CRACOW
UNIVERSITY
OF ECONOMICS

FOUNDATION
OF THE CRACOW UNIVERSITY
OF ECONOMICS

KNOWLEDGE ECONOMY SOCIETY

SELECTED PROBLEMS OF DYNAMICALLY DEVELOPING AREAS OF THE ECONOMY

Edited by
Renata Seweryn, Tomasz Rojek

KNOWLEDGE – ECONOMY – SOCIETY

SELECTED PROBLEMS OF DYNAMICALLY DEVELOPING AREAS OF ECONOMY

CRACOW UNIVERSITY OF ECONOMICS
Faculty of Management
FOUNDATION OF THE CRACOW UNIVERSITY OF ECONOMICS

KNOWLEDGE – ECONOMY – SOCIETY

SELECTED PROBLEMS OF DYNAMICALLY DEVELOPING AREAS OF ECONOMY

Edited by

Renata Seweryn, Tomasz Rojek

Cracow 2017

Reviewer

Joanna Nowakowska-Grunt

All papers have been prepared in English by the Authors

Wydanie publikacji zostało sfinansowane z dotacji na utrzymanie potencjału badawczego przyznanej Uniwersytetowi Ekonomicznemu w Krakowie

The book was financed with subsidies for maintaining the research capacity granted to the Cracow University of Economics

ISBN 978-83-65907-13-4 (printed version)
ISBN 978-83-65907-14-1 (on-line pdf)

Publishing House
Foundation of the Cracow University of Economics
ul. Rakowicka 27, 31-510 Kraków, Poland

Table of contents

Introduction 9

PART I
MACRO AND MICROECONOMIC ASPECTS OF THE FUNCTIONING OF THE CONTEMPORARY ECONOMY

Chapter 1
Czesław Mesjasz
Socio-economic Inequality as a Property of Complex Social Systems 15

Chapter 2
Danijela Durkalić, Katarina Zdravković
European Integration as the Engine of Economic Development: A Comparative Analysis 25

Chapter 3
Anatolii Mazaraki, Ganna Duginets
Sector-specific Stimulation of Integration into Global Value Chains: Experience for Ukraine 37

Chapter 4
Juraj Mišún
Changing Views on Organizational Control in the Countries of the Eastern Bloc 49

Chapter 5
Piotr Bartkowiak, Jarosław Kaczmarek
Restructuring and Effectiveness of the Production Mesostructure 65

Chapter 6
Anna Jonkisz-Zacny
Growth of Productivity as a Measurable Effect of Synergy Between Labour and Tangible Assets 77

Chapter 7
Karol Flisikowski
A Spatio-temporal Approach to Intersectoral Labour and Wage Mobility 87

Chapter 8
Małgorzata Marchewka
Crowdsourcing in Scientific Research – Opportunities and Limitations 97

Chapter 9
Tomasz Kusio
Commercialization Potential at the Entrepreneurial University 105

Chapter 10
Katarzyna Brendzel-Skowera
The Potential of Academic Entrepreneurship in the Region of Częstochowa 113

Chapter 11
Tindara Abbate, Patrizia Accordino, Elvira Tiziana La Rocca, Daniela Rupo
Enabling Factors for the Development of Startups 125

Chapter 12
Maria Cristina Cinici, Mohamed Amara, Daniela Baglieri
Fostering Micro-Entrepreneurship: Does Spatial Proximity Matter? 137

Chapter 13
Ana Krstić, Nemanja Lojanica
The Efficiency of Healthcare Policy: Empirical Evidence from Poland and The Republic of Serbia 145

PART II
INNOVATION IN THE PROCESSES OF THE DEVELOPMENT OF ECONOMIES AND ENTERPRISES

Chapter 14
Elena Tkachenko, Elena Rogova, Ekaterina Buynizkaya, Maria Ganieva
The Real Options Method Implementation in the Management of Innovative Projects 157

