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Abstract

We analyse to what extent spatial interactions affect the labour market matching process. We apply spatial econometrics methods (including spatial panel Durbin model), which are rarely used in labour market matching analysis. We use the data on stocks and the inflows of unemployed individuals and vacancies registered at public employment offices. We conduct the analysis at the NUTS-3 and the NUTS-4 levels in Poland for the period 2003-2014. We find that (1) spatial dependency affects matching processes in the labour market; (2) both close and remote spatial interactions influence the results of the matching process; (3) spatial indirect, direct, and total spillover effects determine the scale of outflows from unemployment; and (4) spatial modelling is a more appropriate approach than classic modelling for matching function.

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

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Introduction

We analyse the question of whether and, if so, to what extent spatial interactions affect the labour market matching process in Poland. Workers flow across local labour markets, which creates spatial interdependencies. We argue that these interactions generate spatial externalities, which in turn influence the estimates of the matching function parameters.

The spatial aggregation calls into question how the aggregate matching function is derived. If we assume that the aggregate labour market is homogenous and that there are no interactions between local markets, we have the aggregate matching function. On the other hand, we can assume that there is disequilibrium in local markets. There are no frictions within these markets, but frictions can arise between these markets. In each market there are either vacancies or unemployed persons, but never both. The aggregate matching function arises when we aggregate over local markets. Limited labour mobility ensures that vacancies and unemployed individuals coexist at the aggregate level (Hansen 1970; Petrongolo and Pissarides 2001).

The spatial interactions affect the returns to scale. If we leave aside potential interactions among local markets and replicate the given market, the number of matches should double. But if the markets interact, the number of matches could more than double, and increasing returns to scale could then arise. Coles and Smith (1996) have argued that spatial aggregation biases the results towards constant returns to scale, while local markets can experience increasing returns. Bennet and Pinto (1994) did not reject the possibility of constant returns to scale while estimating the matching function for local markets (Petrongolo and Pissarides 2001).

Here we deal with spatial interactions, a topic we believe should be given more attention in empirical economics. We 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 use the data on stocks and the inflows of unemployed individuals and vacancies registered at public employment offices. We conduct the analysis at the NUTS-3 (subregion, 66 objects) and the NUTS-4 (county, 379 objects) levels in Poland for the period 2003-2014. The labour market policy is conducted in Poland at the NUTS-4 level. The NUTS-3 level of data spatial aggregation seems reasonable given the commuting behaviour in Poland.

We find that (1) spatial dependency affects matching processes in the labour market; (2) both close and remote spatial interactions influence the results of the matching process; (3) spatial indirect, direct, and total spillover effects determine the scale of outflows from unemployment; and (4) spatial modelling is a more appropriate approach than classic modelling for matching function.

How have spillover effects been measured previously?

Certain authors have analysed whether spillover effects and/or spatial externalities affect the labour market matching process. Burda and Profit (1996) conducted one of the first studies on this topic. They tested spatial explanations for the geographic instability in the matching function. They assumed endogenous search intensity and related the outflows from unemployment to the local and neighbouring labour market conditions. The spatial effects included migration and commuting behaviour. They found that 'foreign' unemployment affects the local matching process. The sign and the strength of this effect were found to depend on the distance. The results showed that shorter distances produce positive externalities, while longer distances produce negative externalities.

Burgess and Profit (1998) 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. The results indicated that high unemployment levels in neighbouring areas raise the number of local filled vacancies, but decrease the local outflow from unemployment; whereas high vacancy levels in neighbouring areas raise the local outflow from unemployment and the local outflow of filled vacancies. They also found that spatial dependence is subject to cyclical volatility. These findings are similar to those of Ilmakunnas and Pesola (2003) and Kosfeld (2006), who showed that unemployment figures in the surrounding areas exert a negative effect on the local labour market, whereas vacancies exert a positive effect. Kosfeld (2006) found that the strength of these effects is not stable across space. Based on her estimate of the stock-flow model, Dmitrijeva (2008) found that vacancy inflows generate a positive spatial externality, while unemployment inflows generate a negative externality for local matches in Latvia. Yet the model also showed that in Slovenia unemployment inflows in the surrounding regions improve local job creation. These findings are, however, disturbed when we account for the population density.

Extending the matching function to account for spatial spillovers across borders (exogenous variables lagged in space) and population density, Hynninen (2005) found that the congestion effect arises among job seekers in local labour markets, and is strengthened by spatial spillovers. This means that job seekers from neighbouring areas cause additional heterogeneity in the matching process in densely populated areas, and that matching efficiency therefore decreases in these areas.

López-Tamayo et al. (2000) focused on the returns to scale. They considered spatial interactions at different levels of data aggregation. Using data on unemployment and vacancies from the contiguous areas, they weighted the neighbouring number of agents by the inverse of the distance between regions. They included unemployment and vacancies from the upper territory unit, but excluded these data from the given region. At the country level constant returns to scale were not rejected. At lower levels of data aggregation, the authors observed decreasing returns to scale (for the NUTS-2 and the NUTS-3 levels).

We are aware of only a few papers that have directly applied the spatial Durbin panel model (SDPM) to labour market matching analysis, and none of these papers referred to the Polish labour market. Lottman (2013) analysed spatial dependence in labour markets by applying first- and higher-order spatial autoregressive models to data on regional labour markets in Germany. The results indicated that geographic distance does not sufficiently capture the spatial dependence between regional labour markets, and that spatial dynamic modelling is more appropriate than a static approach for the matching function.

