0$, to verify if the SDM can be reduced to a Spatial Error model (SEM). Since we have used different types of matrices that affect the estimation results (Elhorst, 2010b; Chasco et al., 2017; Goschin, 2021) we will proceed with model selection process for all five matrices. In all of the cases we strongly reject the null hypothesis, with a p-value lower than one percent, SDM cannot be reduced to SEM:

Table no. 4: Test for SEM

WC1	WC2	Wd	Wid	Wid2
chi2(2) = 37.05 Prob > chi2 = 0.0000	chi2(2) = 24.70 Prob > chi2 = 0.0000	chi2(2) = 60.53 Prob > chi2 = 0.0000	chi2(2) = 65.22 Prob > chi2 = 0.0000	chi2(2) = 73.16 Prob > chi2 = 0.0000

Source: own computation on using Stata 16.1

The tests results from above showed that SDM cannot be simplified to more restrictive SAR or SEM models, no matter the type of matrix we used. Following step is to run the Spatial Autoregressive model with autoregressive errors (SAC) and then to choose between SDM and SAC using Bayesian comparison approach (LeSage, 2014; Elhorst, 2013, 2015) of model specification. In this situation, we select the best-fitted model for our data, from all five spatial weighted matrices used, based on the maximum value of LL (Log Likelihood) and the minimum values of BIC (Bayesian Information Criterion) and AIC (Akaike's Information Criterion) (Appendix 4). Based on the results of information criteria in table no. 5, SDM are the most appropriate models.

In order to determine what type of effects are more appropriate in our analysis we estimated random and fixed-effects models to perform robust Hausman tests, for all models and weight matrices. Fixed-effects are, as expected more suitable for our analysis since we include all Romanian counties and not just a sample. Furthermore, the results of the robust Hausman test strongly rejects the random effects from our best-fitted model (SDM- Spatial Durbin Model):

Ho: difference in coeffs not systematic chi2(4) = 31.37 Prob>=chi2 = 0.0000

*test for appropriateness of a random-effects variant using the Robust Hausman Test, Prob>=chi2 = 0.0000, p-value is lower than one percent, we strongly reject the null hypothesis and we use fixed-effects

Table no. 5: Bayesian comparison

WC1			WC2		Wd		Wid2	
Model	SDM	SAC	SDM	SAC	SDM	SAC	SDM	SAC
R^2 : within	0.5344	0.5506	0.5806	0.0199	0.5292	0.5115	0.5039	0.5117
between	0.2432	0.1787	0.4361	0.4896	0.1044	0.0592	0.1321	0.1080
overall	0.2227	0.1593	0.2403	0.2900	0.1359	0.0973	0.1585	0.1367
Log-pseudolikelihood	-2713.00	-2713.00	-2409.47	-2665.39	-2451.83	-2738.53	-2464.01	-2712.22
AIC	4903.91	5435.48	4832.94	5342.79	4917.66	5489.07	4942.03	5436.44
BIC	4930.63	5435.48	4859.66	5366.4	4944.38	5512.68	4968.75	5460.055

Source: own computation on using Stata 16.1

Based on model selection described above, the goodness of fit for our data set was Spatial Durbin Model (SDM) with fixed effects and first and second order neighbours matrix-WC2, with the results displayed in Table 6. Results are divided in two parts - main results that represents how explanatory variable influence the short-term migration and Wx as regional spillovers, represented influences that neighbouring region have on short-term migration in Romania or spatial spillovers. Moreover, ρ , which describes the intensity of the spatial dependence of the short-term migration, dependent variable, is large and highly significant. The positive value for Rho (ρ) suggests that short-term migration in a county is highly correlated with short-term migration neighbouring counties, and the concentration of the short-term immigration suggest internal spatial disparities within Romanian counties. Covid-19 crisis had a strong negative impact on short-term migration in Romania mostly due to travel restriction and the potential health risk.

Table no. 6. Factors affecting the short term migration in Romania. Results of the SDM with spatial fixed-effects

N=378 Number of groups = 42 Panel length = 9	Variable	Coef.	P> z
Main	Unemployment	51.44419	0.053
	WrWt	0.967	0.004
	COVID	-344.847	0.01
Wx	Unemployment	-192.985	0.01
	WrWt	-0.7031	0.056
	COVID	-714.578	.
Spatial	Rho(ρ)	0.778	0.000
Variance	sigma2_e	91631.84	0.040
R² : within = 0.5806, between = 0.4361, overall = 0.2403 Log-pseudolikelihood = -2409.4735			

Source: own computation on using Stata 16.1

The main findings of our study is that wage disparities ($WrWt$ calculated as distance between Wr - county medium wage and Wt - national medium wage) positively influence the short-term immigration in Romania and our results are not in line with the existence literature (Viñuela, 2022; Crozet, 2004). This result may emphasis a feature of Romania, since there are very few counties that exceed the national wage average. Therefore, wage disparities are not a pull factor of temporary migration. The vicinity effect turns out to be negative: short-term immigration is negatively affected by wages disparities (on the bottom edge of statistically significance 0.056) and unemployment (0.01**) from surrounding counties in Romania. Our findings indicates that immigration in Romania have several particularities: short-term immigration apparently is not influenced by regional wage disparities, higher salaries and job opportunities, overall the county weal, does not seems to be the main trigger that attracts immigrants. This phenomenon can be partially explained by the pendular migration, the returning diaspora in Romania.

