Scientific Journal of Riga Technical University
Sustainable Spatial Development

2011
Volume 2

Spatial Analysis of Regional Employment Rates in Latvia

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Abstract. **This research is focused on analysis of local employment in the districts of Latvia. We utilize a modern approach to discover spatial patterns of employment rates. A spatial econometric model is presented in the research, and its parameters are estimated on the basis of Latvian regional statistical data. We discovered significant relationships between employment and regional economic indicators and also a strong spatial relationship between employment rates in the districts of Latvia.**

Keywords: **regional economics, employment, spatial model.**

I. Introduction

Employment rates are widely known as an indicator of economic health and growth potential. The EU Sustainable Development Strategy [1], renewed in 2006, specifies an employment rate as one of key indicators of sustainable economic growth. There are a significant number of studies related to labour market analysis, but the majority of them are focused on a national level. Determinants of employment rates in a specific country, their prediction and possible improvement are a point of interest of many researchers and state governments, but regional employment disparities become more and more important for personal welfare and economic development. During last decade regional employment disparities and their determinants attracted a significant attention of researchers (see [2] for an overview of regional unemployment studies).

Employment rates are even more important for Latvia after the economic crisis has aggravated the existent problems [3] on Latvian regional labour market. The heterogeneous spatial structure of regional employment rates in Latvia is frequently mentioned as one of the most important problems of economic development.

A vast majority of regional labour market research is focused on finding region-specific factors influencing on an employment rate (like regional GDP per capita, a structure of labour force). Considering this as an appropriate approach, we also believe that regional labour market has strong spatial relationships with surrounding areas. This confidence is based on recent studies [4, 5, 6, 7, 8, 9, 10], which have discovered significant spatial effects of regional employment in Italy, Spain, Turkey, USA, and other countries. Also New Economic Geography points out spatial interdependence of any economic and social activities, so spatial influence of neighbour region economies should be taken into consideration.

While the presence of spatial relationships is well grounded, the nature of spatial effects on labour market is not quite straightforward. On the one hand, development of a region improves economy of the area as a whole and so has many positive cooperative effects on its neighbours. At the same time, competition on labour market is also possible, and a well-developed region draws off labour force from its neighbours. In both cases, if this influence is not taken into consideration in research, the results will be biased and generally incorrect.

II. Aim of the Research

We construct a spatial econometric model for a regional employment rate and estimate its parameters using statistical data for Latvia. To the best of our knowledge, there are no researches of spatial interference of employment rates for Latvian regions.

A structure of regional employment rates in Latvia is highly heterogeneous. Regional distribution of employment rates (calculation of this indicator will be discussed in the next section) is presented in the Figure 1, and this distribution remains similar during the last years. Extremely high employment rate (relative to a nationwide indicator value) is observed in Riga, while eastern regions (Kraslava, Ludzu, Balvu Districts) suffer from a low rate of employed population.

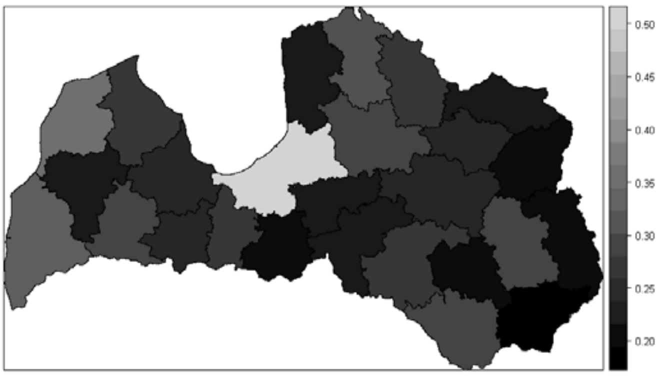

Fig. 1. Spatial distribution of employment rates in the regions of Latvia. Source: developed by the author based on the data provided by the Central Statistical Bureau of Latvia.

In this study we analyze a relationship between employment rates in Latvian regions and their economic and social characteristics. Dependencies between regional employment and GDP per capita, social and health care, and welfare allow forecasting economic situation in the regions and estimating consequences of government decisions on the national level.