Barrett (2014) examined the question of whether there is spatial dependence in short- and long-term unemployment in Great Britain based on data from 379 of the country's 380 districts for the period 2004-2013. Using the unemployment rate as a dependent variable (based on the assumption that an unemployed individual is anyone who is out of work but is searching for employment, and is available to start working), he tested the nature of spatial interactions and applied exploratory spatial analysis (global and local versions of Moran's *I*). The results showed that unemployment in Great Britain is positively spatially correlated; i.e., that proximate areas have similar unemployment rates. He also applied a spatial Durbin model to match the theoretical model of unemployment and to provide evidence for the spatial dependencies.

The spatial Durbin panel model was directly applied in Stops (2011) and Agovino (2013). Stops (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 his 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 are considerable dependencies between similar occupational groups in the matching process.

Agovino (2013) used the static and the dynamic versions of the SDPM in investigating the spatial matching function for disabled workers. Using a panel of 20 Italian regions covering the period 2006-2011, he examined whether the matches for disabled people are spatially correlated. Moreover, he investigated whether the market conditions in the neighbouring regions affect the matching process in the 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.

The data

We analyse the period 2003-2014 using monthly data on the outflow from unemployment to employment, the vacancy and the unemployment stocks, and the vacancy and the unemployment inflows. We base our analysis on registered unemployment data. The data come from public employment offices, and are 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 considered unemployed. During the registration process the individual must complete a questionnaire in which she is asked to specify her occupational category. The individual then appears in the registry and starts waiting for a job match. Thereafter, she will be obliged to update her status regularly, and to declare that she remains ready and willing to work. She will also be required to appear in the public employment office once a month, 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 will be removed from the registry.

For non-employed people, registration in a public employment office is a prerequisite for remaining eligible for health insurance. Thus, it is likely that a certain percentage of the population who are unemployed are not actively seeking employment. Moreover, for various reasons some registered job seekers may be working in the shadow economy or even working abroad while returning periodically to update their status. Polish nationals have a number of incentives to look for work elsewhere in Europe, including the exchange rates of the British pound and the euro, and the fact that it difficult for Polish workers to move within their own country because the Polish housing market is underdeveloped.

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[1]. 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 for which companies have incentives to list publicly, such as subsidised apprenticeships or 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 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 being unemployed. Thus, in the analysis we refer to public employment intermediation only. Table 1 displays the summary statistics of the data.

[1] 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).

Table 1 Summary statistics of unemployment stock and inflow, vacancy stock and inflow, and outflow from unemployment to employment at NUTS-3 and NUTS-4 levels (mean values, 2003-2014)

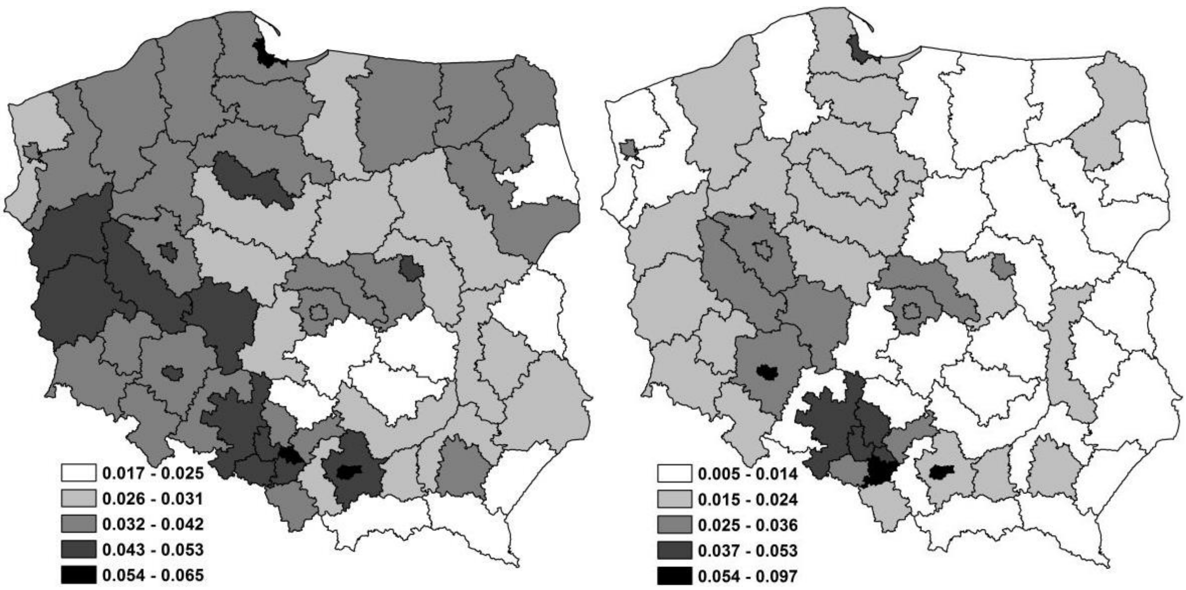
	NUTS-3					NUTS-4				
Variable	**Mean**	**Std. Dev.**	**Min**	**Max**	**Median**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Median**
unemployment inflow	3400	1276	993	10508	3176	592	443	60	6584	486
unemployment stock	34117	15283	5167	99918	31598	5941	4793	268	67647	4876
vacancy inflow	1194	620	110	5826	1076	208	239	0	5500	149
vacancy stock	684	620	0	6601	531	119	257	0	6601	54
outflow from unemployment to employment	1550	653	347	5037	1430	270	205	13	3325	221

Source: own elaboration.