Chapter 15
Paweł Łukasik
Monitoring of Innovation Processes 169

Chapter 16
Tomasz Stefaniuk
New Dimensions of Information and Knowledge Security in Reality of Industry 4.0 177

Chapter 17
Tindara Abbate, Patrizia Accordino, Elvira Tiziana La Rocca, Daniela Rupo
Equity Crowdfunding in Europe: Challenges, Opportunities and Risks for Innovative Startups 187

Chapter 18
Zbigniew Chyba
Technology Entrepreneurship and the Competitiveness of Advanced Technology Sector Enterprises 197

Chapter 19
Milena Tvrdíková
Paradigm Shift in the Established Way of Thinking in Innovation, the Operation of and the Provision of Funds for Company Information System as a Result of the Transformation of ICT into the Services Sector 207

Chapter 20
Jan Ministr
The Innovation of Information Support of the Social Housing 215

Chapter 21
Jarosław Plichta, Karolina Orzeł
The Effectiveness of Managing a Franchise Network in the Cross-Sectional View of the Main Theories of the New Institutional Economics 223

Chapter 22
Karolina Orzeł
The Development of FMCG Franchise Systems in Poland 233

Chapter 23
Agnieszka Mazurek-Czarnecka
Factors and Conditions Determining the Development of Companies Launched Thanks to Grants for Starting One's Own Business 243

Chapter 24
Katarina Borisavljevic, Katarina Radakovic, Anika Jakovljevic
Consumer Rights Protection in E-Business 253

PART III
CONTEMPORARY CONDITIONS AND CHALLENGES OF THE REGIONS AND THE TOURISM SECTOR

Chapter 25
Slavko Arsovski, Zora Arsovski, Aleksandar Đorđević
Knowledge Based Regional Sustainability through Industrial Districts 265

Chapter 26
Magdalena Gorzelany-Dziadkowiec, Julia Gorzelany
Use of Social Capital in Regional Development 281

Chapter 27
Renata Seweryn, Agata Niemczyk
Religious Tourism in the Cities (by the Case of Krakow) 289

Chapter 28
Marian Bursztyn
The Psycho-pedagogy Contexts Animation of Free Time in the Development of Tourism 301

Chapter 29
Jadwiga Berbeka, Krzysztof Borodako, Michał Rudnicki
Social Media as a Tool of Sharing Tourists Opinions about Accommodation Services in Krakow 313

Chapter 30
Rafał Kusa
Adjusting Entrepreneurial Orientation for Researching Micro and Small Travel Agencies and Tour Operators 323

Chapter 31
Ewa Kubejko-Polańska
Managing the Functional Urban Development Through Implementation of the Silver Economy Concept – A Regional Perspective 331

Authors 341

Chapter 7

A Spatio-temporal Approach to Intersectoral Labour and Wage Mobility

Karol Flisikowski

1. Introduction

Mobility of wages and employment is an issue widely understood and analyzed. In this study, mobility is considered as a change in the structure of sectoral wages and labor force over time. This specific type of structural mobility can be characterized by a number of analysis used in the indicators. Its choice influences their interpretation and economic sense. It can also be associated with various factors of its economic environment. These include, among others: human capital specific to the sector (often identified with the sectoral wages), unemployment, institutionalism, wage or income inequality. Several studies confirms the existence of clear links between labor force and wage mobility (not only at the sectoral level) and factors mentioned above, which the author believes are the main reasons to believe that indirectly both of them can be related with each other. The main objective of this paper is an attempt to aggregate and synthesizing of both mobility relationship in the form of one spatial regression model. The selection of a spatial model gives us an additional interpretability of results by implementation of weights matrix based on the economic distances. Another advantage of such an empirical research presented in this article is the form of intersectoral mobility (highly aggregated data[1]).