Also we investigate spatial patterns of employment rates to reveal and predict the influence of changes in a particular region on the labour market of neighbour regions and entire Latvia.

III. Methods and Materials

We utilize modern spatial econometric methods [11] to discover spatial relationships between regional economies.

a. Model Specification

According to the main goal of our research, a dependent variable for a model should describe a level of employment in a particular region. In spite of significant attention to employment in literature, a comprehensive indicator of employment has not been singled out. Obviously, a level of employment is a ratio of employed people to population, but there are some discussion points here – which age range should be used to restrict working population (if any), how to define a person as “employed”, and other. Due to this fact, indicators used in different researches vary depending on research focus and purposes. For example, the EU Sustainable Development Strategy suggests the employment rate indicator calculated by dividing the number of persons aged 20 to 64 in employment by the total population of the same age group. In this research we are interested in a volume of regional labour force, but not directly in unemployment – another important characteristic of the labour market. Therefore we don’t include any restrictions into the indicator and define an employment rate as a ratio of total number of persons, employed at the main job, to total population of a region (of any age).

A set of model explanatory variables should include all factors, related to employment in a region. We consider a set of region-specific factors and related indicators as employment determinants:

- Economic development of a region.
  Indicator: regional GDP per capita.
- Health care in a region.
  Indicator: a number of beds in hospitals per capita.
- Crime in a region.
  Indicator: a number of crimes per capita.
- Housing.
  Indicator: flat prices.
- Personal welfare.
  Indicator: average wages.
- Social conditions.
  Indicators: a number of schools and preschools per capita
- Ethnic structure.
  Indicator: ethnic diversity index.
- Locational data.
  Indicator: a sea-side dummy.

We expect a significant positive effect of regional economic development (in form of GDP per capita) on employment. This expectation is common, because only employed population mainly produce GDP of a region. Also a higher level of economic development usually supports better quality of life and attracts additional labour force into a region.

Social conditions (heath care, social care) in a region are also expected to be positively correlated with employment, but the relationships can be not so strong. Latvia is a very compact country and it’s possible to work in one region and live or use social services in neighbour regions. Due to this fact a short-term relationship can be insignificant, but we still expect significant long-term effects.

A wages factor is also expected to be a significant determinant of employment, but in our sample it is highly correlated with GDP per capita (Pearson’s correlation varies around 0.85-0.90 for different years). This dependence can lead to the multicolleniarity problem, and reduce estimated significance of both factors.

There is no a priori expectation about the influence of ethnic diversity in regions.

We assume significant positive effect of the presence of a sea-side in a region on employment. This assumption is based on overall orientation of economy of Latvia. Geographical position of Latvia makes it very attractive for transit cargos, and sea ports in Riga, Ventspils and Liepaja are ones of the largest companies in Latvia. Another possible evidence of a positive effect of the presence of a sea-side is related with tourism industry. Tourism industry constitutes a substantial part of Latvian economy (8.1% of GDP and 7.6% of employment in 2010, WTTC [12]), and the majority of tourists are attracted by recreation facilities on the Baltic sea-side.

b. Spatial regression model

The classical regression model is the most frequently used method for investigation of stochastic relationships between a dependent variable and a set of determinants:

$$y = X\beta + \varepsilon, \tag{1}$$

where
y is a vector of a dependent variable;
X is a matrix of explanatory variables;
β is a vector of unknown coefficients (model parameters);
ε is a vector of i.i.d. error terms.

The vector of model parameters β is usually estimated using ordinary least squares (OLS) approach. One of the main problems related to the model is omitting of significant explanatory variables. If significant determinants of a dependent variable aren’t included into a model, estimation results will be biased (in econometric literature this situation is usually called omitted variables bias [13]).

