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Spatial Labour Market Matching*

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Abstract

We analyse the extent to which spatial interactions affect the labour market matching process. We apply spatial econometrics methods, including spatial panel Durbin models, which are rarely used in labour market matching analysis. We use the data on stocks and inflows of unemployed individuals and vacancies registered at public employment offices in Poland. We conduct the analysis at the NUTS-3 and NUTS-4 levels in Poland for the period 2003-2014. We find that (1) spatial interactions affect the matching processes in the labour market; (2) workers commute long distances, and many of these commutes involve crossing only one administrative border; (3) spatial indirect, direct, and total spillover effects determine the scale of outflows from unemployment in the focal and adjacent areas; and (4) spatial modelling is a more appropriate approach than classical modelling for the matching function.

Keywords: spatial interaction, spillover effect, matching function, region
JEL codes: C23, J61, J64

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1. Introduction

We analyse whether and to what extent spatial interactions[1] affect the labour market matching process in Poland. We refer to geographic instability in the matching function[2], and argue that worker flows across local labour markets entail spatial dependence, which in turn generates spatial externalities. Local labour markets are neither independent nor homogenous. Thus, we claim that spatial interactions should be incorporated into econometric modelling[3].

Spatial aggregation affects the derivation of the aggregate matching function and returns to scale. We can assume disequilibrium in local markets. Due to frictions between these markets, in each one there are either vacancies or unemployed persons, but never both. Limited labour mobility ensures that vacancies and unemployed individuals coexist at the aggregate level (Hansen 1970; Petrongolo and Pissarides 2001). The spatial interactions also affect returns to scale. Coles and Smith (1996) have argued that spatial aggregation can have a downward bias on the results towards constant returns to scale, if spatial interactions between local labour markets are neglected. Nevertheless, both Coles and Smith (1996) and Bennet and Pinto (1994) found constant returns to scale at the local level.

We base our research on the Polish labour market, for several reasons. Unemployment rates and vacancy rates vary considerably at a regional level. At the NUTS-4 level the unemployment rate in 2014 ranged from 3.1% in certain urban areas (e.g. Poznań, Warsaw and Wrocław, and rural areas of western Poland) to 34.4% in some rural counties (the Szydłowiecki district in Masovia and rural areas of north-eastern Poland)[4]. The vacancy rate ranged from 0%

[1] We understand spatial dependence (interdependence, autocorrelation, interaction, association) in data as a situation in which one observation of an attribute associated with a location can be correlated with the value of the same attribute at other locations (Getis 2008).
[2] We do not consider other potential sources of bias in the matching function parameter estimates, for example: temporal aggregation, worker inflows and outflows, nor search endogeneity.
[3] Anselin (1988) proves that we misspecify a model if we neglect spatial effects when they should be included.
[4] County (NUTS-4) -"A local self-government community (all inhabitants) and the relevant territory, i.e. a unit of basic territorial division, covering the area from several to more than a dozen NUTS-5 units or the entire area of a city with county status (i.e. urban NUTS-5 unit, which was given county rights)", www.stat.gov.pl [accessed 11.03.2016].

in a few rural areas (e.g. Białobrzeski, Przysuski and Zwoleński in south-west Mazovia) to 2.7% in Świętochłowice city in Upper Silesia. The Polish labour market suffers from mismatches in skills, qualifications, and regional distribution of the labour force (Cedefop 2014; OECD 2014). Labour market policy is executed at the NUTS-4 level (although we do not examine it directly). Many Poles commute to work to another city, most often to another NUTS-4 unit (CSO 2014). Thus, we focus on the NUTS-4 units (379 counties). In the discussion section and the Appendix, we provide the results for the NUTS-3 units (66 subregions), for comparison purposes. We use the data on stocks and inflows of unemployed individuals and vacancies registered at public employment offices in Poland for the period 2003-2014. We focus on public employment offices' intermediation[5]. We assume that the outflow from unemployment in a given market depends on the conditions in the local labour market, and in adjacent markets.

We contribute to the literature in several ways. We deal with spatial interactions and apply spatial econometrics methods, which are rarely used in labour market matching analysis. We define the spatial matrix of the first order of contiguity, compute Moran's *I* statistics, and estimate a spatial Durbin model for panel data with fixed effects and spatial error. We compare non-spatial panel results with the spatial econometric methods results to highlight the importance of spatial interdependencies in the labour market matching process analysis.

We find that spatial interactions exist and affect the labour market matching process. These interactions are stronger at the NUTS-4 than at the NUTS-3 level. Compared to a non-spatial model, a spatial approach produces results that better fit the data. Workers commute to surrounding local markets, although many of the flows take place across one administrative border. We find decreasing returns to scale at both levels of data aggregation, and that vacancies are the driving force of the matching process. Vacancies exert positive externalities in

[5] We are aware of the limitations in the data, and that the outflow from unemployment to employment cannot be equated with public employment intermediation. However, based on the common legal conditions, we do not expect any systematic regional bias.

contiguous local labour markets, and thus increase the matching rate there. The unemployed individuals cause the negative externalities. These findings confirm our assumption that workers compete for scarce job opportunities in the focal and adjacent areas. The stock-flow model indicates that the unemployment stock affects matching more than the unemployment inflow, but that the vacancy inflow affects matching more than the vacancy stock. Moreover, only newly unemployed workers (reflected in the unemployment inflow) seek work and cause congestion in adjacent areas, while those in the unemployment stock do not. The spillover effects seem to be stronger than the direct effects. Thus, the focal units affect matching in the contiguous areas more than the reverse effect returns to these units.

2. Prior ways of measuring spillover effects

The impact of spillover effects and/or spatial externalities on the labour market matching process has been already tackled in the literature. Burda and Profit (1996) were the first to test spatial explanations for geographic instability in the matching function. They assumed endogenous search intensity and related outflows from unemployment to local and neighbouring labour market conditions. Spatial effects included migration and commuting behaviour. Burda and Profit (1996) found that ‘foreign’ unemployment affected local matching processes. The sign and the strength of this effect depended on the distance; shorter distances produced positive externalities, while longer distances produced negative externalities.