2. Interindustry labour and wage mobility

Interindustry mobility (IM) can be understood as a cross-sectoral shift of workforce (Lilien, 1982; Wacziarg & Wallack, 2004) – intersectoral labor mobility (ILM). IM can also be defined as the degree of cross-sectoral shifts in wage differentiation (IWM – intersectoral mobility of wages). In the majority of studies (both theoretical and empirical), researchers try to explain the deter-

[1] This analysis was based on 3rd Revision of ISIC (International Standard Industrial Classification of All Economic Activities). To avoid the non-comparability of results (missing data, different revisions of ISIC), the empirical analyses were performed with the use of data reduced to the same time dimension (1994-2012) for 20 OECD countries.

minants affecting the level of ILM and IWM. This leads to the conclusion that in studies on that relationship still difficulties exist in explaining its cause and effect, so there is a presumption that a hypothetical relationship might be called as feedback.

The ratio of ILM to the level of equal pay is a very popular subject of many studies in the literature, but rarely can meet its reference to the scale of IWM. Behind the titles of publications of this type it lies mostly the comparison of the ILM to the dynamics or growth of wage levels. In a study on the relationship between the mobility of employment and wage growth common conclusions can be found. Examples of such analyzes are works that led i.e.: Bartel and Borjas (1981), Mincer (1986), Topel and Ward (1992), Antel (1983), Antel (1986). It has been proven here that the mobility of resources leads to an increase in wages (usually 10 to 20 percent). Slightly cautious estimates can be found in: Antel (1983), Moore et al. (1998), McLaughlin (1990). There are many theoretical approaches that bind together the mobility of wage and labor force. The movers-stayers model presented by (Blumen, 1955; Ng & Chung, 2012) and is rooted in psychological arguments. In this model, some workers are expected to be more likely to move than others. More unstable units would therefore be less productive and would receive lower wages than others (stayers).

Other models that consider the connection between ILM and IWM are classified as static or dynamic due to the rejection of the assumptions about the dynamism of wages in the range of positions (Naticchioni & Panigo, 2004). The on-the-job search theory could therefore be classified as static, whereas e.g. current specific human capital theory as dynamic. Static models allow the inclusion of such an interdependency only in the range of the specific changes in occupation or industry, whereas dynamic models recognize changes in wages combined with shifts of resources between and in the range of the same occupation or sector. In search models it is most often indicated that shorter seniority is correlated with an increase in the level of wage mobility and that fact brings the most "profitable" gains in wage at the beginning of careers. The same conclusions are met by modification of that theory introduced by Jovanovic (1979) or Burdett (1978). In human capital theory (Becker, 1962; Light & McGarry, 1998) however, an inversed relationship between mobility of labor force and investments in specific job skills is indicated, but does not define clearly and precisely the relationship between ILM and IWM. It points out that the more specific the human capital transfers, the lower the expected decline in wages in relation to the expected mobility of employment. Another dynamic approach represents the theory, in which the employee is looking for job to find the best fit to his expectations. Jovanovic (1979) believed that the worse the quality of such a match, the shorter the period of employment and the increase of wage might be related to the reward for the search for a better fit, regardless of the accumulation of specific human capital. The job-match theory does not conclude directly on the exact relationship of ILM and IWM (Naticchioni & Panigo, 2004). It is a theoretical model where optimum conditions for job changes determine a positive correlation between the length of employment and short-term increases in the scale of mobility. Institutional factors can affect both the shift in the structure of employment and wages growth in a number of ways. In the first case, the legal protection of employment has a significant role in the dismissal of workers and new employment for a temporary period. The more flexible the labor market, the greater the expected effects might be met (mobility can have erosive effect on wages). In countries with a higher degree of employment security any changes can be more profitable, due to the fact that they are usually met among occupations/industries with relatively higher wages. Another important institutional factor is specific level of unemployment compensation. In more liberal economies we can expect longer periods of unemployment and increased wage gap of people losing their jobs (although this effect is not as clear for people voluntarily changing jobs). They believe that wage formation process is influenced also by the degree of unionization and centralized, collective agreements. Countries with low level of union density and collective bargaining should record higher growth in real wages. Finally, the more decentralized collective agreements, the higher potential increases or decreases in wage levels (in terms of mobility) are expected.