Alongside with employment determinants discussed in the previous section, we expect significant spatial effects on employment. Employment rate in a region can be affected by a number of factors in neighbour regions. This set of factors can include employment determinants and employment rates in neighbour regions. These effects are discovered in a number of recent researches [4, 5, 6]. In case of presence of spatial effects, classical OLS estimates will be biased (so estimates, directions of influence, estimates significance, and other model characteristics will be wrong).

We require a metric of spatial dependence to include it into the model. The famous geographical Tobler's Law [14] says "everything is related to everything else, but near things are more related than distant things", so researchers usually expect that spatial dependence can be measured by distance of different kinds. A set of these distances for every two objects is usually compiled into a spatial weights matrix W. Matrix W is a square n x n matrix (n is a number of objects in a study sample), where each element w_{ij} represents a distance (generally, a relationship) between objects i and j. Diagonal elements of the matrix W are set to 0. There are some different approaches to specification of this matrix based on different nature of objects of interest [15]. In this research we use inverse Euclidean distances between regional centres as a metric of spatial dependence.

There are two main components of spatial dependency. Firstly, spatial dependency is presented in form of influence of economic characteristics in neighbour regions on employment in a given region. This form of dependency is usually called spatial lags. Direction of spatial lags influence on employment rate can be both negative and positive, so we don't have strong a priori expectation here. Our other research, related to tourism in Latvian regions [16], demonstrates negative spatial lags, so we can expect negative spatial lags in employment rates too. Another form of spatial dependency is a correlation of error terms in neighbour regions (called spatial errors). For example, employment rates in regions located in a particular area can be lower than expected on the basis of their economic characteristics. We expect (on the basis of common sense) that spatial dependency in errors should be positive. Omission of spatial errors doesn't lead to a bias of model parameter estimates, but decreases estimate efficiency. In real situations, both forms of spatial dependency can be present at the same time.

There are some statistical approaches developed to discover the presence of spatial effects. Generally, all test statistics are based on assumption that if spatial effects are present in error terms, they become apparent in model residuals:

$$e = y - Xb, \quad (2)$$

where b is a vector of a model parameter estimates β.

Moran's I is a popular test statistics for spatial dependency [17]:

$$MoranI = \frac{e^T We}{e^T e} \sim i.i.d.\, normal, \quad (3)$$

Moran's I coefficient allows discovering spatial autocorrelation of model residuals, but cannot distinguish between spatial lags and spatial errors. Moreover, if spatial lags and spatial errors have different directions of influence, Moran' I can lead to incorrect conclusion about absence of spatial correlation (Type I error). This shortcoming appears in this study and will be discussed in the "Main results" section.

Presence of spatial lags and errors can be tested separately using Lagrange Multiplier tests. The tests are proposed by Anselin [11]. Later robust specifications were developed [18] for tests, which should be used when both spatial lags and spatial errors are present in data.

Robust Lagrange Multiplier test statistics for spatial lags (RLM-lags) and for spatial errors (RLM-errors) are:

$$\begin{aligned} RLM - lags &= \frac{1}{nJ - t}\left(\frac{e^T Wy}{\sigma_\varepsilon^2} - \frac{e^T We}{\sigma_\varepsilon^2}\right)^2 \\ RLM - errors &= \frac{nJ}{t(nJ - t)}\left(\frac{e^T We}{\sigma_\varepsilon^2} - \frac{t}{nJ}\frac{e^T Wy}{\sigma_\varepsilon^2}\right)^2 \\ RLM - lags, RLM - errors &\sim \chi^2(1) \end{aligned} \quad (4)$$

where

$$\begin{aligned} \sigma_\varepsilon^2 &= \frac{1}{n}\varepsilon^T \varepsilon, \\ t &= trace(WW + W^T W), \\ J &= \frac{(WXb)^T \left(I - X(X^T X)^{-1} X\right)(WXb)}{\varepsilon^T \varepsilon} + \frac{t}{n}, \end{aligned}$$

Noted statistics test for spatial lags and spatial errors separately, so if both tests recognize spatial effects, it doesn't exactly mean that both forms of spatial dependency are present at the same time. Additional model investigations are required in this case.

