A spatio-temporal approach to intersectoral labour and wage mobility

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Abstract

The article presents the spatio-temporal approach for intersectoral labor and wage mobility. Analyses of interindustry mobility were performed with the use of general entropy mobility indices (GEMM). Spatio-temporal approach was obtained thanks to the separate measurement of spatial autocorrelation and regression for each set of sectoral wage and employment structure and was conducted in each year of the research period separately. Calculations of economic distance were based on the level of GDP, whereas in spatial regression data of previously calculated mobility indices were used. Because of the availability of homogeneous, highly aggregated sectoral data only for the period 1994-2011, the analyses were performed for 20 selected OECD countries. The use of spatial error model (SEM) and spatial lag model (SLM) improved explanatory abilities of the analysis and revealed that the higher level of interindustry wage mobility is accompanied by increased movement of labor force across sectors.

Keywords: *intersectoral mobility, spatial autocorrelation, wage mobility, labour mobility, spatial regression*

JEL Classification: J62, J21

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 measures. Its choice influences their interpretation and economic sense and can be also associated with various factors of its economic environment. These include, among others: sector-specific human capital (often identified with the sectoral wages), unemployment, institutionalism, wage or income inequality. Several studies confirms the existence of clear links between employment and wage mobility at the micro-data level and form the basis for further investigations at highly aggregated sectoral level. 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 weight matrix based on the economic distances. Another advantage of empirical analysis presented in this article is the form of intersectoral mobility[2].

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[2] 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

2 Interindustry labour and wage mobility

Interindustry mobility (IM) can be understood as a cross-sectoral shift of workforce (Chiarini and Piselli, 2000) - 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 majority of studies (both theoretical and empirical) researchers try to explain the determinants affecting the level of ILM and IWM. This leads to the conclusion that in studies on that relationship still many difficulties exist in explaining its cause and effect nature, 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. Those studies cover 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. It has been proved here that employment mobility leads to an increase in wages (usually from 10 to 20 percent). Slightly cautious estimates can be found in: Moore et al. (1998), McLaughlin (1990). The movers-stayers model also bind together both types of mobility (Ng and 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 and Panigo, 2004). The on-the-job search theory could therefore be classified as static, whereas 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 Burdett (1978). In human capital theory 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

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.

mobility of employment. Another dynamic approach represents the theory in which the employee is looking for a job to find the best fit to his potential expectations. Many researchers believe 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 and Panigo, 2004; Göke et al., 2014). 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 (Baulch and Hoddinott, 2000). The more flexible the labor market, the greater the expected effects might be met (mobility can have erosive effect on wages).

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 three steps 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 weight matrix based on economic distances[3]. This kind of statistical analysis 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 it was concluded that those indices meet most of the requirements for measurement of mobility. 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).

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

[3] The value of real GDP was chosen for that measure.

where: $S=S_{1},\ldots,S_{n}$ is a vector of permanent or aggregated wages/employment in time T, $Y_t=Y_{1t},\ldots,Y_{nt}$ 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.

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 greater the smaller is the distance between objects. Thus, in the analysis we must consider the spatial interactions, which may relate to the dependent variable and random component. In a situation where the value of the dependent variable in each location affect the value of this variable from other locations the so-called spatial autoregression exists. 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). We can consider the specific relationship between the observation units (resulting from their location) thanks to the design of spatial weight matrix (Anselin, 1988; LeSage and Pace, 2008; Elhorst, 2014). It is a square matrix with $n\times n$ dimensions, which elements reflect the existing spatial structure. 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. It is assumed that links of spatial entities are positively affected by mutual proximity and negatively by shared distance.

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.

In the last stage of analysis, in case of spatial autocorrelation (Rogerson, 2001) two types of regression models with spatial effects were proposed[4]: SAR – spatial autoregressive model (also classified as spatial lag model – SLM) and spatial error model (SEM). The response to the negative impact of the spatial interaction to estimate the structural parameters of the OLS (ordinary least squares regression) 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 weight matrix) from the value of this variable occurring in the neighborhood. We can formulate SLM in equation (3).

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

Spatial error model (SEM) allows us to consider the spatial dependence of the sampling error (Rogerson, 2001). 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).

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

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

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. The coefficient λ 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.

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

[4] 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.

previously calculated measures of mobility, a spatial autocorrelation Moran's measure was estimated. 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 and Reis, 1999) was 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).

In Table 1. 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. The obtained results (presented in Table 1.) have correct statistical properties (LR and BP tests, significance of coefficients, Akaike criterion, R^2) and correct economic interpretation. The spatial error models (SEM) showed better performance and statistical significance of parameters than linear model (LM) and spatial lag model (SLM) in considered periods.

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)

Table 1. Estimation of linear and spatial regression functions for intersectoral mobility (p-values in brackets).

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.

Conclusions

In this article the problem of use of the spatial weight 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 use of weight 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 interindustry wage mobility is accompanied by increased movement of labor force across sectors. Moreover, the strength of this association increased over time.

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References

Baulch, B., & Hoddinott, J. (2000). Economic mobility and poverty dynamics in developing countries. *The Journal of Development Studies*, 36(6), 1-24.

Burdett, K. (1978). A theory of employee job search and quit rates. *The American Economic Review*, *68*(1), 212-220.

Chiarini, B., & Piselli, P. (2000). Unemployment, wage pressure and sectoral shifts: permanent and temporary consequences of intersectoral shocks. *Journal of Policy Modeling*, 22(7), 777-799.

Elhorst, J. P. (2014). Linear Spatial Dependence Models for Cross-Section Data. In *Spatial Econometrics* (pp. 5-36). Springer Berlin Heidelberg.

Göke, S., Prinz, J., & Weimar, D. (2014). Diamonds are Forever: Job-Matching and Career Success of Young Workers. Jahrbücher für Nationalökonomie und Statistik, 234(4), 450-473.

LeSage, J. P., & Pace, R. K. (2008). Spatial Econometric Modeling of Origin- Destination Flows. *Journal of Regional Science*, 48(5), 941-967.

Longley, P. A., Goodchild, M. F., Maguire, D. J., & Rhind, D. W. (2006). GIS. *Teoria i praktyka. Wydawnictwo naukowe PWN, Warszawa*, 164-182.

Maasoumi, E., & Zandvakili, S. (1986). A class of generalized measures of mobility with applications. *Economics Letters*, *22*(1), 97-102.

McLaughlin, K. J. (1990). General productivity growth in a theory of quits and layoffs. *Journal of Labor Economics*, *8*(1, Part 1), 75-98.

Moore, W. J., Newman, R. J., & Turnbull, G. K. (1998). Do academic salaries decline with seniority?. *Journal of Labor Economics*, *16*(2), 352-366.

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.

Ng, M. K., & Chung, Y. (2012). Double Mover–Stayer model on customer switching in telecommunications industry. *Naval Research Logistics (NRL)*, 59(8), 663-674.

Rogerson, P., 2001, Statistical methods for geography, SAGE Publications, London–Thousand Oaks–New Delhi.

Shorrocks, A. F. (1978). The measurement of mobility. *Econometrica: Journal of the Econometric Society*, 1013-1024.

Tobler, W. R. (1970). A computer movie simulating urban growth in the Detroit region. *Economic geography*, *46*(sup1), 234-240.