Burgess and Profit (2001) extended the analysis of Burda and Profit (1996). They explored the impact of unemployment and vacancy inflows on the matching process. Using the travel-to-work areas (TTWA) methodology, they investigated the impact of surrounding areas on local labour markets. Their results indicated that high unemployment levels in neighbouring areas increased the number of filled vacancies in a given (local) area, , but decreased the local outflow from unemployment; whereas high vacancy levels in neighbouring areas raised the local outflow from unemployment and the local outflow of filled vacancies. Burgess and

Profit's (2001) findings were similar to those of Ilmakunnas and Pesola (2003) and Kosfeld (2007), who showed that unemployment figures in surrounding areas exerted a negative effect on local labour markets, whereas vacancies exert a positive effect. Kosfeld (2007) found that the strength of these effects was not stable across space.

Hynninen (2005) extended the matching function to account for spatial spillovers across borders (exogenous variables lagged in space) and population density, and found that the congestion effect arose among job seekers in local labour markets, and was strengthened by spatial spillovers. Job seekers from neighbouring areas caused additional heterogeneity in the matching process in densely populated areas, and matching efficiency decreased there.

We found few papers which employed the spatial Durbin panel model (SDPM) to labour market matching analysis, and none referred to the Polish labour market. For example, Hujer et al. (2009) estimated the augmented matching function that accounted for the spatial interactions. They used a dynamic panel estimator and examined various weighting matrices. Qualitatively, they found no evidence of positive effects of active labour market programmes on the matching process.

Stops[6] (2011) used the SDPM with fixed effects and random effects to analyse matching processes in occupational labour markets in Germany. He constructed an "occupational topology", and tested the hypothesis of non-separated occupational labour markets using a restricted version of the spatial Durbin panel that included only the "spatial" lags for regressors. The results indicated that there were considerable dependencies between similar occupation groups in the matching process.

Agovino (2013) used static and dynamic versions of the SDPM to investigate the spatial matching function for disabled workers. Using panel data for 20 Italian regions covering the period 2006-2011, he examined whether the matches for disabled people were spatially

[6] Stops (2014) and Stops and Fedorets (2015) also analysed the matching function (and augmented matching function). They accounted for spatial dependence but employed other methods.

correlated. Moreover, he investigated whether market conditions in neighbouring regions affected the matching process in a given region. He demonstrated the importance of new matches, vacancy stocks, and unemployment stocks. Moreover, he estimated a spatial Durbin model using panel data. To overcome the problem of spatial dependence in the residuals, he checked for the presence of spatial correlation in the error term.

In our research, we deal with spatial interactions and apply spatial econometrics methods, which are rarely used in labour market matching analysis. Unlike previous studies, we estimate a spatial Durbin model for panel data with fixed effects and spatial error term. The closest to our approach is Stops (2011), but unlike him, we focus on how mobility of job seekers affects the labour market matching process at different regional levels (he examined if new hires are influenced by exogenous regressors in other occupation groups). Moreover, we extend our analysis to account for inflow variables and to estimate a stock-flow model. Unlike previous research (Hautsch and Klotz 2003; Lottmann 2012; Stops 2014; Stops and Fedorets 2015), we describe the proximity of two regions by the order adjacency using queen criteria. Most often, the spatial weights matrix is defined by the geographic distance between centroids of districts. We also examine more distant contiguity matrices. We compare non-spatial estimates with spatial ones to identify potential advantages of the spatial analysis in the labour market matching process. Spatial interactions have not been studied in the Polish labour market from a matching perspective before.

3. The data

We analysed the period 2003-2014 using monthly data on the outflow from unemployment to employment, vacancy and unemployment stocks, and vacancy and unemployment inflows. We based our analysis on registered unemployment data from public employment offices, collected at the NUTS-4 level.

Registered unemployment data have certain characteristics. An individual can register as unemployed, or as a job seeker if she does not fulfil the criteria for being designated unemployed. During the registration process the individual must complete a questionnaire in which she is asked to specify her occupation category. The individual then appears in the registry and waits for a job match. Thereafter, she is obliged to update her status regularly, and to declare that she remains ready and willing to work. She is also obliged to appear at the public employment office monthly, and to accept a socially useful job if no other job is offered to her within a certain time period. If the individual fails to meet these requirements, she is removed from the registry.

Unemployed workers should register at a public employment office to find a job. There are, however, other factors that motivate registration. Relatively few unemployed individuals are eligible for unemployment benefits (around 14% of the unemployment stock at the end of 2015). However, for non-employed workers, registration is a prerequisite to obtain free health insurance. Thus, we are aware that a certain percentage of unemployed individuals do not actively seek employment, work in a shadow economy, or work abroad while they remain in the official unemployment registry.

Job seekers and companies use various search and recruitment methods. Although enterprises are supposed to publish every job vacancy in a public employment office, this regulation is frequently disregarded[7]. Thus, public employment offices do not have listings of every job available in the market. A large share of the jobs that are posted at public employment offices may be positions which companies have incentives to list publicly, such as subsidised apprenticeships and positions for the disabled. An unemployed individual may also search for a job on her own. Thus, the number of publicly registered job offers is lower than the actual

[7] Act on promotion of employment and labour market institutions of 2004, art. 36, p. 5 (Dz. U. 2004, no. 99, 1001 with later amendments). In 2012 only around 16.5% of companies posted job offers at public employment offices (NBP 2012).

number of jobs available, and the outflow from unemployment to employment often exceeds the number of publicly listed job offers. Thus, we cannot equate the unemployment-to-employment flow with public employment intermediation. Nevertheless, the registration data are useful to us for a number of reasons. They provide consecutive time series of the necessary stocks and flows of unemployment and vacancies, and the job offers in the data are directed at the individuals who have registered as unemployed. Thus, in our analysis we referred to public employment intermediation only. Table 1 displays the summary statistics of the data.