We apply Hendry's (backward step-wise) strategy [19] and start with the most general model (with both spatial lags and errors). If some spatial effects are insignificant, we will reduce the model.

The general model specification we considered is a spatial mixed autoregressive Durbin model:

$$y = \rho Wy + X\beta + \gamma WX + \varepsilon, \quad (5)$$

where ρ and γ are vectors of unknown coefficients reflecting spatial influence and Wy and WX are usually denoted as spatial lags.

We understand that under selected specification the dependent variable is limited ($0 \le$ Employment Rate ≤ 1), and the linear model is not quite appropriate in this case. A value of an employment rate can be considered as a probability that a randomly selected person in a region is employed, so the model can be interpreted as a well-known linear probability model [13]. The most serious shortcoming of this model is potential model predictions for a dependent variable, which don't match the range of possible values. We tested this shortcoming and it is not present in our sample. As this research is focused on determinants of employment rates, and we don't apply it as a predictor of employment rates, we can continue with the linear model. If predicted values are the main point of interest, we can recommend using popular probability-based model specifications (logistic, logit, probit, etc).

c. Data

A set of statistical regional-level data is received from the Central Statistical Bureau of Latvia (CSB, [20]) and includes socio-economic information about 26 Latvian districts.

The data set includes indicator values for years 2005-2008. Possible time lags are not included into the model specification (so the model is clearly spatial, but not a space-temporal model). We run estimation of model parameters for every year and the pooled dataset, which allows discovering some potential weaknesses of model specification.

Riga, the capital of Latvia, is considered as a separate statistical unit by CSB in the same manner as any other Latvian region, but generally it is significantly different. Riga is a centre of Latvian economy; it accounts for more than 55% of Latvian GDP and obviously cannot be compared with other regions directly. In this study we decided to exclude Riga from the sample as outlier, to get rid of potential well-known estimation problems.

Most indicators are obtained from CSB directly; only two of them where calculated by the authors. Regional employment rates were calculated as a ratio of a total number of persons employed to total population of a region as described earlier. Ethnic diversity index is calculated as a form of Herfindahl–Hirschman Index [21]:

$$EDI = 1 - \sum_{i=1}^{G} p_i^2 , \quad (6)$$

where p_i is a proportion of ethnicity i in a region and G is a total number of ethnicities registered.

Data descriptive statistics are presented in the Table 1.

TABLE 1
DATA DESCRIPTIVE STATISTICS

	MEAN	STANDARD DEVIATION	MIN	MAX
Employment Rate	0.26	0.04	0.19	0.34
Population	54181.08	31207.10	24746	149551
GDP per capita	2700.91	996.55	1092.62	5918.32
Crimes per capita	22.42	5.47	11.21	35.02
Hospital Beds per capita	6.14	3.62	2.52	17.09
Average Wages	190.56	20.11	157.00	251.63
Flat Price	6.04	3.41	1.20	17.70
Ethnic Diversity Index	0.39	0.15	0.15	0.67

Source: Author's calculations.

GIS information about Latvian districts is obtained from the GADM database [22].

The spatial weight matrix is calculated using inverse Euclidean distance approach.

Quantitative variables were used in logarithms to estimate dependencies in the form of elasticity.

IV. MAIN RESULTS

In the previous section we presented a general approach to construction of econometric model for regional employment rates. The first step is to discover possible spatial effects in our sample. We started with estimating of the model with a full set of supposed explanatory variables using classic OLS technique. We encountered a usual estimation problem, connected with multicolleniarity (just as we expected), and also discovered insignificance of some supposed factors. Further in this paper we include only the factors, which are significant in at least one of the model specifications.

The regression equation, estimated with OLS (1), is:

$$\begin{aligned} \ln EmploymentRate &= -8.48 + \\ &+ \underset{(0.000)}{0.33} \ln GDPPerCapita - \\ &- \underset{(0.161)}{0.07} \ln CrimesPerCapita + \\ &+ \underset{(0.011)}{0.06} \ln HospitalBedsPerCapita - \\ &+ \underset{(0.25)}{0.03} sea + \varepsilon \end{aligned} \quad (7)$$

Relationships between employment rates and GDP per capita and a number of beds in hospitals are significant, and positive signs of their coefficients match our expectations. Surprisingly, there is no significant difference between seaside and inland regions. Note that OLS estimates presented can be biased due to spatial effects.