3. Methodology

Interindustry mobility in majority of the empirical research is measured with the use of the individual micro-data. This entailed consequences in the application of specific statistical methods. Hence, most of the research rely on the same or very similar methodological solutions. The empirical analysis was performed in a few stages for 20 selected countries (for the period: 1994-2012), which are not in every case reciprocal neighbours. Thus, it was necessary to construct a spatial weights matrix based on economic distances (Pietrzak, 2010). The value of real GDP was chosen for that measure. This kind of technical nests inside the spatial model an additional interpretation of coefficients.

First stage of analysis covers calculations of Shorrocks (1978) mobility indices (for each country, its structure of wages and labor force, keeping 2-years subperiods). The measure proposed by Shorrocks belongs to the group of generalized entropy mobility measures (GEMM) and was generalized by Maasoumi and Zandvakili (1986). They allow us to observe the degree of structural substitution between employment or wages in different periods of time. In previously conducted studies Maasoumi (1998) concluded that those indices meet most of the requirements for mobility measurement. Let Y_{it} be the wage (or employment) for sector i in period $t=1,\dots,T$. Hence, the Shorrocks index of mobility (M) can be defined in formula (1).

$$M = 1 - \frac{I(S)}{\sum_{t=1}^{t} \alpha_t I(Y_t)} \tag{1}$$

where:
$S=(S_1,\dots,S_n)'$ is a vector of permanent or aggregated wages/employment in time T,
$Yt=(Y1t,\dots,Ynt)'$ is a vector of sectoral wages/employment in time t,
α_t is related weight and $I()$ stands for chosen inequality measure.

This measure is a negative function of the relative stability of the distribution and shows the ratio of long-term inequality (permanent and aggregate) $I(S)$ to the short-term inequality $I(Y_t)$. The level of mobility will increase if the long-term inequalities will be reduced more than the short-term. If the initial inequality of wages or employment of will be removed completely, the index will take a maximum value equal to 1. On the other hand, the total lack of mobility, here considered as total equality between the long- and short-term inequality will set the index to 0. For example, the value of M equal to 0.10 means that in the range of two years the inequality of distribution was reduced by 10 percent. As a result, mobility between sectors can thus be analyzed using the phenomenon of sectoral inequality. Jarvis and Jenkins (1998) emphasize that the inequality is much better tolerated in terms of mobility because it smooths out any short-term variability of distributions and therefore persistent irregularities are smaller than those observed. Through the use of Shorrocks index we can have the possibility of a closer and more comprehensive look at the distribution of wages and employment. This fact, as well as simplicity in the construction of the index (1), make the indices constructed on this basis extremely popular and widely used in various types of empirical research.

In the second stage of analysis, the spatial autocorrelation for previously obtained wage and employment mobility measures was checked. According to the first law of geography formulated by Tobler (1970), all objects in space (observation units) interact, and spatial interactions are the greater, the smaller is the distance between objects. Thus, in the analysis and modeling of data located we must consider the spatial interactions, which may relate to both the dependent variable and the random component. In a situation where the value of the dependent variable in each location affect the value of this variable from other locations, there is the so-called spatial autoregression. On the other hand, a case where certain spatially autocorrelated variables are omitted or cannot be considered relates to spatial autocorrelation of the random component (Rogerson, 2001; Suchecki, 2010). The spatial autocorrelation is defined as "the degree of correlation of observed values of the variable at his different locations" (Suchecki & Olejnik, 2010). This means that the value of the modeled variable is related to values of the same variable in other locations, and the degree of relationship in accordance with Tobler's rule (closer objects are more relevant than distant) affect the relative position of objects and their geographical (or economic) distance. We can consider the specific relationship between the observation units (resulting from their location) thanks to the design of spatial weights matrix (Anselin, 1988). It is a square matrix with $n \times n$ dimensions, "which elements reflect the existing spatial structure" (Ludwiczak, 1991). Specification of that matrix belongs to arbitrary decisions taken by a researcher and a choice of the alternative method of weighing is often due to the knowledge of the spatial structure of the phenomenon and links between units (Kossowski, 2010; Łaszkiewicz, 2014a). It is assumed that links of spatial entities are positively affected by mutual proximity and negatively by shared distance (Łaszkiewicz, 2014b). Spatial weights matrix is a structure whose elements w_{ij} take the value 0 when the two objects i, j are not neighbors, and 1 otherwise. In order to construct a matrix of spatial weights based on economic distances by analogy the 0 and 1 value is selected as the euclidean distance and the optimal cut-off point (usually 0.5) is computed.