Graphs 1 and 2 present the labour market tightness indices at the NUTS-3 and the NUTS-4 levels. At each level of data aggregation, we built two indices using the vacancy inflow and the vacancy stock. If there are large discrepancies between unemployment and vacancies, new vacancies will be filled relatively quickly. Thus, a substantial portion of these vacancies may not be reflected in the stock value. The vacancy inflow is therefore a more accurate reflection of the job opportunities in local labour markets.

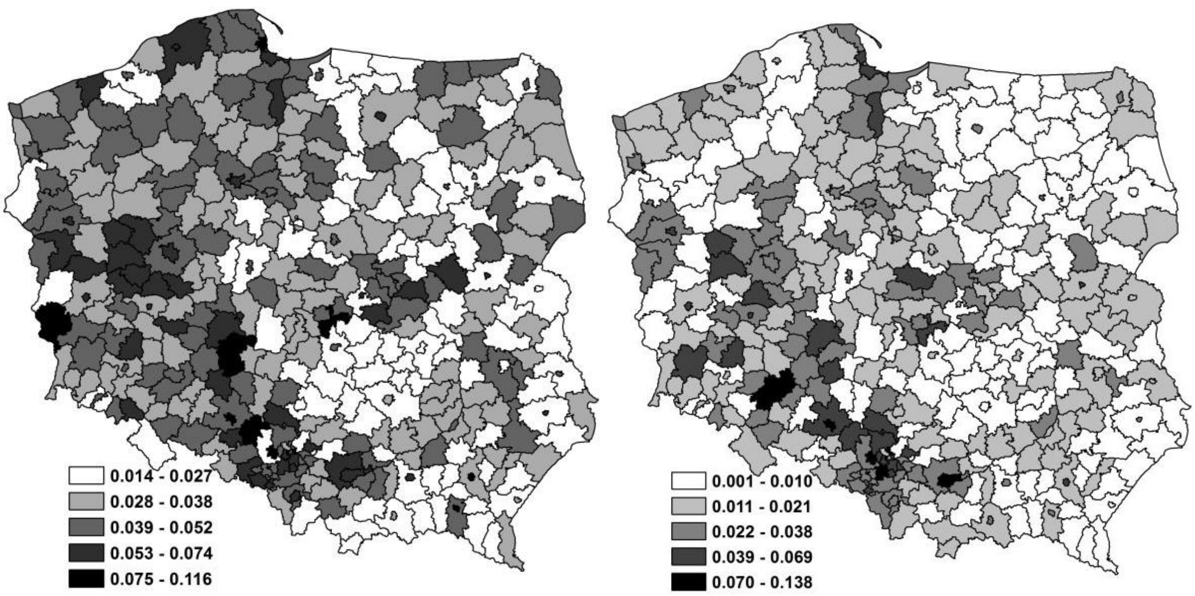
The values of the indices indicate the relative difficulty of finding work for job seekers and the relative ease of finding workers for companies. At the NUTS-3 level, an average of 15 to 60 individuals were competing for each new vacancy. At the NUTS-4 level, an average of nine to 70 individuals were competing for each new vacancy. The data show that, in general, the spatial units with large labour market indices based on the vacancy inflow also had large labour market indices based on the vacancy stock. There were, however, some exceptions (e.g., żarski and słupski). More jobs were posted in the western part of the country. At the NUTS-3 level the subregions trójmiejski, tyski, katowicki, Kraków, and Wrocław had the tightest labour markets. At the NUTS-4 level it was more common for a tight labour market to have been located next to a market that was less tight. Still, the south-western part of the country (e.g., Opole, Gliwice, and strzelecki) had the largest number of vacancies per unemployed person.

Graph 1 **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 (2-column fitting image)**



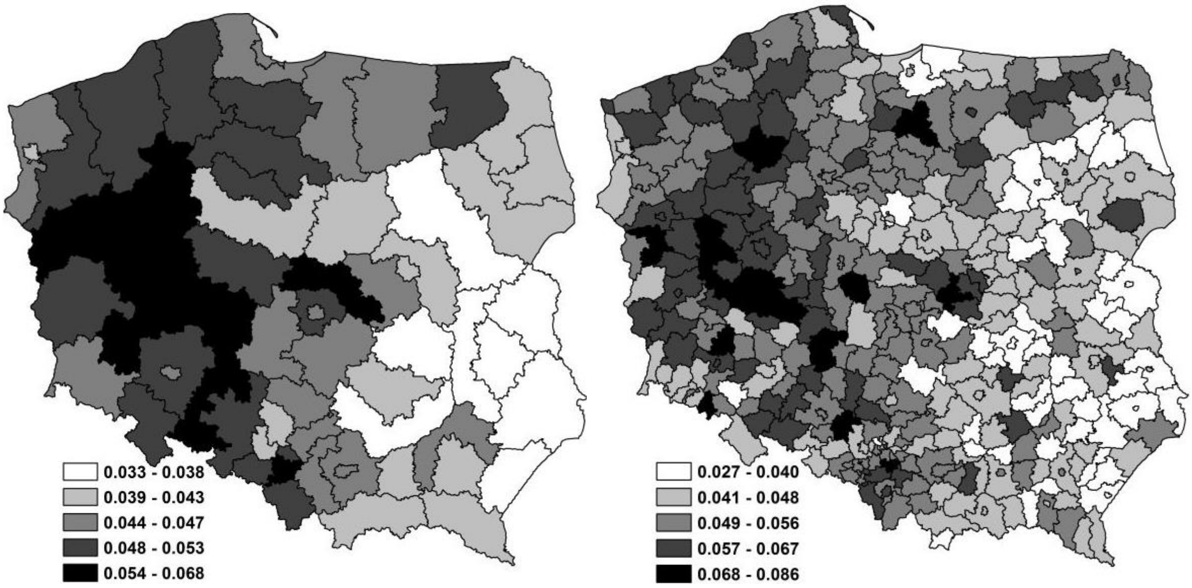
Source: own elaboration.