Moran's I test statistics doesn't reject a null hypothesis (absence of spatial effects):

$$MoranI = 0.0325,$$
$$Significance_{MoranI} = 0.123,$$

but robust Lagrange multiplier diagnostics for spatial lags and spatial errors (4) says that both forms of spatial effects are present:

$$RLM - lags = 7.3394,$$
$$Significance_{RLM-lags} = 0.007,$$
$$RLM - errors = 5.0013,$$
$$Significance_{RLM-errors} = 0.025.$$

This contradiction between Moran's I and Lagrange multiplier diagnostics can be explained by different directions of influence of spatial lags and errors. We expect positive relationship of spatial errors (it's very difficult to explain negative spatial errors economically), so an expected direction of spatial lags should be negative to compensate positive correlation of spatial errors (and make Moran's I insignificant). It is statistically impossible to estimate spatial lags and spatial errors in one model, so we preferred a model with spatial lags on the basis of higher significance level of RLM-lags statistics. Finally spatial mixed autoregressive Durbin model was estimated:

$$\begin{aligned} \ln EmploymentRate = -21.04 + \\ + \underset{(0.000)}{0.29} \ln GDPPerCapita - \\ - \underset{(0.470)}{0.03} \ln CrimesPerCapita + \\ + \underset{(0.000)}{0.11} \ln HospitalBedsPerCapita - \\ + \underset{(0.002)}{0.11} sea - \\ - \underset{(0.058)}{0.19} \mathrm{sp.lag}(\ln GDPPerCapita) + \\ + \underset{(0.055)}{0.55} \mathrm{sp.lag}(\ln HospitalBedsPerCapita) + \\ + \underset{(0.002)}{0.97} \mathrm{sp.lag}(sea) - \\ - \underset{(0.004)}{1.91} \mathrm{sp.lag}(\ln EmploymentRate) + \varepsilon \end{aligned} \quad (8)$$

The model is estimated in linearized Cobb-Douglass form, so estimated coefficients represent elasticity values for explanatory variables.

Some spatial lag variables (marked as sp.lag in the formula 8) are significant in this model, which supports our assumption about strong spatial effects. Formal comparison of models with and without spatial effects can be performed using Akaike Information Criterion (AIC) value. AIC value for the model with spatial effects is significantly better than for the non-spatial model (–105.58 versus –100.13).

Directions of influence observed mostly match our economic expectations. Positive elasticity of GDP per capita represents obvious relationship between overall development of regional economy and employment rate. The only indicator of social care included into the final model, a number of hospital beds per capita in a region, has an expected positive influence. All other indicators of social and health care are excluded from the model mostly due to the multicolleniarity problem. We also discovered a significant positive effect of a sea-side in a region. This effect was expected on the basis of our economic knowledge, and it wasn't discovered in biased OLS estimates of the classical regression.

One of the main goals of this research is investigation of spatial dependencies in calculating employment rates. A coefficient for a spatial lag of GDP per capita has insignificant negative value, so we can directly conclude that economic development in neighbour regions has a negative influence on employment rates in a given region. This conclusion is in contradiction with usual understanding of regional politics as being cooperative. Negative spatial lag can be explained as an effect of competition between regions for labour force in the situation of high level working population mobility. This conclusion can be very important for regional and state economic policies and can be considered as a potential for overall economic growth via improvement of the cooperation level between Latvian regions. This finding matches the results of the related research [13], where it was stated that in the tourism sector competition effects are also stronger than cooperation ones.

Two other spatial lags (hospital beds and sea-side) are significantly positive in the model, and this influence matches our expectations. Latvian regions share their social services and a person can easily use hospitals in neighbour regions (of course, it can't be applied to emergencies). Also the presence of sea-side has a significant positive effect which is not completely captured by seaside regions, but spreads over all neighbour territories.