Specification of spatial weight matrices is a prerequisite and the first step in the analysis of spatial autocorrelation. Among many measures used for spatial relationships testing the most commonly used is Moran's I statistic (Longley et al., 2008). This statistic is calculated based on the formula (2).

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} \left(z_i - \bar{z}\right)\left(z_j - \bar{z}\right)}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \sum_{i=1}^{n} \left(z_i - \bar{z}\right)^2} \tag{2}$$

where:
n – number of observations (locations),
z_i – the observed value of the z variable for all n observations (locations),
w_{ij} – weight of spatial interactions (connections) between observations (locations) i and j.

The statistical significance of spatial autocorrelation measured by Moran's I statistic assuming null hypothesis of a random distribution of *z*-values (lack of spatial autocorrelation) is verified with the standardized normal Z_I statistic (Kossowski, 2010; Suchecki & Olejnik, 2010).

In the last stage of analysis, in case of spatial autocorrelation (Rogerson, 2001; Kossowski, 2010) two regression models with spatial effects were estimated[2]: SAR – spatial autoregressive models (also classified as spatial lag models – SLM) and spatial error model (SEM). The response to the negative impact of the spatial interaction to estimate the structural parameters of the OLS models is an implementation to the classical form of the regression equation an additional independent variable and its parameter of ρ relating to this variable (called spatial autoregression coefficient). This variable (spatial lag) determines spatially delayed values of dependent variable, calculated as a weighted average (according to the adopted spatial weights matrix) from the value of this variable occurring in the neighborhood (Suchecki, 2010). We can formulate SLM in equation (3).

$$y_r = \rho\left(\sum_{s=1}^{n} w_{rs} y_s\right) + \sum_{i=1}^{k} \beta_i x_{ir} + \varepsilon_r \tag{3}$$

The formula $\rho\left(\sum_{s=1}^{n} w_{rs} y_s\right)$ determines the impact of the dependent variables of the adjacent p-th locations (according to the matrix of spatial weights) on the value of the variable in the r-th location (Rogerson, 2001).

Spatial error model (SEM) allows us to consider the spatial dependence of the sampling error (Rogerson, 2001; Kopczewska, 2010). In this model, the overarching scheme of linear spatial autocorrelation of the random component is considered. It can be written as shown in equation (4).

$$y_r = \sum_{i=1}^{k} \beta_i x_{ir} + \varepsilon_r \tag{4}$$

$$\varepsilon_r = \lambda\left(\sum_{s=1}^{n} w_{rs} \varepsilon_s\right) + u_r \tag{5}$$

where ε_r presented in equation (5) stands for the original random component with spatial autocorrelation (residuals from OLS regression for *r*-th location), which is a function of spatially delayed random error $\sum_{s=1}^{n} w_{rs}\varepsilon_s$ (residuals from adjacent *p*-th locations) and "cleaned" random component u_r (that satisfies OLS assumptions). λ coefficient however, is a measure of interdependency of OLS residuals and on its basis we can infer the existence of significant factors influencing on values of dependent variable, which were not included in the regression model (i.e. unmeasurable or random factors) (Kopczewska, 2010; Kossowski, 2010; Suchecki, 2010).