Table 1 Summary statistics of unemployment stock and inflow, vacancy stock and inflow, and outflow from unemployment to employment at NUTS-4 level (mean values, 2003-2014)

	NUTS-4				
Variable	**Mean**	**Std. Dev.**	**Min**	**Max**	**Median**
unemployment inflow	592	443	60	6584	486
	(-7)	(-14)	(-15)	(-1)	(-7)
unemployment stock	5941	4793	268	67647	4876
	(-38)	(-31)	(-53)	(-17)	(-38)
vacancy inflow	208	239	0	5500	149
	(48)	(95)	(150)	(149)	(41)
vacancy stock	119	257	0	6601	54
	(282)	(172)	(0)	(345)	(529)
outflow from unemployment to employment	270	205	13	3325	221
	(-1)	(-7)	(-39)	(-1)	(0)

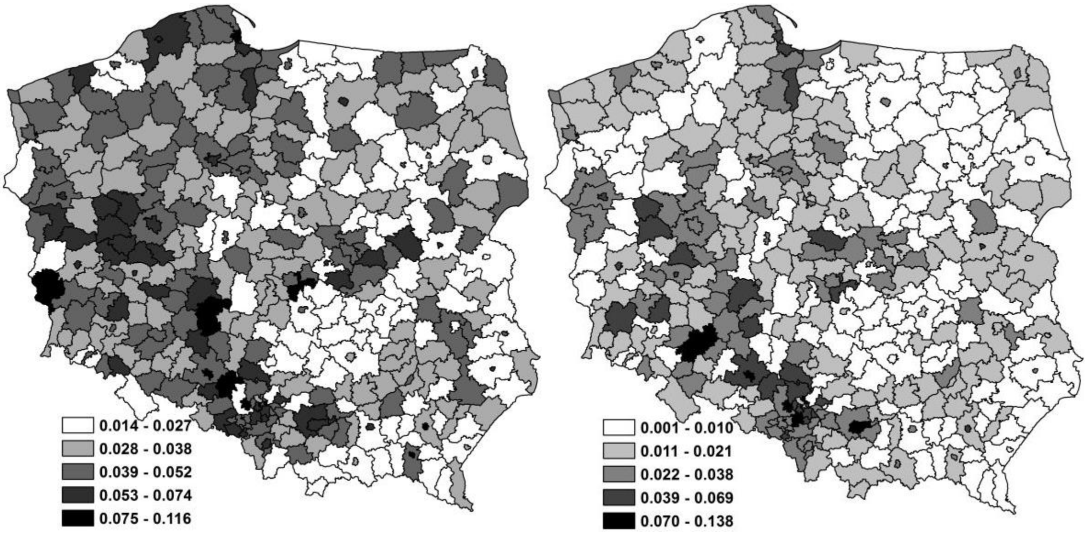
In parentheses we computed the changes between 2003 and 2014 to show diversity over time, with values in %.
Source: Authors.

We computed two labour market indices[8]: the ratio of the vacancy inflow to the unemployment stock, and the ratio of the vacancy stock to the unemployment stock. They are presented in graph 1, and the exit rate from unemployment is presented in graph 2. The values of the indices indicate the relative difficulty of finding work for job seekers and the relative ease of finding workers for companies. An average of 9 to 70 individuals were competing for each new vacancy. Spatial units with large labour market indices based on the vacancy inflow usually had large labour market indices based on the vacancy stock. Quite often a tight labour

[8] Labour market tightness index is usually based on stock variables. We argue that the vacancy inflow may be a more accurate measure of the number of available job offers, especially if vacancies are filled quickly and thus do not appear in end-of-the period stocks.

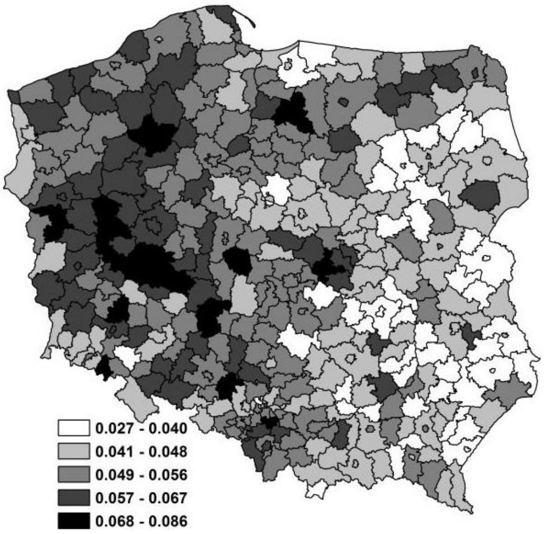
market was located next to a market that was less tight. Still, the south-western part of the country had the largest number of vacancies per unemployed person. The mean exit rate differed substantially between the western and the eastern regions of the country. The largest exit rates were observed among the counties that had the tightest labour markets, especially in terms of the vacancy inflow. This was primarily visible in the surroundings of large urban agglomerations.

Graph 1 Vacancy inflow to unemployment stock ratio (on the left) and vacancy stock to unemployment stock ratio (on the right), NUTS-4, 2003-2014 mean value



Labour market tighntess indicies: vacancy inflow to unemployment stock (on the left) and vacancy stock to unemployment stock (on the right). Labour market tightness index reflects how many job offers fall on one worker. The darker the county the tighter labour market.
Source: Authors.

Graph 2 Exit rate at NUTS-4, averaged over the years 2003-2014



The exit rate from unemployment: the ratio of the outflow from unemployment to employment to unemployment stock.
Source: Authors.

4. How we measure the spatial interactions

We applied several methods to test for the spatial interactions in labour market matching. First, we used the concept of factual justifications[9] to build spatial weights matrices (adjacency matrices)[10]. An adjacent matrix reflects the spatial structure of the worker flows. Next, we computed Moran's I indices to identify spatial multidimensional interactions among the variables. For a single variable, say X, of its observed values x_i in n different regions or locations ($i = 1, 2, \ldots, n$), having weights matrix $\mathbf{W}$ standardised in rows and original non-transformed observation values, Moran's I will measure whether each pair of x_i-th observations is associated (Cliff and Ord 1973):

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} = \frac{\mathbf{z}^T\mathbf{W}\mathbf{z}}{\mathbf{z}^T\mathbf{z}} \qquad (1)$$

where n is the number of observations; x_i and x_j are the values of a variable x in locations i and j; $\bar{x}$ is the mean value of x_i observations; w_{ij} are the elements of spatial weights matrix

[9] For more on these kinds of matrices, see Cliff and Ord (1973) and Suchecki (2010).
[10] Compare Agovino (2013) on justification for using commuting data to build a matrix.

$\mathbf{W}$; $\mathbf{z} = \begin{bmatrix} z_1 \\ z_2 \\ \dots \\ z_n \end{bmatrix}$, where $z_i = x_i - \bar{x}$ (Antczak and Lewandowska-Gwarda 2015). If the adjacent spatial objects are similar to one another (which means that they form clusters), the value of the statistics is positive. If the objects are different from each other (i.e., their spatial distribution is regular and they do not form clusters), the value of the statistics is negative (we notice polarisation, or dispersion, because dissimilar values are next to each other). The values of Moran's *I* statistic are from the range $\langle -1; 1 \rangle$.