One of the most interesting and conflicting results of this research is a negative spatial autoregressive lag of employment rates. We can expect a positive value on the basis of literature reviews. For example, studies [4, 5, 8] identify significant positive spatial lags of employment (or unemployment) rates in Italy, Spain, and Russia. Usually spatial lags are explained by regional disparities sustaining for a long time. They are expected to be positive in this case. Although competition between regions for financial and labour resources is widely acknowledged, positive cooperation effects usually overweight competition. The only known to us research where negative spatial lag of unemployment was discovered is related to the study of Turkey regions [6]. In that study the author identified a negative spatial lag of unemployment in 1980, which changed to positive in 2000. General specification of spatial models doesn't allow distinguishing between simultaneous completion and cooperation effects, and this problem will be a subject of our further research.

Comparison of real and predicted values of regional employment rates are presented in Table 2.

We can note good quality of model fitting and as result relatively small model residuals. We compare residuals from non-spatial and spatial model specifications on Figure 2.

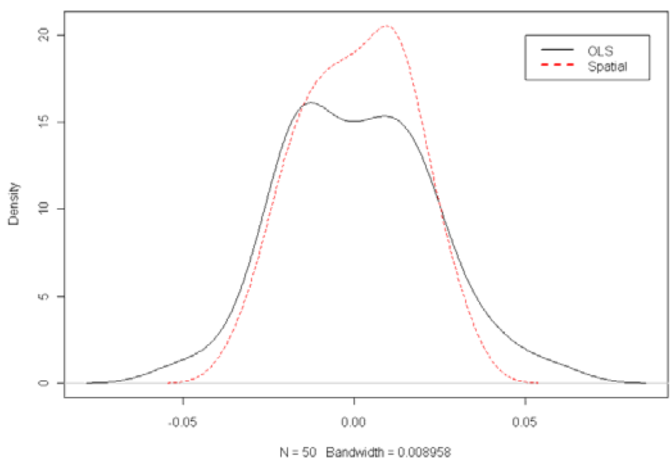

Fig. 2. Distribution of spatial and non-spatial (OLS) model residuals. Source: Author's graph based on models (7) and (8) estimation data.

Residuals of the spatial model are concentrated around zero more closely than those of non-spatial ones. Tighter tails of non-spatial model residuals show higher probability of significant errors in model predictions (extreme values of non-spatial model residuals exceed 5%, which is significantly higher than differences of values presented in Table 2).

TABLE 2

REAL AND PREDICTED EMPLOYMENT RATE VALUES FOR LATVIAN REGIONS

REGION	REAL	SPATIAL MODEL PREDICTION
Aizkraukle	22.92%	23.73%
Aluksne	23.84%	22.75%
Balvi	19.10%	19.44%
Bauska	20.86%	21.69%
Cesis	28.48%	25.88%
Dobele	24.21%	27.64%
Gulbene	25.11%	26.27%
Jekabpils	27.17%	26.97%
Kraslava	19.43%	18.44%
Kuldiga	23.18%	21.78%
Limbazi	22.48%	23.60%
Ludza	21.29%	19.26%
Madona	24.80%	24.61%
Ogre	22.98%	24.99%
Preili	22.11%	23.66%
Saldus	28.28%	27.16%
Talsi	27.84%	27.35%
Tukums	25.23%	25.18%
Valka	26.77%	29.71%
Valmiera	32.70%	29.80%
Duagavpils	30.02%	28.50%
Jelgava	28.41%	29.12%
Liepaja	32.87%	30.88%
Rezekne	30.01%	28.47%
Ventspils	34.43%	34.56%

Source: Author's calculations.

V. CONCLUSIONS

The main goal of this research was to investigate differences in employment rates in Latvian regions. We applied modern spatial econometric methods to discover and analyse spatial patterns in data.