[2] It should be mentioned, that these are only the most popular examples of the wide range of spatial models reported in the literature multiplied with their numerous extensions and modifications.

4. Results

In the first stage of the analysis, the calculations of Shorrocks mobility indices were made (separately for labor and wage structures). In the second stage, for each subperiod and for previously calculated measures of mobility, a spatial autocorrelation Moran's measure was estimated (see Tab. 1). When spatial autocorrelation statistics are computed for variables, they assume constant variance. This is usually violated when the variables are for areas with greatly different populations. That is why the Assunção-Reis empirical Bayes standardization (Assunção & Reis, 1999) should be implemented here to correct it. For each subperiod (2-years) between 1994 and 2012 negative, statistically significant ($p < 0.01$) spatial autocorrelation statistics for ILM and IWM measures were obtained (from -0.2 in first subperiod to -0.27 in the last one). This was the basis for estimation of structural parameters of spatial regression models in the third stage of analysis (Rogerson, 2000; Kossowski, 2010).

Table 1. Moran's spatial autocorrelation statistics for interindustry labor and wage mobility (p-values in brackets)

Time period / Spatial autocorrelation	Interindustry wage mobility	Interindustry labor mobility
1994-1996	-0.209 (0.031)	-0.215 (0.001)
1996-1998	-0.276 (0.000)	-0.247 (0.000)
1998-2000	-0.277 (0.000)	-0.200 (0.036)
2000-2002	-0.205 (0.033)	-0.226 (0.000)
2002-2004	-0.201 (0.032)	-0.208 (0.030)
2004-2006	-0.208 (0.029)	-0.134 (0.035)
2006-2008	-0.274 (0.000)	-0.201 (0.039)
2008-2010	-0.201 (0.031)	-0.249 (0.011)
2010-2012	-0.239 (0.016)	-0.227 (0.019)

Source: own calculation.

Negative, statistically significant spatial autocorrelation statistics of both measures is the basis to make the estimation of the structural parameters of spatial regression models in the third stage of analysis (Rogerson, 2000; Kossowski, 2010). In Table 2 the results of an estimation of linear regression models LM and regression models based on the matrix of spatial weights: SEM (spatial error model) and SLM (spatial lagged model) in two opposite subperiods are presented.

Table 2. Estimation of linear and spatial regression functions for intersectoral mobility (p-values in brackets)

Interindustry labor mobility (ILM)	LM	SEM	SLM	LM	SEM	SLM
	1994-1996			2010-2012		
constant	0.003 (0.016)	0.003 (0.039)	-0.153 (0.017)	0.008 (0.010)	0.0087 (0.000)	0.008 (0.002)
Interindustry wage mobility (IWM)	0.319 (0.001)	0.3113 (0.000)	0.301 (0.000)	0.298 (0.001)	0.313 (0.000)	0.307 (0.000)
λ / ρ		-0.179 (0.035)	-0.153 (0.037)		-0.195 (0.013)	-0.187 (0.031)
R^2	0.536	0.538	0.553	0.626	0.664	0.632
Log-likelihood	82.680	82.710	83.032	84.838	85.672	84.979
Akaike criterion	-159.361	-159.420	-158.064	-163.678	-165.346	-157.977
LM		4.653 (0.030)	3.967 (0.045)		4.923 (0.026)	3.172 (0.074)

Source: own calculation.