Graph 2 **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 (2-column fitting image)**



Source: own elaboration.

Graph 3 Exit rate at NUTS-3 (on the left) and NUTS-4 (on the right), averaged over the years 2003-2014 (2-column fitting image)



Source: own elaboration.

Graph 3 shows the exit rates at the NUTS-3 and the NUTS-4 levels. The mean exit rate differed substantially between the western and the eastern parts of the country. This discrepancy occurred at both the NUTS-3 and the NUTS-4 levels. The largest exit rates are observed among the units that had the tightest labour markets, especially in terms of the vacancy inflow. At the subregional level, it was easiest to find a job in gorzowski, pilski, poznański, leszczyński, kaliski, legnicko-głogowski, nyski, tyski, and skierniewicki; while at the county level it was easiest to find a job in iławski, złotowski, nowotymski, międzychódzki, sulęciński, wolsztyński, turecki, skierniewicki, leszczyński, rawicki, lubański, kamiennogórski, strzelecki, Tychy and bieruńsko-lędziński.

How do we analyse the spatial interactions?

We applied a few methods to test for the spatial interactions in labour market matching. First, we used the concept of factual justifications[2] to build spatial weights matrices (adjacency matrices). An adjacent matrix reflects the spatial structure of the worker flows. Next, we computed Moran's *I* indices to identify spatial multidimensional interactions among

[2] For more on these kinds of matrices, see Cliff and Ord (1973) and Suchecki (2010).

the variables. For a single variable, say X, of its observed values x_i in n different regions or locations ($i = 1, 2, \dots, n$), 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):

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

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 $\mathbf{W}$; $\mathbf{z} = \begin{bmatrix} z_1 \\ z_2 \\ \dots \\ z_n \end{bmatrix}$, 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 the 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 a few methods for addressing the 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. They explain the differences in the levels of various objects in a given period and the differences in the levels in a selected object during the period (Anselin et al. 2008; Elhorst 2003). Spatial interactions in panel Durbin models can be addressed in various ways: namely, 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 parameters' estimates and correct standard errors. This conclusion holds even if the data generation process is from one of the above-mentioned spatial regression models in which all of the parameters are identifiable[3]. Hence, we chose a spatial Durbin panel data model that allows for unobserved individual heterogeneity in the data. We estimated spatial Durbin panel fixed effects model (SDP-FEM) with spatial error:

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

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.

Spatial Durbin panel model as a matching function

We distinguish two main technological processes that describe labour market matching: random and non-random processes. 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 the equilibrium the stock trades with the inflow: the unemployment stock trades with the vacancy inflow and the vacancy stock trades with the unemployment inflow.

[3] 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.

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 estimated the above-mentioned matching function models (stock-based, job queuing, and stock-flow) as the spatial Durbin panel fixed effects with spatial error model (SDPFE-SEM). We used the spatial weights matrix, separately at the NUTS-3 and the NUTS-4 levels. The final models specifications took the following form for the stock-based model:

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

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

The job queuing model:

$$m_{i,t} = \alpha_i + \alpha_2 U_{i,t} + \alpha_3 v_{i,t} + \gamma_2 \mathbf{W}_m U_{i,t} + \gamma_3 \mathbf{W}_m v_{i,t} + \vartheta_{i,t}, \quad (4)$$

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

The stock-flow model:

$$m_{i,t} = \alpha_i + \alpha_1 V_{i,t} + \alpha_2 U_{i,t} + \alpha_3 v_{i,t} + \alpha_4 u_{i,t} + \gamma_1 \mathbf{W}_m V_{i,t} + \gamma_2 \mathbf{W}_m U_{i,t} + \quad (5)$$

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

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.

