ECONOMETRIC MODELLING OF MIGRATION FLOWS

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Abstract

Methodological and empirical literature offers several possibilities how to model migration flows. The main goal of this paper is to compare two different specifications of spatial econometric models of migration flows (spatial error model and first-order spatial autoregressive model) employing three different ways of handling the intraregional flows (setting them to zero; eliminating them; adding a separate intercept term for these observations as well as a set of explanatory variables). Our empirical analysis is based on internal migration flows among the Slovak districts (territorial level LAU-1) using 2009-2013 data. The results suggest that different models offer similar estimates, however few differences can be observed.

Key words: Migration, spatial econometric interaction models, Slovakia.

JEL Code: C21, J61, R23

Introduction

Modelling migration becomes high importance, as e.g. population growth (or the number of population itself) is strongly related to the migration phenomenon (Megyesiova and Hajduova, 2012). There have been several studies dealing with modelling the linkages between regional labour market variables and internal migration. In this paper we focus on spatial econometric models, especially spatial econometric interaction models which are useful in analysing flows between origin and destination regions. Selection of explanatory variables is inspired mainly by studies by Etzo (2007), Alecke et al. (2010), Mitze andReinkowski(2011), Jivraj et al. (2013).For a review of labour market factors as the most significant determinants of the see e.g. Champion (1998).

Spatial econometrics[1] offers a number of possibilities how to model migration flows. The most simplified way is to model the net migration of each region, but it leads to the loss of information, as we lose information on the absolute number of immigrants and/or

[1]There are also many other approaches suitable for modelling migration flows, such as gravity models, but we limit our analyses to spatial econometric models only.

emigrants. Taking into account the volumes of both types of flows can be hence considered as necessary. In order to address the spatial aspect of the phenomenon, spatial econometric interaction models can be considered as a proper method for analysing migration flows in space. The main goal of this paper is to compare different specifications of spatial econometric models of migration flows and different ways of handling the intraregional flows (which can strongly influence the estimates). Our empirical analysis is based on internal migration flows among the Slovak districts (territorial level LAU-1) estimating two different spatial econometric models (and comparing the results to OLS estimates), and three different ways of handling the intraregional flows (i.e. flows within the same district), and comparing the results to a situation with no special attention to the intraregional flows. We hence compare and discuss twelve different specifications of the model.

1 Methods

1.1 Spatial Econometric Interaction Models

Modelling migration flows is one of the typical examples of the empirical illustration of spatial interaction data analysis. In this paper the interaction is defined as movements of individuals from one location to another. In our paper we assume a spatial system in which each origin is also a destination, and the migration flows can be depicted by the following interaction matrix **Y** (Fischer and Wang, 2011):

$$\mathbf{Y} = \begin{bmatrix} y(1,1) & \cdots & y(1,j) & \cdots & y(1,n) \\ \vdots & & \vdots & & \vdots \\ y(i,1) & \cdots & y(i,j) & \cdots & y(i,n) \\ \vdots & & \vdots & & \vdots \\ y(n,1) & \cdots & y(n,j) & \cdots & y(n,n) \end{bmatrix}, \tag{1}$$

where $y(i, j)$ is the number of observed origin-destination flows from origin location i (i = 1, ..., n) to destination location j (j = 1, ..., n) and the elements on the main diagonal, $y(i, i)$ represent the intraregional flows.

As the flows are directional, i.e. $y(i, j) \neq y(j, i)$, the re-organisation of the data is necessary. Basically there are two main notational conventions introduced by LeSage and Pace (2008b): origin-centric (the one we also employ in this paper) or destination-centric.

The regression model can be then specified (LeSage and Fischer, 2010):

$$\mathbf{y} = \alpha\, \boldsymbol{\iota}_\mathbf{N} + \mathbf{X_o}\boldsymbol{\beta} + \mathbf{X_d}\boldsymbol{\gamma} + \theta\, \mathbf{d} + \boldsymbol{\varepsilon}, \tag{2}$$

where

$\mathbf{y}$ is N-by-1 vector of origin-destination flows,

$\mathbf{X_o}$ is N-by-Q matrix of Q origin-specific variables,

$\boldsymbol{\beta}$ is the associated Q-by-1 parameter vector that reflects the origin effects,