Spatial econometrics proposes several methods to address spatial interactions. The mixed spatial panel models (spatial Durbin panel models, SDPM) take into consideration spatial autoregression and cross-regression effects; i.e., the impact of spatially non-lagged and lagged exogenous variables. These models explain differences in the levels of variables between objects in a given period and the differences in the levels of variables in selected objects during the period (Anselin et al. 2008; Elhorst 2003). Spatial interactions in panel Durbin models can be addressed in various ways: as spatial autoregression processes of the dependent variable (spatial autoregressive, SAR), autocorrelation of the random element (spatial error model, SEM), or spatial "lags" of independent variables (spatial crossregressive model, SCM). Spatial heterogeneity (spatial structure, diversification) can be represented by fixed or random effects.

Elhorst (2010) has provided an overview of the spatial panel econometric models that are currently most relevant, and has argued that the SDPM is the only model that produces unbiased estimates of parameters and correct standard errors. This argument holds even if the data generation process is from one of the spatial regression models mentioned above, in which all of the parameters are identifiable[11]. Hence, we chose a spatial Durbin panel data model that

[11] LeSage and Pace (2009) showed that the SDPM captures the data-generating process even when the relevant spatially related variables are omitted from the model formulation.

allows for unobserved individual heterogeneity in the data. We estimated spatial Durbin panel fixed effects model (SDP-FEM) with spatial error:

$$y_{i,t} = \alpha_i + \mathbf{x}_{i,t}^T\boldsymbol{\beta} + \mathbf{W}\mathbf{x}_{i,t}^T\boldsymbol{\gamma} + u_{i,t}, u_{i,t} = \lambda\mathbf{W}u_{i,t} + \varepsilon_{i,t},\ \ \varepsilon_{i,t}{\sim}N(0, \sigma_\varepsilon^2) \qquad (2)$$

where $y_{i,t}$ is the endogenous variable, α_i are the fixed effects, $\boldsymbol{x}_{i,t}^T$ is the matrix of exogenous variables; $\boldsymbol{\beta}$ is the vector of structural parameters; $\mathbf{W}$ is the spatial weights matrix of $N \times N$ dimension and zero diagonal elements standardised in rows; $u_{i,t}$ is the error term; λ is the spatial autocorrelation (autoregression) parameter of the random element; and $\varepsilon_{i,t}$ is the error term $i.i.d.$ across i and t with zero mean and constant variance σ_ε^2.

5. Spatial Durbin panel model as a matching function

We distinguish two main technological processes that describe labour market matching: random and non-random. They can be formalised in three economic models. In random matching, the trade occurs randomly between demand and supply. In the stock-based model, the unemployment stock trades with the vacancy stock. In the job queuing model, we assume that there are large discrepancies between unemployment and vacancies, and that the unemployment stock trades with the vacancy inflow. The stock-flow model presents non-random matching. Heterogonous agents have perfect information about the market, and in equilibrium the stock trades with the inflow: the unemployment stock trades with the vacancy inflow and the vacancy stock trades with the unemployment inflow. Particular models can be formalised in the following way, usually assuming the Cobb-Douglas matching function. The stock-based model is $m = m(U, V)$, the job queuing model is $m = m(U, v)$, and the stock-flow model is $m = m(U, V, u, v)$ (Blanchard and Diamond 1994, Coles and Smith 1998, Gregg and Petrongolo 2005); where U is the unemployment stock, V is the vacancy stock, u is the unemployment inflow, and v is the vacancy inflow.

We applied the following estimation strategy. First, we focused on the random model and estimated the stock-based matching function as the non-spatial panel and then as the spatial

Durbin panel fixed effects model with spatial error (SDPFEM-SE). In the next step, we repeated this exercise for the stock-flow model. Thus, we were able to focus on the importance of spatial interdependencies in labour market matching. We left aside the job queuing model. It combines two other theoretical models, but the results did not provide qualitatively different findings. In the spatial Durbin panel fixed effects model, we used the spatial weights matrix separately at the NUTS-3 and NUTS-4 levels (the results for the NUTS-3 are presented in the Appendix). The final models specifications for the SDPFEM-SE models took the following form, for the stock-based model:

$$m_{i,t} = \alpha_i + \alpha_1 V_{i,t} + \alpha_2 U_{i,t} + \gamma_1 \mathbf{W}_m V_{i,t} + \gamma_2 \mathbf{W}_m U_{i,t} + \vartheta_{i,t}, \qquad (3)$$

$$\vartheta_{i,t} = \lambda \mathbf{W}_m \vartheta_{i,t} + \varepsilon_{i,t}, \varepsilon_{i,t} \sim N(0, \sigma_\varepsilon^2),$$

and the stock-flow model:

$$m_{i,t} = \alpha_i + \alpha_1 V_{i,t} + \alpha_2 U_{i,t} + \alpha_3 v_{i,t} + \alpha_4 u_{i,t} + \gamma_1 \mathbf{W}_m V_{i,t} + \gamma_2 \mathbf{W}_m U_{i,t} + \qquad (4)$$

$$\gamma_3 \mathbf{W}_m v_{i,t} + \gamma_4 \mathbf{W}_m u_{i,t} + \vartheta_{i,t}, \vartheta_{i,t} = \lambda \mathbf{W}_m \vartheta_{i,t} + \varepsilon_{i,t},\ \varepsilon_{i,t} \sim N(0, \sigma_\varepsilon^2),$$

where $m_{i,t}$ is outflow from unemployment to employment, $V_{i,t}$ and $U_{i,t}$ are vacancy and unemployment stocks at the beginning of the month, and $v_{i,t}$ and $u_{i,t}$ are vacancy and unemployment inflows during the month. i denotes a region, t denotes time, and $\mathbf{W}_m$ denotes the spatial weights matrix. All of the variables are expressed in natural logarithms. $\varepsilon_{i,t} \sim NID(0, \sigma_\varepsilon^2)$ and $\vartheta_{i,t}$ are independently distributed non-negative random variables, obtained by truncation at zero of the normal distribution.