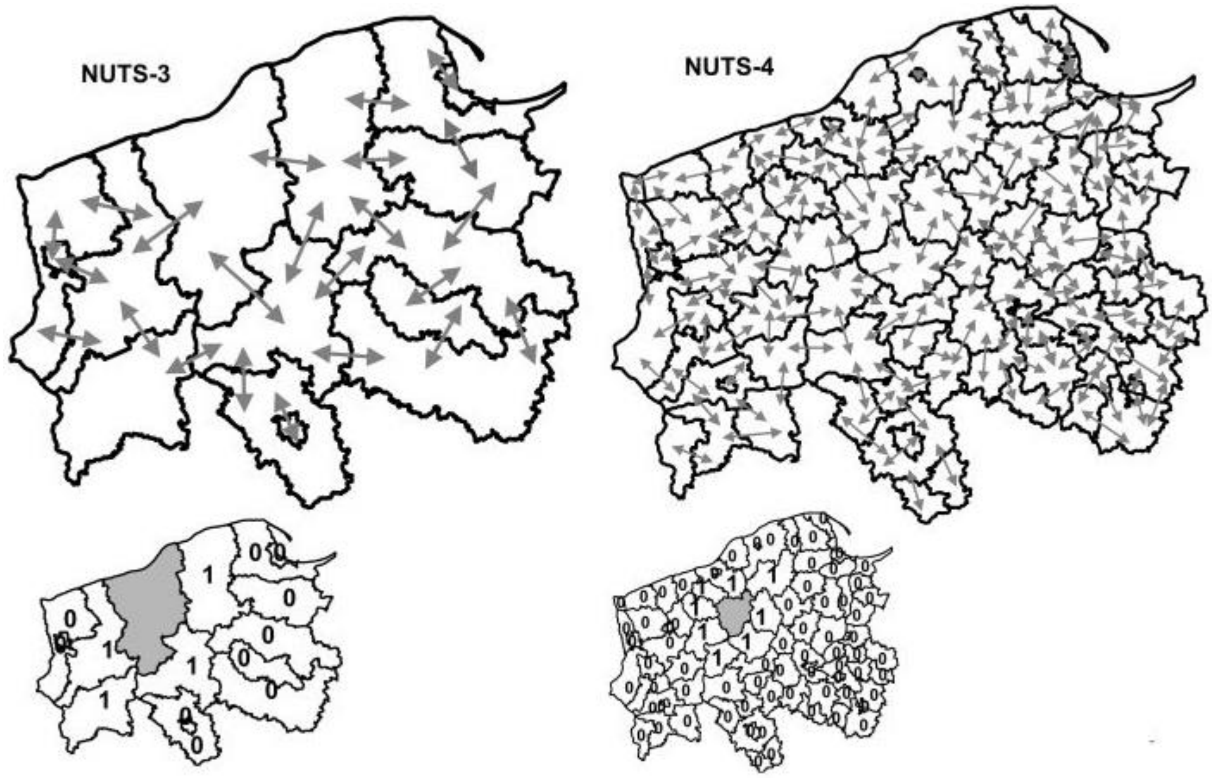
Spatial matrices and spatial autocorrelation results

We built spatial weights matrices using the commuting behaviour data. The data came from income tax records and from social and agricultural insurance records (GUS 2014). This information allowed us to identify individuals who were commuting from their place of residence to a workplace. The data did not contain information on the means of transportation, the frequency of the commute, or the travel time. We found that most of the flows were very close to the border of a given unit (e.g., 20% to 50% of the intensity of the work-related population flows to voivodship capitals, subregions, and counties were very close to the border).

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$^{\text{th}}$ row of contiguity. However, up to 5% of the worker flows were in the units from the seventh to the 11$^{\text{th}}$ 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 (at the NUTS-3 and the NUTS-4 levels).

Graph 4 presents the idea of constructing the first order of contiguity matrix using queen criteria in selected units. The neighbours in the queen criterion are the units that have at least one point in common, including boundaries 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 is otherwise zero. By convention, the diagonal elements of the matrix are set to zero. The binary contiguity matrix is then transformed into 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 4 **The idea of the 1st order of contiguity in selected NUTS-3, NUTS-4 units (2-column fitting image)**



Source: own elaboration in ArcMap 9.3.

We computed the Moran's I statistic for each year and each level of data aggregation to detect spatial autocorrelation. Tables 2 and 3 display the results. The subregions were positively spatially autocorrelated in terms of the stock and the inflow variables, except for the vacancy inflow. The spatial interactions were stronger for stocks than for inflows. Thus, the units displayed a tendency to cluster in space when the variable levels were similar, which may have had an impact on the level of this variable in the surrounding areas. Spatial interactions increased over time: between 2003 and 2014 spatial interactions increased 500% for the vacancy stock and 81% for the unemployment stock.

Table 2 **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: own elaboration in OpenGeoDa.

Table 3 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: own elaboration in OpenGeoDa.

At the NUTS-4 level, we obtained statistically significant Moran's I statistics 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, but the polarisation could have occurred in terms of the unemployment stock or the vacancy inflow. Certain values fluctuated over time, and the changes had no clear pattern. The spatial interactions were weaker than the interactions of the subregions.

Matching function – regular and spatial Durbin panel model estimations

We estimated each model 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. The results were used for comparative purposes to reveal the potential advantage of the spatial econometrics. Tables 4 and 5 show the results of the regular estimates; and Tables 6, 7, and 8 display the results of the SDPM estimates.

Non-spatial panel data models proved that the vacancies affected the matching process more than unemployment. The coefficients were larger for a vacancy inflow than for a vacancy stock. The impact of the unemployment figures was negligible at both the NUTS-3 and the NUTS-4 levels. The stock-flow matching produced the best fit of the model to the data. All of the specifications reflected decreasing returns to scale.

Table 4 Random, stock-flow, and job queuing model estimates at NUTS-3 level, panel estimates

Independent variable/ statistics	Random	Job queuing	Stock-flow
α_1 ($V_{i,t}$)	0.156*** 0.025	-	0.153*** 0.025
α_2 ($U_{i,t}$)	0.025*** 0.004	0.022*** 0.003	0.026*** 0.004
α_3 ($v_{i,t}$)	-	0.271*** 0.028	0.259*** 0.029
α_4 ($u_{i,t}$)	-	-	0.048 0.032
R^2	0.829	0.846	0.851
(adj. R^2)	0.827	0.845	0.850
ADF Fisher test for residuals (p-value)	1362.98 0.000	1346.87 0.000	1346.54 0.000
Redundant fixed effects test F p-value	17.285 0.000	16.871 0.000	14.085 0.000
Wald (χ^2)	1019.845	612.027	98.545
p-value	0.000	0.000	0.000
Sum of the parameters	0.181	0.293	0.486

Source: own elaboration.