$\mathbf{X_d}$ is N-by-R matrix of R destination specific variables,

$\boldsymbol{\gamma}$ is the associated R-by-1 parameter vector that reflects the destination effects,

$\mathbf{d}$ is N-by-1 vector of distances between origin and destination zones,

θ is the scalar distance sensitivity parameter,

$\boldsymbol{\iota}_\mathbf{N}$ is N-by-1 vector of ones,

α is the constant term parameter,

$\boldsymbol{\varepsilon}$ is N-by-1 vector of disturbances with $\boldsymbol{\varepsilon}\sim\mathbf{N}(\mathbf{0}, \sigma^2\mathbf{I_N})$.

In this study we compare traditional OLS estimates of regression model specified in (2) with two extensions incorporating spatial dependence.

The first one is based on specifying a spatial process for the disturbance terms to follow a first order spatial autoregressive process (Fischer and Griffith, 2008) and the most general variant takes the form (Lesage and Fischer, 2010):

$$\mathbf{y} = \alpha\,\boldsymbol{\iota}_\mathbf{N} + \mathbf{X_o}\boldsymbol{\beta} + \mathbf{X_d}\boldsymbol{\gamma} + \theta\,\mathbf{d} + \mathbf{u} \tag{3}$$

with

$$\mathbf{u} = \rho_o \mathbf{W_o}\mathbf{u} + \rho_d \mathbf{W_d}\mathbf{u} + \rho_w \mathbf{W_w}\mathbf{u} + \boldsymbol{\varepsilon}, \; \boldsymbol{\varepsilon}\sim\mathbf{N}(\mathbf{0}, \sigma^2\mathbf{I_N}), \tag{4}$$

where

$\mathbf{W_o u}$ is N-by-1 spatial lag vector of $\mathbf{u}$ that captures origin-based spatial dependence with the associated scalar spatial dependence parameter ρ_o, and $\mathbf{W_o} = \mathbf{W} \otimes \mathbf{I_N}$ is a spatial weights matrix that captures origin-based dependence,

$\mathbf{W_d u}$ is N-by-1 spatial lag vector of $\mathbf{u}$ that captures destination-based spatial dependence with the associated scalar spatial dependence parameter ρ_d, and $\mathbf{W_d} = \mathbf{I_N} \otimes \mathbf{W}$ is a spatial weights matrix that captures destination-based dependence,

$\mathbf{W_w u}$ is N-by-1 spatial lag vector of $\mathbf{u}$ that captures origin-to-destination spatial dependence with the associated scalar spatial dependence parameter ρ_w, and $\mathbf{W_w} = \mathbf{W_o} \otimes \mathbf{W_d}$ is a spatial weights matrix which reflects an average of flows from neighbours to the origin to neighbours of the destination (LeSage and Pace, 2008a), Fischer and Wang (2011) propose a simplified model constructed by imposing restrictions on the specification given by equation (4) and **u** takes form:

$$\mathbf{u} = \rho\ \tilde{\mathbf{W}}\mathbf{u} + \boldsymbol{\varepsilon},\ \boldsymbol{\varepsilon}\sim\mathbf{N}(\mathbf{0},\ \sigma^2\mathbf{I}_\mathrm{N}), \tag{5}$$

where $\tilde{\mathbf{W}}$ is a single spatial weights matrix consisting of the sum of $\mathbf{W_o}$ and $\mathbf{W_d}$. The model given by equation (3) along with equation (5) is then the spatial error model.

The second extension is based on the general spatial autoregressive interaction model proposed by LeSage and Pace (2008b):

$$\mathbf{y} = \rho_o\mathbf{W_o}\mathbf{y} + \rho_d\mathbf{W_d}\mathbf{y} + \rho_w\mathbf{W_w}\mathbf{y} + \alpha\ \boldsymbol{\iota}_\mathbf{N} + \mathbf{X_o}\boldsymbol{\beta} + \mathbf{X_d}\boldsymbol{\gamma} + \theta\ \mathbf{d} + \boldsymbol{\varepsilon},\quad \boldsymbol{\varepsilon}\sim\mathbf{N}(\mathbf{0},\ \sigma^2\mathbf{I}_\mathrm{N}) \tag{6}$$

and the simplified model is constructed by imposing restrictions on **y**:

$$\mathbf{y} = \rho\ \tilde{\mathbf{W}}\mathbf{y} + \alpha\ \boldsymbol{\iota}_\mathbf{N} + \mathbf{X_o}\boldsymbol{\beta} + \mathbf{X_d}\boldsymbol{\gamma} + \theta\ \mathbf{d} + \boldsymbol{\varepsilon},\quad \boldsymbol{\varepsilon}\sim\mathbf{N}(\mathbf{0},\ \sigma^2\mathbf{I}_\mathrm{N}) \tag{7}$$

where $\tilde{\mathbf{W}}$ is constructed as in (5), which simplifies the model (7) to the first-order spatial autoregressive model.

As already mentioned, our comparisons are based on estimating three models: OLS model given by eq. (2), SEM model given by eq. (3) along with (5) and SAR model given by eq. (7). Before estimating the models, spatial weights matrix and the way of handling intraregional flows have to be pre-determined.

In our study the approach proposed by Fischer and Griffith (2008) is adopted, and in accordance with LeSage and Fischer (2008) the basic conventional *n*-by-*n* spatial weights matrix **W** is based on six nearest neighbours.

As for handling the intraregional flows (i.e. migration within the same region), the literature (e.g. LeSage and Pace, 2008a) suggests basically three main approaches:

1. Setting the diagonal elements of interaction matrix **Y**to zero, i.e. $y(i, j) = 0$ for all $i = j$.
2. Intraregional unit flows can be eliminated by removing the *n* cases for which the origin and destination IDs are the same (Fischer and Griffith, 2008),
3. Adding a separate intercept term for these observations as well as a set of explanatory variables (LeSage and Pace, 2008b). The intraregional explanatory variables contain non-zero observations for the intraregional observations extracted from the explanatory variables matrix **X**, and zeroes elsewhere. The adjusted models (3) and (7) can be then written as:

$$\mathbf{y} = \alpha_1 \boldsymbol{\iota}_\mathbf{N} + \alpha_2 \mathbf{c} + \mathbf{X_o}\boldsymbol{\beta} + \mathbf{X_d}\boldsymbol{\gamma} + \mathbf{X_i}\boldsymbol{\delta} + \theta\ \mathbf{d} + \mathbf{u}\,,\ \mathbf{u} = \rho\ \tilde{\mathbf{W}}\mathbf{u} + \boldsymbol{\varepsilon}\,,\quad \boldsymbol{\varepsilon}\text{~}\mathbf{N}(\mathbf{0},\ \sigma^2\mathbf{I_N}), \tag{8}$$

and

$$\mathbf{y} = \rho\ \tilde{\mathbf{W}}\mathbf{y} + \alpha_1 \boldsymbol{\iota}_\mathbf{N} + \alpha_2 \mathbf{c} + \mathbf{X_o}\boldsymbol{\beta} + \mathbf{X_d}\boldsymbol{\gamma} + \mathbf{X_i}\boldsymbol{\delta} + \theta\ \mathbf{d} + \boldsymbol{\varepsilon}\,,\quad \boldsymbol{\varepsilon}\text{~}\mathbf{N}(\mathbf{0},\ \sigma^2\mathbf{I_N}) \tag{9}$$

respectively, where $\mathbf{X_i}$ the matrix with the intraregional explanatory variables, $\mathbf{c}$ the associated intercept term, and α_2 is the coefficient associated with the matrix $\mathbf{X_i}$, to capture intraregional variation in flows.

We also report estimates for models without any special attention to the intraregional flows. We hence present three different specifications of models and four different approaches to dealing with the intraregional flows.

1.2 Observation Units and Description of the Data

Our sample includes 79 observations of complete data sets of regions at LAU-1 level in Slovakia for the period of 2009-2013. Districts of the two largest cities (Kosice and Bratislava) which are officially divided into districts, were merged into single city districts. The data are obtained from the Statistical Office of the Slovak Republic and from Office of Labour, Social Affairs and Family of the Slovak Republic.

Internal migration of persons within the Slovak districts is the response variable in this study. For our purposes internal migration (Alecke, 2010) is defined as a movement of people from one district to another district for the purpose of taking up permanent or semipermanent residence.