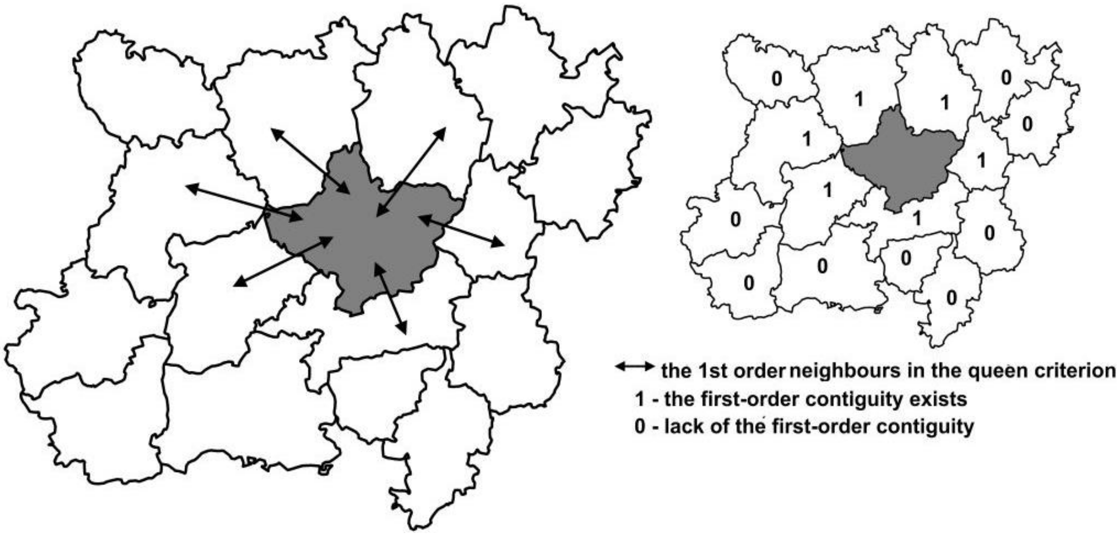
6. Spatial matrices and spatial autocorrelation results

We built spatial weights matrices using the commuting behaviour data. The data came from income tax records and from social and agricultural insurance records (CSO 2014). We were able to identify individuals who commuted from their place of residence to a workplace. We found that up to 50% of the commuting flows were across just one administrative border, e.g. from one county to another. The data did not contain information on the means of transportation, the frequency of the commute, or the travel time.

To determine the intensity of spatial interactions, we built spatial weight matrices, or adjacency matrices. The data indicated that there were statistically significant spatial interactions up to the 11^{th} row of contiguity, but less than 5% of the worker flows occurred in the units from the seventh to the 11^{th} degree of contiguity. The first-order contiguity matrix $(\mathbf{W}_1)$ produced the strongest spatial autocorrelation. Thus, we decided to include the $\mathbf{W}_1$ matrix in the explanatory spatial data analysis and the modelling.

Graph 3 shows how we constructed the matrix of the first order of contiguity using queen criteria. For simplicity of presentation, the graph refers only to one county. The neighbours in the queen criterion are the units that have at least one point in common, including borders and corners. The dimension of this binary contiguity matrix $(\mathbf{W}_1)$ is equal to the number of units. When units i and j are neighbours, the value of the matrix is one, and zero otherwise. The diagonal elements of the matrix are set to zero, by convention. The binary contiguity matrix is then transformed into a row standardised spatial weights matrix. Each element in i-th row is divided by the row's sum. The elements of the row standardised matrix take values between zero and one. The sum of the row values is always one.

Graph 3 The idea of the 1st order of contiguity in selected NUTS-4 units



Source: Authors.

We computed the Moran's *I* measure for each year at the NUTS-4 level (table 2; the results for the NUTS-3 level are presented in the Appendix). The Moran's *I* statistics were significant for the selected years. Most of the autocorrelation coefficients were positive, but some were negative (although not statistically significant). The adjacent counties tended to cluster according to the vacancy stock and inflow, but the polarisation could have occurred in terms of the unemployment stock or inflow. Certain values fluctuated over time, and the changes had no clear pattern.

Table 2 Values of global Moran's *I* statistics for outflows and inflows using the W_1 matrix at NUTS-4 level

Year/Var.	$V_{i,t}$	$U_{i,t}$	$v_{i,t}$	$u_{i,t}$
2003	0.01	-0.01	-0.004	-0.01
2004	0.02*	-0.01	0.001	-0.01
2005	0.02**	-0.01	0.01	-0.01
2006	0.004	-0.01	-0.0001	-0.01
2007	0.02*	0.005	0.01	-0.01
2008	0.07***	0.04***	0.02*	-0.01
2009	0.05***	0.02*	-0.01	-0.01
2010	0.03***	-0.004	-0.01	-0.01
2011	0.03***	-0.003	0.01	-0.02
2012	0.04***	-0.002	0.01	-0.01
2013	0.02**	0.02**	0.03***	0.02**
2014	0.02**	0.001	-0.01	-0.01

Note: significance levels: α = 0.10*, 0.05 **, 0.01 ***.
Source: Authors.

7. Matching function – regular and spatial Durbin panel model estimates

We estimated stock-stock and stock-flow models of a matching function as a simple panel and as a spatial Durbin panel model. We assumed that the matching function had a Cobb-Douglas form. We compared the results to reveal potential advantages of the spatial econometrics. Table 3 displays the results for the random model (non-spatial and SDPM estimates) and Table 4 shows the results of the stock-flow model estimates (non-spatial and SDPM estimates). The respective results for the NUTS-3 level are presented in the Appendix.

Table 3 Random matching model estimates at NUTS-4 level, panel non-spatial and spatial models

Independent variable/ statistics	Non-spatial model Parameter	Spatial model Parameter	Direct	Indirect	Total
α_1 ($V_{i,t}$)	0.091***	0.02***	0.01***	0.08***	0.09***
α_2 ($U_{i,t}$)	0.023***	0.63***	0.68***	4.83***	5.51***
γ_1 ($\mathbf{W}_1 V_{i,t}$)	NA	0.01***	0.07***	0.18***	0.25***
γ_2 ($\mathbf{W}_1 U_{i,t}$)	NA	-0.03**	-0.03**	-0.23**	-0.26**
λ ($\mathbf{W}_1 \vartheta_{i,t}$)	NA	0.89***	NA	NA	NA
(pseudo) R^2	0.84	0.83			
(adj. R^2)	0.84				
ADF Fisher test for residuals	9155.02***				
Redundant fixed effects F test	21.26***	4355.53***			
Wald (χ^2)	5910.95***				
Sum of the parameters	0.11				
Moran's I of residuals	0.11***				

Note: significance levels: α = 0.10*, 0.05 **, 0.01 ***, NA – not available, grey – estimates to compare spatial model with non-spatial one.
Source: Authors.