Table 5 Random, stock-flow, and job queuing model estimates at NUTS-4 level, panel estimates

Independent variable/ statistics	Random	Job queuing	Stock-flow
α_1 ($V_{i,t}$)	0.091*** 0.011	-	0.091*** 0.013
α_2 ($U_{i,t}$)	0.023*** 0.003	0.021*** 0.003	0.023*** 0.003
α_3 ($v_{i,t}$)	-	0.186*** 0.016	0.173*** 0.016
α_4 ($u_{i,t}$)	-	-	0.059*** 0.023
R^2	0.838	0.846	0.853
(adj. R^2)	0.837	0.846	0.852
ADF Fisher test for residuals (p-value)	9155.02 0.000	9110.53 0.000	9125.52 0.000
Redundant fixed effects test F	21.258 0.000	21.546 0.000	15.289 0.000

p-value			
Wald (χ^2)	5910.948	2406.256	496.458
p-value	0.000	0.000	0.00
Sum of the parameters	0.114	0.207	0.346

Source: own elaboration.

Spatial Durbin model estimates proved that in each type of matching unemployment, the figures in the local labour markets affected the outflow from unemployment to employment more than the vacancies did. Unemployment in the adjacent areas exerted negative externalities on the local labour market, whereas the vacancies exerted positive externalities. This means than an increase in unemployment in the contiguous local labour market caused congestion effects, and decreased the local matching rate of the unemployed. The increase in vacancies in the contiguous local labour markets improved the matching possibilities, and increased the outflow from unemployment to employment in the given local market.

The mean *direct effect* captures the effect of a unit change in an explanatory variable within a focal county on the dependent variable in that county (zero-order neighbour). The average *indirect* (*spillover*) *effect* is the effect of a unit change in an explanatory variable in neighbouring units other than the dependent variable in that county. The total effect of an explanatory variable consists of the *direct effect* of the explanatory variable on the dependent variable within the focal unit, and the *indirect effect* of the explanatory variable (spillover effect) from the neighbouring units. The direct and the indirect spatial effects differed. Among the direct effects, the unemployment stock and inflow were more closely related to $m_{i,t}$ than the vacancy stock and inflow. Among the indirect effects, the unemployment figures had the expected (negative) impact. For example, a 1% increase in the vacancy stock led on average to a 0.009% increase in the outflow from unemployment to employment at the NUTS-4 level. An increase in $V_{i,t}$ in adjacent counties induced an increase in $m_{i,t}$ in a given county at an average level of 0.01%. The direct, the indirect, and the total effects of the unemployment inflow were positive in the focal units and negative in the first-order adjacent areas. The direct, the indirect, and the total effects were the same as those of the zero-order and the first-order neighbour of the vacancy flow. In terms of the combined direct and indirect effects, all of the variables produced spillover effects, but unemployment had the strongest spillover effect.

The lambda estimates indicated that spatial dependency positively affected the matching process in the labour market. The stock-flow model estimates produced the best fit of the model to the data. In all cases, the sum of the parameters was lower than one, which indicated decreasing returns to scale.

Table 6 Estimation results of the stock-based function for NUTS-3 and NUTS-4 using $\mathbf{W}_1$, monthly data

		NUTS-3				NUTS-4			
Variable		**Parameter**	**Direct**	**Indirect**	**Total**	**Parameter**	**Direct**	**Indirect**	**Total**
constant	α_0	1.76*** (0.078)	NA	NA	NA	0.22*** (0.036)	NA	NA	NA
$V_{i,t}$	α_1	0.01*** (0.002)	0.02***	0.04***	0.06***	0.02*** (0.001)	0.01***	0.08***	0.09***
$U_{i,t}$	α_2	0.53*** (0.012)	0.69***	1.72***	2.41***	0.63*** (0.007)	0.68***	4.83***	5.51***
$\mathbf{W}_1 V_{i,t}$	γ_1	0.06*** (0.006)	0.07***	0.18***	0.25***	0.01*** (0.003)	0.07***	0.18***	0.25***
$\mathbf{W}_1 U_{i,t}$	γ_2	-0.04** (0.019)	-0.05*	-0.13*	-0.18*	-0.03** (0.012)	-0.03**	-0.23**	-0.26**
$\mathbf{W}_1 \vartheta_{i,t}$	λ	0.78*** (0.006)	NA	NA	NA	0.89*** (0.004)	NA	NA	NA
pseudo R^2			0.79					0.83	
F			1486.16***					4355.53***	

Note: significance levels: α = 0.10*, 0.05 **, 0.01 ***, NA-not available; standard errors in brackets
Source: own elaboration.

Table 7 Estimation results of the job queuing function for NUTS-3 and NUTS-4 using $\mathbf{W}_1$, monthly data

		NUTS-3				NUTS-4			
Variable		**Parameter**	**Direct**	**Indirect**	**Total**	**Parameter**	**Direct**	**Indirect**	**Total**
constant	α_0	1.25*** (0.056)	NA	NA	NA	0.03*** (0.029)	NA	NA	NA
$U_{i,t}$	α_2	0.51*** (0.012)	0.63***	1.41***	2.05***	0.61*** (0.006)	0.65***	4.23***	4.88***
$v_{i,t}$	α_3	0.11*** (0.005)	0.14***	0.31***	0.45***	0.08*** (0.002)	0.08***	0.52***	0.60***
$\mathbf{W}_1 U_{i,t}$	γ_2	-0.08*** (0.017)	-0.10***	-0.22***	-0.33***	-0.04*** (0.012)	-0.05***	-0.29***	-0.34***
$\mathbf{W}_1 v_{i,t}$	γ_3	0.11*** (0.009)	0.15***	0.33***	0.48***	0.05*** (0.009)	0.05***	0.32***	0.37***
$\mathbf{W}_1 \vartheta_{i,t}$	λ	0.75*** (0.007)	NA	NA	NA	0.88*** (0.004)	NA	NA	NA
pseudo R^2			0.83					0.84	
F			1726.46***					5507.97***	

Note: significance levels: α = 0.10*, 0.05 **, 0.01 ***, NA-not available; standard errors in brackets

Source: own elaboration.