The developed model considers the influence of such factors within regions as GDP per capita and a number of hospital beds on employment rates. Also we discovered a significant level of spatial dependency of regional employment rates, and thereby we can conclude that research of regional development without taking into consideration spatial effects can yield inconsistent results.

Competition for labour resources between regions was demonstrated by negative spatial lags. This finding is critically important, it should be taken into consideration in development of regional and state policies, because decisions made on the level of a particular region have significant influence on its entire neighbourhood.

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Dmitrijs Pavļuks. Telpas nodarbinātības līmeņa analīze Latvijas reģionos
Šis pētījums ir veltīts nodarbinātības līmeņa telpas statistiskai analīzei. Tiek novērtēta un izanalizēta savstarpējā sakarība starp reģionālo nodarbinātības līmeni un ekonomikas un sociālas nodrošināšanas rādītājiem. Pētījuma pamatdarbarīks ir telpas regresijas modelis; tiek izskatīta telpas modeļa savdabība un izdarīts modeļa statistisks salīdzinājums ar klasisko daudzfaktoru regresiju. Telpas modeļa parametru vērtējumam tiek izmantoti LR Centrālās statistikas pārvaldes dati par ekonomikas un demogrāfisko stāvokli Latvijas reģionos no 2005. gada līdz 2008. gadam. Izstrādātajā modelī tiek iekļauti faktori, kuri ietekmē reģionālo nodarbinātības līmeni – IKP uz vienu iedzīvotāju (kā ekonomikas attīstības rādītājs), reģistrētie noziedzīgie nodarījumi un gultu skaits slimnīcās uz vienu iedzīvotāju (kā sociālās nodrošināšanas rādītāji). Tiek izskatīta arī nodarbinātības līmeņa atšķirība starp piekrastes un iekšējiem reģioniem. Atklātā minēto faktoru ietekmes ievirze atbilst ekonomiskajai gaidīšanai – tiek atklāta pozitīva ekonomikas attīstības un sociālās nodrošināšanas līmeņu ietekme un pozitīvs jūras krasta efekts. Pētījuma oriģinalitāte ir tāda, ka šāda veida telpas savstarpējā kopsakara analīze Latvijas reģioniem līdz šim brīdim netika veikta un tai ir būtisks un lietderīgs pielietojums. Tiek atklāta zīmīga negatīva savstarpējā sakarība starp nodarbinātības līmeņiem reģionā un tādiem pašiem līmeņiem kaimiņreģionos. Šo efektu var izskaidrot ar konkurenci starp reģioniem darbaspēka tirgū.

Дмитрий Павлюк. Пространственный анализ региональных уровней занятости в Латвии
Данное исследование посвящено статистическому анализу влияния экономических факторов на уровень занятости в регионах Латвии, а также выявлению взаимовлияния уровней занятости в соседних регионах. В качестве основного инструмента анализа в исследовании использовалась пространственная регрессия; рассмотрены особенности ее применения и проведено статистическое сравнение с классической регрессией. Для оценивания параметров пространственной регрессии были использованы данные Центрального статистического бюро Латвии об экономической и демографической ситуации в регионах Латвии в период с 2005 по 2008 год. В качестве основных факторов, оказывающих влияние на уровень занятости в регионе, использовались ВВП на душу населения (как показатель экономического развития региона) и количество преступлений и количество мест в больницах на душу населения (как показатель социальной обеспеченности региона). Кроме того, рассматривалось различие в уровнях занятости в прибрежных и внутренних регионах страны. Выявленная направленность влияния указанных факторов соответствует экономическим ожиданиям – установлено позитивное влияние уровней экономического развития и социальной обеспеченности, а также положительный эффект наличия морского побережья. Особенностью исследования является рассмотрения взаимосвязей между уровнями занятости в соседних регионах. Статистический анализ этой пространственной взаимосвязи ранее не проводился для регионов Латвии и обладает существенной прикладной полезностью. Автором была выявлена значимая отрицательная взаимосвязь между уровнем занятости в регионе и уровнями занятости в смежных с ним регионах. Данный эффект может быть объяснен конкуренцией между регионами на рынке рабочей силы.