5. Conclusions

The position of the immigrant population in the sustainability of the national pension system and in the efforts against fiscal imbalances to reduce its force is an ongoing debate among European countries. Western, more developed countries in Europe seem to understand the advantages and have policies that promote the settlement of new residents. Confronted with aging and depopulation, Romania needs to identify the main factors that attract the immigrant population.

Our paper aim is to analyze the spatial dependences on temporary immigration data and the appealing characteristics of a region to attract immigrants. Immigration in Romania is shaped by location, but our findings suggest that temporary immigration in Romania does not follow labour market characteristics. Thus, higher salaries and job opportunities are not the main factors of attraction and temporary immigration is not influenced by regional disparities.

The first indicator of regional disparities used in our model was the unemployment rate (Miroslav Sić, 2004) and second, we measured the income inequalities as the distance of the income level for each county from the national income level. Using spatial panel data analysis, we tested if the short-term immigration is shaped by location and if it follows the labour market characteristics - higher salaries and job opportunities are the main factors of regional attraction.

This research has some limitations; we manage to find that there are spatial dependences on temporary immigration data, but is not influenced by regional disparities. Further research should focus on finding more relevant factors that better describe the spatial dependences in short-term immigration in Romania.

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Appendix 1

Results for Moran's I test Immigration

year	WC1		WC2		Wd		Wid		Wid2	
	I	P-value	I	P-value	I	P-value	I	P-value	I	P-value
1	0.0131	0.6994	-0.0334	0.8619	0.1891	0.0798	0.1158	0.2520	0.0764	0.4328
2	0.0869	0.2510	-0.0114	0.8015	0.2231	0.0423	0.1926	0.0761	0.1732	0.1239
3	0.1526	0.0684	0.0095	0.5127	0.2439	0.0279	0.2518	0.0241	0.2511	0.0322
4	0.2193	0.0123	0.0310	0.2853	0.2580	0.0209	0.3089	0.0066	0.3286	0.0062
5	0.2713	0.0024	0.0483	0.1614	0.2531	0.0233	0.3474	0.0025	0.3876	0.0014
6	0.3089	0.0006	0.0603	0.1016	0.2450	0.0272	0.3731	0.0012	0.4285	0.0004
7	0.3311	0.0002	0.0673	0.0748	0.2155	0.0480	0.3828	0.0008	0.4578	0.0002
8	0.3419	0.0001	0.0707	0.0629	0.1829	0.0855	0.3778	0.0009	0.4662	0.0001
9	0.3461	0.0001	0.0736	0.0552	0.1610	0.1238	0.3720	0.0010	0.4688	0.0001

Results for Moran's I test Unemployment

year	WC1		WC2		Wd		Wid		Wid2	
	I	P-value	I	P-value	I	P-value	I	P-value	I	P-value
1	0.2473	0.0051	0.0888	0.0284	0.0243	0.6894	0.2258	0.0408	0.3176	0.0077
2	0.2381	0.0070	0.0859	0.0333	-0.0043	0.8693	0.2084	0.0577	0.3064	0.0102
3	0.2172	0.0131	0.0928	0.0239	-0.0135	0.9291	0.1787	0.0983	0.2671	0.0239
4	0.2461	0.0054	0.0879	0.0302	0.0341	0.6318	0.2120	0.0538	0.2958	0.0129
5	0.2781	0.0018	0.1094	0.0097	0.1186	0.2410	0.2747	0.0146	0.3445	0.0041
6	0.2647	0.0030	0.1003	0.0162	0.0931	0.3364	0.2549	0.0229	0.3279	0.0063
7	0.2880	0.0013	0.1044	0.0127	0.1783	0.0960	0.3119	0.0059	0.3645	0.0024
8	0.2609	0.0033	0.0815	0.0407	0.1658	0.1191	0.2818	0.0125	0.3258	0.0065
9	0.2604	0.0034	0.0845	0.0353	0.1783	0.0965	0.2869	0.0110	0.3278	0.0062

Results for Moran's I test wrwt (wage disparities)

year	WC1		WC2		Wd		Wid		Wid2	
	I	P-value	I	P-value	I	P-value	I	P-value	I	P-value
1	0.3474	0.0000	0.1020	0.0080	-0.0285	0.9705	0.3334	0.0015	0.5182	0.0000
2	0.3699	0.0000	0.1041	0.0072	0.0031	0.8072	0.3569	0.0007	0.5402	0.0000
3	0.2908	0.0005	0.0733	0.0419	-0.0364	0.9154	0.2780	0.0077	0.4393	0.0001
4	0.2563	0.0020	0.0504	0.1232	-0.0615	0.7454	0.2300	0.0265	0.3808	0.0008
5	0.2514	0.0022	0.0289	0.2681	-0.0794	0.6272	0.2276	0.0267	0.3856	0.0006
6	0.2191	0.0071	0.0081	0.5006	-0.0444	0.8602	0.2173	0.0339	0.3502	0.0017
7	0.1938	0.0145	0.0007	0.5981	-0.0673	0.7017	0.1791	0.0707	0.3033	0.0056
8	0.1604	0.0388	-0.0202	0.9300	-0.0847	0.5913	0.1496	0.1230	0.2643	0.0148
9	0.1270	0.0911	-0.0356	0.8153	-0.0911	0.5531	0.1152	0.2167	0.2151	0.0435