Table 8 Estimation results of the stock-flow function for NUTS-3 and NUTS-4 using W_1, monthly data

Variable		NUTS-3				NUTS-4			
		Parameter	Direct	Indirect	Total	Parameter	Direct	Indirect	Total
constant	α_0	-0.33*** (0.101)	NA	NA	NA	0.16*** (0.051)	NA	NA	NA
$V_{i,t}$	α_1	0.0005 (0.002)	NA	NA	NA	0.009*** (0.001)	0.01***	0.06***	0.07***
$U_{i,t}$	α_2	0.46*** (0.012)	0.59***	1.33***	1.92***	0.51*** (0.007)	0.55***	3.42***	3.97***
$v_{i,t}$	α_3	0.12*** (0.005)	0.16***	0.35***	0.51***	0.07*** (0.002)	0.07***	0.45***	0.53***
$u_{i,t}$	α_4	0.23*** (0.011)	0.30***	0.67***	0.97***	0.25*** (0.005)	0.27***	1.69***	1.96***
$\mathbf{W}_1 V_{i,t}$	γ_1	0.03*** (0.006)	0.03***	0.08***	0.11***	0.01*** (0.002)	0.01***	0.04***	0.05***
$\mathbf{W}_1 U_{i,t}$	γ_2	-0.006 (0.018)	NA	NA	NA	-0.01 (0.011)	NA	NA	NA
$\mathbf{W}_1 v_{i,t}$	γ_3	0.11*** (0.009)	0.13***	0.30***	0.43***	0.07*** (0.009)	0.07***	0.45***	0.52***
$\mathbf{W}_1 u_{i,t}$	γ_4	-0.09*** (0.019)	-0.12***	-0.26***	-0.38***	-0.20*** (0.022)	-0.21***	-1.33***	-1.54***
$\mathbf{W}_1 \vartheta_{i,t}$	λ	0.76*** (0.007)	NA	NA	NA	0.87*** (0.004)	NA	NA	NA
pseudo R^2		0.83				0.85			
F		1048.21 ***				3503.74***			

Note: significance levels: α = 0.10*, 0.05 **, 0.01 ***, NA-not available; standard errors in brackets
Source: own elaboration.

Discussion

The results prove that spatial dependence in labour market matching has been taking place in the Polish labour market. The data indicate that relative to the rest of Poland, the western parts of the country (at both the NUTS-3 and the NUTS-4 levels) had tighter labour markets and higher exit rates from unemployment to employment during the period studies. These units, which had relatively high labour market tightness indices based on the vacancy inflow, also had relatively high labour market tightness indices based on the vacancy stock. Thus, the spatial units in which a greater number of new job offers were registered at the public employment offices had also more job offers (stock) per unemployed individual. The spatial distribution of the labour market tightness indices and the exit rate from unemployment to employment proved that the two measures were correlated. The units that had relatively tight labour markets also had also relatively high job creation rates. This correlation seems to indicate that the labour market matching process depended more on the vacancies (especially on the vacancy inflow) than on the unemployed individuals.

The contiguity matrix using queen criteria proved that workers were covering long distances when commuting to work. The data indicated that some individuals crossed up to 11 borders in their commute to work. However, a large share (up to 50%) of these commuting flows were across just one border. The Moran's *I* statistics proved that the subregions clustered in terms of the unemployment stock and inflow and the vacancy stock. No clear spatial autocorrelation pattern was observed for the vacancy inflow.

At the NUTS-4 level, we found positive and negative autocorrelation coefficients, and spatial interactions that were weaker than those of the subregions. Thus, both clustering and polarisation could have occurred for certain variables. This suggests that local labour markets at the NUTS-4 level can be more heterogeneous than those at the NUTS-3 level.

The non-spatial panel model estimates showed that the job creation process depends more on the number of job offers than on the number of job seekers. Moreover, in the stock-flow model estimates the vacancy inflow had a higher degree of matching function elasticity than the stock. This finding confirms our inferences from the statistics on labour market tightness and exit rate values. At both the NUTS-3 and the NUTS-4 levels, there were decreasing returns to scale. It thus appears that larger negative externalities can be present at lower levels of data spatial aggregation.

The spatial Durbin model estimates proved the existence of the spatial externalities. The number of agents in the contiguous local labour markets affected the matching process in the focal unit. As expected, we found that a relatively high number of vacancies in the surrounding markets increased the number of local matches. Thus, our assumption that job seekers look for work in local and contiguous labour markets was confirmed. On the other hand, the unemployed individuals exerted negative externalities. The congestion effect emerged when the unemployed were competing for scarce job offers. In line with the non-spatial estimates, we found that the stock-flow model best reflected the matching process. The goodness of fit was better for the spatial than for the non-spatial analysis.

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, job queuing, and stock-flow) using non-spatial panel models and spatial panel Durbin models.

The results of the statistical and the econometric analyses showed that spatial interactions exist and influence 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 contiguous units exerted negative externalities on the focal labour markets, while the vacancies exerted positive externalities. The vacancies seem to have been the driving force of the matching process, as they eased the trade. The unemployed competed for scarce job offers, and caused congestion effects. We found decreasing returns to scale at both the NUTS-3 and the NUTS-4 levels.