Selection of the most powerful predictors of spatial migration is based on a number of studies (see e. g. Alecke, 2010; Etzo, 2007; Jivraj, 2013; Mitze and Rienkowski, 2011):

[dens] ***population density***(number of inhabitants per square kilometre),

[unempl] ***total unemployment*** (the fraction of inhabitants out of work (not working for pay or profit) within the particular district, actively seeking for the job position and immediately prepared to join job position),

[empl] ***total employment***(proportion of working inhabitants between working age 15-64 years old),

[flats] ***number of completed rooms in apartments*** in particular year**,**

[wage] ***average monthly earnings*** in EUR,

[EAP] ***number of economic active person*** (fraction of the inhabitants aged 15 and over within the districts either employed or actively seeking employment), [y_unempl] ***youth unemployment rate*** **(**fraction of inhabitants aged 15 – 24 out of work out of work, and

[jobs] ***number of available job positions***(number of job positions for which the employer is taking active steps to find the most suitable candidate from the outside of the environment of the company).

In case of all variables, values are standardized and log of mean values are used in estimations. Distance between regions' centroids is denoted as D.

2 Results and Discussion

Our main findings are presented in Tab. 1. It is obvious that to some extent different models and different ways of treating intraregional flows offer different estimates of regression coefficients.

In most cases different models offer similar estimates. However few differences can be observed: certain regression coefficients are not statistically significant in all models, or only some of the models identify them as statistically significant (the differences are obvious mainly among models in which intraregional migration flows are eliminated and other models). In few cases even the signs of coefficients differ, e.g. according to most models the variable unemployment rate has negative impact on outward migration, but according to model (3) specified as SAR model the impact is positive. Similarly, the effect of employment is ambiguous. Some of the models identify the relationship as positive, and few of them as negative. However, the positive sign is yielded only in models estimated by OLS method, in which special dependence is not taken into account.

From the table 1 we can also see that spatial dependence parameters (λ for SEM and ρ for SAR models) are statistically significant and they indicate very strong positive spatial dependence. According to AIC and likelihood-ratio test, spatial error model based on LeSage's and Pace's (2008b) approach to handling intraregional flows (i.e. a separate intercept term as well as a set of explanatory variables are added for intraregional observations) can be considered as best.

The results based on the "best" model suggest that outward migration is in positive relationship with number of available job positions, negative relationship with unemployment, economically active population, and in positive relationship with total employment and population density. Taking into account the intraregional migration flows, youth unemployment rate is the only significant variable.

Tab. 1: Estimation results

	(1)			(2)			(3)		
	OLS	SEM	SAR	OLS	SEM	SAR	OLS	SEM	SAR
(Intercept)	19.8033***	36.0329***	13.2090***	19.8730***	15.8465***	13.7749***	0.0363	0.6009	–2.7460***
o.wage	0.1277	–0.3927*	0.0114	0.1302	–0.1592	0.0254	0.7703***	0.3083	0.5216***
o.jobs	0.3890***	0.3454***	0.2213***	0.3756***	0.3616***	0.2351***	0.3834***	0.3640***	0.2287***
o.unempl	–0.0710	–0.4373***	0.0562	–0.0589	–0.3682***	0.0402	0.1389*	–0.1685	0.2078***
o.y_unempl	–1.1161***	–1.0655***	–0.4749 ***	–1.1284***	–0.9067***	–0.5616***	–0.6509***	–0.4166**	–0.1112
o.EAP	–2.5808***	–1.4936***	–1.8897***	–2.6211***	–1.5439***	–1.9831***	–1.5715***	–0.3734	–1.0635***
o.flats	–0.0865**	–0.0576	–0.1093***	–0.0708**	–0.0373	–0.1010***	–0.0829**	–0.0769*	–0.1189***
o.empl	0.1086*	0.3346***	0.2668***	0.1490***	0.2808***	0.2567***	0.0752	0.2552***	0.2019***
o.dens	0.1740***	0.0603*	0.0273	0.1530***	0.0635*	0.0382*	0.1689***	0.0682**	0.0429**
d.wage	0.4899**	–0.0708	0.0906	0.4924***	0.2018	0.1637	1.1325***	0.7096***	0.6341***
d.jobs	0.3741***	0.3226***	0.2009***	0.3607***	0.3299***	0.2154***	0.3685***	0.3289***	0.2084***
d.unempl	–0.4361***	–0.6775***	–0.0488	–0.4240***	–0.6623***	–0.0924	–0.2262***	–0.3879***	0.1020*
d.y_unempl	–1.5986***	–1.1792***	–0.4390***	–1.6108***	–1.0099***	–0.5630***	–1.1334***	–0.4374**	–0.0572
d.EAP	–1.9644***	–1.9003***	–1.7105***	–2.0048***	–1.4760***	–1.7249***	–0.9551***	–0.5484	–0.8465***
d.flats	0.0207	0.0099	–0.0926***	0.0364	0.0393	–0.0744***	0.0243	–0.0045	–0.1017***
d.empl	–0.1125*	0.2920***	0.2155***	–0.0722	0.1943**	0.1832***	–0.1459***	0.2037***	0.1454***
d.dens	0.1840***	0.0218	0.0085	0.1630***	0.0504	0.0220	0.1789***	0.0442	0.0237
D	–0.4993***	–3.0437***	–0.0347***	–0.3847***	–0.2332***	–0.0530***	–0.4134***	–1.5243***	–0.0715***
λ/ρ		0.9987***	0.9686***		0.8741***	0.8525***		0.9908***	0.9507***
Log-lik		–6 277	–6 638		–6 818	–6 895		–5 993	–6 478
AIC	16 774	12 595	13 316	15 838	13 677	13 831	15 699	12 025	12 995