We tested the spatial autocorrelation in the residuals in both random and stock-flow models. The global Moran's I statistics were positive and statistically significant, which suggests spatial dependency in the data and the effect of clustering (congestion) the similar values. The spatial autocorrelation test indicated that spatial dependency positively affected the matching process in the labour market.

A non-spatial panel random matching model proved that vacancies affected the matching process more than unemployment. Both coefficients were at a negligible level, although statistically significant. The sum of the elasticities indicated decreasing returns to scale. A spatial Durbin model estimates yielded different results. The unemployment stock elasticity increased, while the vacancy stock elasticity decreased. Unemployment in adjacent areas ($\mathbf{W}_1 U_{i,t}$) exerted negative externalities on the local labour market, whereas vacancies exerted positive externalities. A 1% increase in unemployment in the contiguous local labour market caused congestion effects, and decreased the local matching rate of unemployed individuals by 0.03%. The increase in the vacancies in the contiguous local labour markets improved the matching possibilities, and increased the outflow from unemployment to employment in a given local market (by 0.01%).

The mean *direct effect* captures the effect of a unit change in an explanatory variable in a focal county on the dependent variable in that county. This measure also includes the feedback effect, which arises when the impact of an increase in an explanatory variable in a focal county affects the neighbouring counties, passes through them, and returns to the initial focal county. The average *indirect* (*spillover*) *effect* is the effect of a unit change in an explanatory variable in a focal county on the dependent variable in the neighbouring counties[12]. The total effect of an explanatory variable consists of the *direct effect* and the *indirect effect* (LeSage and Pace 2009).

The direct and the indirect spatial effects were consistent for certain variables. The unemployed individuals competed for scarce job opportunities, which resulted in congestion effects, while the number of job offers increased the matching rate. The indirect effects were generally stronger than direct ones. For example, a 1% increase in the vacancy stock in the

[12] The second possible interpretation of the indirect effect reflects the change in the dependent variable in a focal county as a result from an increase in the independent variable in the adjacent counties (Seldadyo et al. 2010).

given local labour market increased the outflow from unemployment to employment in this unit by 0.07%; and it increased the $m_{i,t}$ in adjacent counties by 0.18%.

Table 4 Stock-flow matching model estimates at NUTS-4 level, panel non-spatial and spatial models

Independent variable/ statistics	Non-spatial model	Spatial model			
	Parameter	Parameter	Direct	Indirect	Total
α_1 ($V_{i,t}$)	0.091***	0.01***	0.01***	0.06***	0.07***
α_2 ($U_{i,t}$)	0.023***	0.51***	0.55***	3.42***	3.97***
α_3 ($v_{i,t}$)	0.173***	0.07***	0.07***	0.45***	0.53***
α_4 ($u_{i,t}$)	0.059***	0.25***	0.27***	1.69***	1.96***
γ_1 ($\mathbf{W}_1 V_{i,t}$)	NA	0.01***	0.01***	0.04***	0.05***
γ_2 ($\mathbf{W}_1 U_{i,t}$)	NA	-0.01	NA	NA	NA
γ_3 ($\mathbf{W}_1 v_{i,t}$)	NA	0.07***	0.07***	0.45***	0.52***
γ_4 ($\mathbf{W}_1 u_{i,t}$)	NA	-0.20***	-0.21***	-1.33***	-1.54***
λ ($\mathbf{W}_1 \vartheta_{i,t}$)	NA	0.87***	NA	NA	NA
(pseudo) R^2 (adj. R^2)	0.86	0.85			
ADF Fisher test for residuals	9125.52***				
Redundant fixed effects F test	15.29***	3503.74***			
Wald (χ^2)	496.46***				
Sum of the parameters	0.35				
Moran's *I* of residuals	0.07***				

Note: significance levels: α = 0.10*, 0.05 **, 0.01 ***, NA – not available, grey – estimates to compare spatial model with non-spatial one.
Source: Authors.

The stock-flow framework estimates produced a better fit of the model to the data. Non-spatial panel data model proved that vacancies affected the matching process more than unemployment, and that the vacancy inflow experienced the highest elasticity. The impact of the unemployment figures was negligible, although it remained statistically significant. The sum of the coefficients indicated decreasing returns to scale.

Spatial Durbin model estimates yielded different results. As in random matching, the unemployment variables experienced an increase in the coefficients, while those of the vacancies decreased. The direct and indirect effects of the unemployment inflow were positive in the focal units and negative in the first-order adjacent areas. Thus, the unemployment inflow in the given local markets caused the congestion effect in adjacent areas, but the vacancies in the given local market exerted positive externalities in the adjacent areas.

8. Discussion

Our findings proved that spatial interactions affected the labour market matching in Poland. We built a contiguity matrix using queen criteria, which proved that workers commuted long distances, with some individuals crossing several administrative borders of different units. However, a large share (up to 50%) of these commuting flows were across just one border.

At the NUTS-4 level, we found positive and negative autocorrelation coefficients. Thus, both clustering and polarisation could have occurred for certain variables. The Moran's *I* statistics for the subregions (Table 6 in the Appendix) indicated clustering in terms of the unemployment stock and inflow, and the vacancy stock. No clear spatial autocorrelation pattern was observed for the vacancy inflow. Spatial interactions were stronger than those of the subregions. These findings suggest that local labour markets at the NUTS-4 level are more heterogeneous than those at the NUTS-3 level.

The units which enjoyed tighter labour markets experienced higher job creation rates, and the exit rate from unemployment to employment was correlated to labour market tightness indices. This suggests that vacancies affected matching more than the number of unemployed individuals did. This finding was confirmed by the non-spatial panel model estimates.

Moreover, in the stock-flow model, the vacancy inflow enjoyed higher elasticity than the vacancy stock.