The results confirm that vacancies play a large role in the labour market matching process. Thus, the outflow from unemployment to employment can increase if more job offers are created. Moreover, most of the commuting flows take place across a single border. Thus, if the mobility of workers improves, the spatial mismatch should decrease and the number of matches should increase. We plan to extend our analysis by broadening the spatial dimension. While our current results show that workers cross up to 11 borders when commuting, in the future we will try to find out whether there are any non-linearites in the externalities between the first and the 11th border.

References

1. Act on promotion of employment and labour market institutions of 2004, art. 36, p. 5 (Dz. U. 2004, no. 99, 1001 with later amendments).
2. Antczak E., Lewandowska-Gwarda K., 2015, Migration Processes in European Cities – A Spatio-Temporal Analysis Using Different Spatial Weights Matrices, Estudios de Economía Aplicada 33(1), pp. 53–80.
3. Agovino M., (2013), Estimating a spatial matching function for disabled people: evidence from Italy, online: http://www.aiel.it/Old/bacheca/LUISS/papers/agovino.pdf, (accessed 12.06.2015).
4. Anselin L., Le Gallo J., Jayet H., 2008, Spatial panel econometrics. Chapter 19 In: Matyas L., Sevestre P. (eds.) The Econometrics of Panel Data: Fundamentals and Recent Developments in Theory and Practice. Springer, Berlin, pp. 625–60.
5. Barrett A., 2014, Spatial dependence in unemployment in Great Britain, Master's Thesis, Rotterdam, online: http://thesis.eur.nl/pub/16302/MA-thesis-Alasdair-Barrett.pdf, (accessed 11.01.2015).
6. Bennet R., Pinto R., 1994, The Hiring Function in Local Labour Markets in Britain, Environment Planning 26(12), pp. 1957–74.
7. Blanchard O., Diamond P., 1994, Ranking, Unemployment Duration, and Wages, Review of Economic Studies 61, pp. 417–34.
8. Burda M., Profit S., 1996, Matching across Space: Evidence on Mobility in the Czech Republic, Labour Economics 3(3), pp. 255–78.
9. Burgess S., Profit S., 1998, Externalities in the Matching of Workers and Firms in Britain, CEPR Discussion Paper No. 1854.
10. Cliff A.D., Ord J.K., 1973, Spatial Autocorrelation. Pion, London.
11. Coles M., Smith E., 1996, Cross-Section Estimation of the Matching Function: Evidence from England and Wales, Economica 63, pp. 589–97.
12. Coles M., Smith E., 1998, Marketplace and Matching, International Economic Review 39(1), pp. 239–54.
13. Dmitrijeva J., 2008, Matching and Labour Market Efficiency across Space and through EU accession: Evidence from Latvia, Estonia and Slovenia, Document de recherche no 08-05.
14. Elhorst J.P., 2003, Specification and estimation of spatial panel data models, International Regional Science Review 26(3), pp. 244–68.

15. Elhorst J.P., 2010, Spatial panel data models. In: Fischer M.M., Getis A. (eds.) Handbook of applied spatial analysis. Springer, Berlin, Heidelberg and New York, pp. 377–407.
16. Gregg P., Petrongolo B., 2005, Stock–flow matching and the performance of the labor market, European Economic Review 49, pp. 1987–2011.
17. GUS, 2014, Territorial variation of commuting, Central Statisical Office in Poland, Warszawa, online: http://stat.gov.pl/spisy-powszechne/nsp-2011/nsp-2011-wyniki/dojazdy-do-pracy-nsp-2011,7,1.html, (accessed 30.06.2015).
18. Hansen B., 1970, Excess Demand, Unemployment, Vacancies and Wages, Quarterly Journal of Economics 84, pp. 1–23.
19. Hynninen S.M., 2005, Matching across space: evidence from Finland. Labour 19(4), pp. 749–65.
20. Ilmakunnas P., Pesola H., 2003, Regional Labour Market Matching Functions and Efficiency Analysis, Labour, vol. 17, issue 3, pp. 413-37.
21. Kosfeld R., 2006, Regional spillovers and spatial heterogeneity in matching workers and employers in Germany, (Universität Kassel, Fachbereich Wirtschaftswissenschaften. Volkswirtschaftliche Diskussionsbeiträge, 89/06), Kassel.
22. LeSage J., Pace R., 2009, Introduction to Spatial Econometrics. Chapman & Hall, Boca Raton.
23. López-Tamayo J., López-Bazo E., Suriñach J., 2000, Returns to matching: the effect of spatial interactions in labour markets, 40th ERSA Congress, Barcelona.
24. Lottoman F., 2013, Spatial dependence in German labor markets, Dissertation, Humboldt-Universität zu Berlin, Wirtschaftswissenschaftliche Fakultät, publiziert am 16.07.2013.
25. NBP, 2012, Badanie Ankietowe Rynku Pracy. Raport 2012. Instytut Ekonomiczny National Bank of Poland, online: http://www.nbp.pl, (accessed 01.03.2013).
26. Petrongolo B., Pissarides C., 2001, Looking Into the Black Box: A Survey of the Matching Function, Journal of Economic Literature 39, pp. 390–431.
27. Stops M., 2011, Job Matching on non-separated Occupational Labour Markets, online: http://www-sre.wu.ac.at/ersa/ersaconfs/ersa11/e110830aFinal00372.pdf, (accessed 12.06.2015).
28. Suchecki B. (ed.), 2010, Ekonometria przestrzenna. Metody i modele analizy danych przestrzennych, BECK, Warszawa.