The obtained results (presented in Tab. 2) have correct statistical properties (LR and BP tests, significance of coefficients, Akaike criterion, R^2) and the correct economic interpretation. The spatial regression models (both SLM and SEM) showed slightly better performance and statistical significance of parameters than linear model without spatial effects. Its strength however increased over time, so in the last subperiod the spatial error model proved us the highest (66.42%) determination coefficient and high statistical significance. The use of spatio-economic weight matrices gave us a very good fit of the model to the empirical data, which can be seen in the values of the logarithm of the likelihood function, values of the coefficient of determination and Akaike criterion. The considered matrix of such a specific type of spatial weights led to the discovery of negative spatial autocorrelation – the intensity of interindustry labor force and wage mobility for neighboring countries (in terms of economic proximity) occurred to be completely different. What is more, statistically significant relationship between ILM and IWM was synthesized in form of one final version of regression model (SEM) and highlighted the negative value of the correlated random component. This means that specific individual effects influence the intensity of both phenomena among OECD countries. It may be a recommendation for further research in this area in order to discover the causes of such a situation.

4. Conclusion

In this article the problem of use of the spatial weights matrix based on the economic distance within the framework of the author's analysis of interindustry mobility phenomena was presented. The results of empirical analysis indicate that in case of the research on employment and wage mobility even studies at the most aggregate level of observation should be taken into account. Furthermore, the assumption of the existence of certain spatially dependent variables significantly shapes the intensity of their interdependence. This means that the use of weights matrix based on the economic distance in statistical models of employment mobility greatly increases the correct interpretive impact of explanatory variable like intersectoral wage mobility, and thus significantly improves the quality of research. The higher level of the interindustry wage mobility is accompanied by increased movement of labor force across sectors. Moreover, the strength of this association increased over time, also taking into account the spatial factor.

The presented results are mainly due to the more complete description of the spatial autocorrelation of interindustry mobility. The choice of the spatial form of the regression model caused a further significant improvement of explanatory abilities of the analysis.

Bibliography

1. Anselin, L. (1988). Lagrange Multiplier Test Diagnostics for Spatial Dependence and Spatial Heterogeneity. *Geographical Analysis*, 20(1), 1-17.
2. Antel, J.J. (1986). Human Capital Investment Specialization and the Wage Effects of Voluntary Labor Mobility. *The Review of Economics and Statistics*, 477-483.
3. Assuncao, R.M., & Reis, E.A. (1999). A New Proposal to Adjust Moran's I for Population Density. *Statistics in Medicine*, 18(16), 2147-2162.
4. Bartel, A.P., & Borjas, G.J. (1981). Wage Growth and Job Turnover: An Empirical Analysis. [in:] *Studies in Labor Markets*. University of Chicago Press.
5. Becker, G.S. (1962). Investment in Human Capital: A Theoretical Analysis. *Journal of Political Economy*, 70(5, Part 2), 9-49.
6. Blumen, I. (1955). *The Industrial Mobility of Labor as a Probability Process* (No. 6). Cornell University.
7. Burdett, K. (1978). A Theory of Employee Job Search and Quit Rates. *The American Economic Review*, 68(1), 212-220.
8. Jarvis, S., & Jenkins, S. (1998). How Much Income Mobility is there in Britain? *The Economic Journal*, 108(447), 428-443.
9. Jovanovic, B. (1979). Job Matching and the Theory of Turnover. *Journal of Political Economy*, 87(5, Part 1), 972-990.
10. Keith, K., & McWilliams, A. (1997). Job Mobility and Gender-based Wage Growth Differentials. *Economic Inquiry*, 35(2), 320.
11. Keith, K., & McWilliams, A. (1999). The Returns to Mobility and Job Search by Gender. *ILR Review*, 52(3), 460-477.
12. Kopczewska, K. (2010). Modele zmian stopy bezrobocia w ujęciu przestrzennym. *Wiadomości Statystyczne*, 5, 26-40.
13. Kossowski, T. (2010). Teoretyczne aspekty modelowania przestrzennego w badaniach regionalnych. [in:] P. Churski (Ed.), *Praktyczne aspekty badań regionalnych*, Varia vol. III. Biuletyn IGSEiGP UAM, Seria Rozwój Regionalny i Polityka Regionalna, 12, Poznań: Bogucki Wydawnictwo Naukowe.
14. Light, A., & McGarry, K. (1998). Job Change Patterns and the Wages of Young Men. *Review of Economics and Statistics*, 80(2), 276-286.
15. Lilien, D.M. (1982). Sectoral Shifts and Cyclical Unemployment. *Journal of Political Economy*, 90(4), 777-793.
16. Longley, P.A., Goodchild, M.F., Maguire, D.J., & Rhind, D.W. (2006). *Teoria i praktyka.* Warszawa: PWN.