The spatial models produced contrary findings. Once we accounted for spatial interactions, the elasticity on vacancy variables decreased and the elasticity on the unemployment variables increased (compared to non-spatial models). Quantitatively it appears that lack of spatial interactions in econometric modelling underestimates the role of job seekers and overestimates the role of vacancies in the labour market matching process (compare Stops 2014; Stops and Fedorets 2015). Qualitatively, this finding indicates that when we neglect spatial dependence, we disregard the worker flows. The unemployed individuals seek work in adjacent areas and form matches there. They exert negative externalities by competing for scarce job offers. Vacancies are assigned to a given public employment office, and cannot freely flow between local markets. That is why they may matter relatively less than job seekers in the matching process (compared to non-spatial models). However, vacancies attract unemployed individuals from adjacent areas, so they exert positive externalities. All variables (for the stock-based and the stock-flow model estimates) produced spillover effects that were stronger than the direct effects. This means that in terms of spatial interdependencies, the situation in the local labour markets affects the matching process in the surrounding areas more than the reverse effect influences the focal market.

The spatial Durbin model estimates proved the existence of the spatial externalities. Spatial models fit the data better than non-spatial models. The global Moran's *I* statistics were positive and statistically significant once we tested the spatial autocorrelation in the residuals at the NUTS-4 level. Thus, if we neglected the spatial interactions between the local labour markets, the results would be biased. The global Moran's *I* statistics were not statistically significant at the NUTS-3 level, but there were some local spatial interdependencies. Thus, the non-spatial panel model can be applied at this level of data aggregation, and should not produce biased results. Spatial error term parameters $\lambda\left(\mathbf{W}_1\vartheta_{i,t}\right)$ were significant and had positive signs. This means that a random shock implemented in a given unit (county or subregion) affected not only the outflow from unemployment to employment in the same region, but it also influenced matching in the neighbouring regions (compare Rey and Montouri 1999; Avogino 2013).

At both the NUTS-3 and the NUTS-4 levels, there were decreasing returns to scale. It appears that larger negative externalities were present at lower levels of data spatial aggregation.

In the future, we plan to extend our analysis of the spatial dimension. We plan to construct the spatial weight matrix in a different way to examine if there are any non-linearities or asymmetries in the externalities in more distant spatial interactions. We also think that accounting for the determinants of the efficiency of the matching process can enrich the analysis. Thus, we will try to estimate the augmented matching function. We also plan to examine how the data spatial aggregation interacts with data temporal aggregation and how they jointly affect the matching function elasticities.

9. Concluding remarks

In this study we analysed how spatial interactions affect labour market matching. We based our analysis on Polish regional data at the NUTS-3 and the NUTS-4 levels. We used monthly registered unemployment data and estimated matching function models (stock-based and stock-flow) using non-spatial panel models and spatial panel Durbin models.

The results of the statistical and the econometric analyses confirmed that spatial interactions exist and affect the matching process in the local labour markets. We found heterogeneity among the local labour markets, and some indications of both clustering and polarisation processes. The spatial panel Durbin model estimates produced robust results, which indicated that the unemployed individuals in the focal units exerted negative externalities in the contiguous areas, while the vacancies exerted positive externalities. The unemployed competed for scarce job offers, and caused congestion effects. The vacancies seem to have been the driving force of the matching process, as they eased the trade. Thus, the outflow from unemployment to employment can increase if more job offers are created. We found decreasing returns to scale at both the NUTS-3 and the NUTS-4 levels.

The results confirmed that spatial interactions exist and affect labour market matching in Poland. Thus, we argue that labour market policy measures should be directed at exploiting these interdependencies to improve public employment intermediation and the efficiency of the matching process. This can be done by, for example, improving the information in the labour market about the available matching partners. The explanatory power of the stock-flow model in turn indicates that policy actions aimed at increasing the number of available trading partners (i.e., increasing the inflows of unemployment and vacancies) should increase the number of matches. Finally, most of the commuting flows take place across one administrative border. Thus, if the mobility of workers improves, the spatial mismatch should decrease and the number of matches should increase.

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Appendix

Table 5 Summary statistics of unemployment stock and inflow, vacancy stock and inflow, and outflow from unemployment to employment at NUTS-3 level (mean values, 2003-2014)

	NUTS-3				
Variable	**Mean**	**Std. Dev.**	**Min**	**Max**	**Median**
unemployment inflow	3400	1276	993	10508	3176
	(-7)	(-9)	(13)	(4)	(-6)
unemployment stock	34117	15283	5167	99918	31598
	(-38)	(-32)	(-56)	(-25)	(-37)
vacancy inflow	1194	620	110	5826	1076
	(48)	(40)	(113)	(66)	(52)
vacancy stock	684	620	0	6601	531
	(282)	(180)	(>500)	(226)	(329)
outflow from unemployment to employment	1550	653	347	5037	1430
	(-1)	(-18)	(48)	(-4)	(4)

In parentheses we computed the changes between 2003 and 2014 to show diversity over time, values in %.
Source: Authors.

Table 6 Values of global Moran's *I* statistics for outflows and inflows using the W_1 matrix at NUTS-3 level

Year/Var.	$V_{i,t}$	$U_{i,t}$	$v_{i,t}$	$u_{i,t}$
2003	0.03	0.16**	0.11*	0.12*
2004	0.07	0.17**	0.05	0.11*
2005	0.08	0.17**	0.05	0.11*
2006	0.01	0.17**	0.08	0.12*
2007	0.08*	0.19***	0.06	0.10*
2008	0.30***	0.23***	0.11*	0.12*
2009	0.26***	0.22***	0.03	0.12**
2010	0.18**	0.22***	0.01	0.12*
2011	0.22***	0.24***	0.07	0.12**
2012	0.22***	0.24***	0.06	0.15**
2013	0.15**	0.26***	0.03	0.16***
2014	0.15**	0.29***	0.11*	0.19***

Note: significance levels: α = 0.10*, 0.05 **, 0.01 ***.
Source: Authors.

Table 7 Random matching model estimates at NUTS-3 level, panel non-spatial and spatial models

Independent variable/ statistics	Non-spatial model Parameter	Spatial model Parameter	Spatial model Direct	Spatial model Indirect	Spatial model Total
α_1 ($V_{i,t}$)	0.16***	0.01***	0.02***	0.04***	0.06***
α_2 ($U_{i,t}$)	0.05***	0.53***	0.69***	1.72***	2.41***
γ_1 ($\mathbf{W}_1 V_{i,t}$)	NA	0.06***	0.07***	0.18***	0.25***
γ_2 ($\mathbf{W}_1 U_{i,t}$)	NA	-0.04**	-0.05*	-0.13*	-0.18*
λ ($\mathbf{W}_1 \vartheta_{i,t}$)	NA	0.78***	NA	NA	NA
(pseudo) R^2	0.83	0.79			
(adj. R^2)	(0.83)				
ADF Fisher test for residuals	1362.98***				
Redundant fixed effects F test	17.29***	1486.16***			
Wald (χ^2)	1019.85***				
Sum of the parameters	0.18				
Moran's *I* of residuals	-0.03				

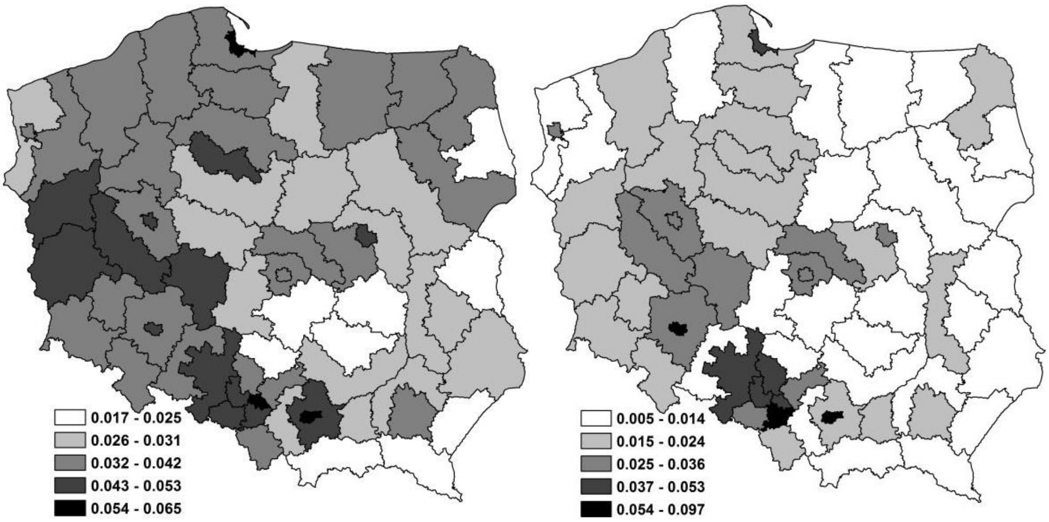
Note: significance levels: α = 0.10*, 0.05 **, 0.01 ***, NA – not available.
Source: Authors.

Table 8 Stock-flow matching model estimates at NUTS-3 level, panel non-spatial and spatial models

Independent variable/ statistics	Non-spatial model	Spatial model			
	Parameter	Parameter	Direct	Indirect	Total
α_1 ($V_{i,t}$)	0.15***	0.001***	NA	NA	NA
α_2 ($U_{i,t}$)	0.03***	0.46***	0.59***	1.33***	1.92***
α_3 ($v_{i,t}$)	0.26***	0.12***	0.16***	0.35***	0.51***
α_4 ($u_{i,t}$)	0.05***	0.23***	0.30***	0.67***	0.97***
γ_1 ($\mathbf{W}_1 V_{i,t}$)	NA	0.03***	0.03***	0.08***	0.11***
γ_2 ($\mathbf{W}_1 U_{i,t}$)	NA	-0.006	NA	NA	NA
γ_3 ($\mathbf{W}_1 v_{i,t}$)	NA	0.11***	0.13***	0.30***	0.43***
γ_4 ($\mathbf{W}_1 u_{i,t}$)	NA	-0.09***	-0.12***	-0.26***	-0.38***
λ ($\mathbf{W}_1 \vartheta_{i,t}$)	NA	0.76***	NA	NA	NA
(pseudo) R^2 (adj. R^2)	0.85	0.83			
ADF Fisher test for residuals	1346.54***				
Redundant fixed effects F test	14.09***	1048.21***			
Wald (χ^2)	98.55***				
Sum of the parameters	0.49				
Moran's *I* of residuals	0.01				

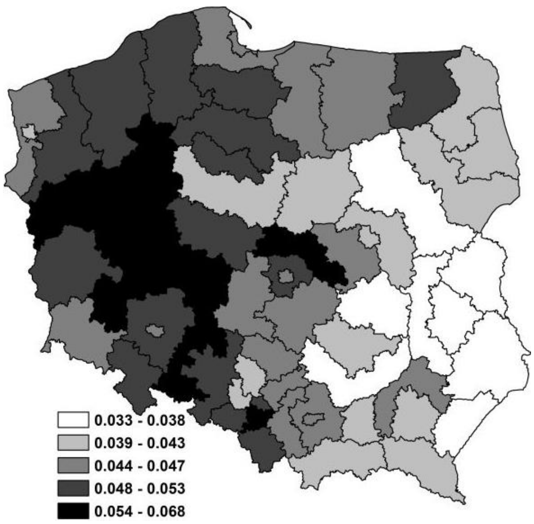
Note: significance levels: α = 0.10*, 0.05 **, 0.01 ***, NA – not available.
Source: Authors.

Graph 4 Vacancy inflow to unemployment stock ratio (on the left) and vacancy stock to unemployment stock ratio (on the right), NUTS-3, 2003-2014 mean value



Source: Authors.

Graph 5 Exit rate at NUTS-3, averaged over the years 2003-2014



The exit rate from unemployment: the ratio of the outflow from unemployment to employment to unemployment stock.
Source: Authors.

Abstrakt

Ve své práci analyzujeme, do jaké míry ovlivňuje prostorová interakce proces párování poptávky a nabídky na trhu práce. Za tímto účelem používáme metody prostorové ekonometrie, a to včetně panelových prostorových Durbinových modelů, jež se obvykle při analýze párování poptávky a nabídky na trhu práce nepoužívají. Data o nezaměstnanosti a volných pracovních pozicích, která ve své práci používáme, pocházejí z evidencí pracovních úřadů. Tato data popisují stavy nezaměstnaných a volných pracovních pozic a dále také změny v těchto stavech. Analyzujeme polská data na úrovních NUTS-3 a NUTS-4 v průběhu období 2003-2014. Naše výsledky ukazují že, (1) prostorové interakce ovlivňuje proces párování poptávky a nabídky na trhu práce, (2) mnoho pracovníků musí při cestě na pracoviště překonávat velké vzdálenosti, nicméně při této cestě překonává pouze jednu administrativní hranici, (3) nepřímé, přímé i celkové vedlejší efekty ovlivňují snížení míry nezaměstnanosti, a to v rámci územních oblastí i mezi sousedními územními oblastmi, (4) prostorový model párování je vhodnější než klasický model.

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