17. Ludwiczak, B. (1991). Korelacja przestrzenna. [in:] A. Zeliaś (Ed.), *Ekonometria przestrzenna*. Warszawa: PWE.
18. Łaszkiewicz, E. (2014a). Operacjonalizacja zależności przestrzennych w postaci macierzy wag. [in:] J. Suchecka (Ed.), *Statystyka przestrzenna. Metody analiz struktur przestrzennych*. Warszawa: Wydawnictwo C.H. Beck.
19. Łaszkiewicz, E. (2014b). Przegląd macierzy wag przestrzennych. [in:] J. Suchecka (Ed.), *Statystyka przestrzenna. Metody analiz struktur przestrzennych* (169-197). Warszawa: Wydawnictwo C.H. Beck.
20. Maasoumi, E., & Zandvakili, S. (1986). A Class of Generalized Measures of Mobility with Applications. *Economics Letters*, 22(1), 97-102.
21. Maasoumi, E. (1998). On Mobility. *Statistics Textbooks and Monographs*, 155, 119-176.
22. McLaughlin, K.J. (1990). General Productivity Growth in a Theory of Quits and Layoffs. *Journal of Labor Economics*, 8(1, Part 1), 75-98.
23. Mincer, J. (1986). Wage Changes in Job Changes. *Research in Labor Economics*, 8(A), 1-41.
24. Moore, W.J., Newman, R.J., & Turnbull, G.K. (1998). Do Academic Salaries Decline with Seniority? *Journal of Labor Economics*, 16(2), 352-366.
25. Naticchioni, P., & Panigo, D. (2004). *Employment Protection, Job-tenure and Short Term Mobility Wage Gains – A New Explanation for the Italian Case* (No. 4-DEISFOL). Dipartimento di Economia, Sapienza University of Rome.
26. Pietrzak, M.B. (2010). Wykorzystanie odległości ekonomicznej w przestrzennej analizie stopy bezrobocia dla Polski. *Oeconomia Copernicana*, 1(1), 79-98.
27. Rogerson, P. (2001). *Statistical Methods for Geography*. London–Thousand Oaks–New Delhi: SAGE Publications.
28. Shorrocks, A.F. (1978). The Measurement of Mobility. *Econometrica: Journal of the Econometric Society*, 46(5), 1013-1024.
29. Suchecki, B. (Ed.). (2010). *Ekonometria przestrzenna: metody i modele analizy danych przestrzennych*. Warszawa: Wydawnictwo C.H. Beck.
30. Suchecki, B., & Olejnik, A. (2010). Miary i testy statystyczne w eksploracyjnej analizie danych przestrzennych. [in:] B. Suchecki (Ed.), *Ekonometria przestrzenna. Metody i modele analizy danych przestrzennych*. Warszawa: Wydawnictwo C.H. Beck.
31. Tobler, W.R. (1970). A Computer Movie Simulating Urban Growth in the Detroit Region. *Economic Geography*, 46(sup1), 234-240.
32. Topel, R.H., & Ward, M.P. (1992). Job Mobility and the Careers of Young Men. *The Quarterly Journal of Economics*, 107(2), 439-479.
33. Wacziarg, R., & Wallack, J.S. (2004). Trade Liberalization and Intersectoral Labor Movements. *Journal of international Economics*, 64(2), 411-439.