Source: own calculations

Notes: Type of model: (1): no handling of intraregional flows; (2): Tiefelsdorf's (2003) approach; (3) Fischer's and Griffith's (2008) approach; (4) LeSage's and Pace's (2008-paper) approach; OLS: ordinary least squares; SEM: spatial error model; SAR: first order spatial autoregressive model. S.E. estimates are not reported in this part of table, but can be provided by the authors upon request. The "o." variables denote variable at origin, the "d." variables denote variables at destination, and the "i." variables denote variables taken into account when modelling intraregional flows. Indication of significance levels: 0 *** 0.01 ** 0.05 * 0.1.

Tab. 1: continued

	(4)		
	OLS	**SEM**	SAR
(Intercept)	20.3172 (3.0525)***	**21.6579 (4.2938)*** **	14.1322 (0.0000)***
o.wage	0.1371 (0.1848)	**–0.3024 (0.2167)**	0.0126 (0.9192)
o.jobs	0.3873 (0.0188)***	**0.3609 (0.0222)*** **	0.2254 (0.0000)***
o.unempl	–0.0696 (0.0807)	**–0.4449 (0.1089)*** **	0.0526 (0.3358)
o.y_unempl	–1.1607 (0.1493)***	**–0.9731 (0.2148)*** **	0.5364 (0.0000)***
o.EAP	–2.6664 (0.3204)***	**–1.3834 (0.4598)*** **	–1.9976 (0.0000)***
o.flats	–0.0751 (0.0326)**	**–0.0415 (0.0441)**	–0.1000 (0.0000)***
o.empl	0.1396 (0.0554)**	**0.3081 (0.0669)*** **	0.2902 (0.0000)***
o.dens	0.1623 (0.0279)***	**0.0630 (0.0305)** **	0.0220 (0.2404)
d.wage	0.4993 (0.1848)***	**0.0449 (0.2311)**	0.1004 (0.4187)
d.jobs	0.3725 (0.0188)***	**0.3296 (0.0236)*** **	0.2052 (0.0000)***
d.unempl	–0.4347 (0.0807)***	**–0.6887 (0.1156)*** **	–0.0603 (0.2828)
d.y_unempl	–1.6432 (0.1493)***	**–1.0435 (0.2394)*** **	–0.5163 (0.0000)***
d.EAP	–2.0501 (0.3204)***	**–1.6356 (0.4907)*** **	–1.8051 (0.0000)***
d.flats	0.0321 (0.0326)	**0.0235 (0.0451)**	–0.0806 (0.0003)***
d.empl	–0.0816 (0.0554)	**0.2625 (0.0707)*** **	0.2338 (0.0000)***
d.dens	0.1723 (0.0279)***	**0.0370 (0.0328)**	0.0041 (0.8286)
Const	–4.6331 (18.313)	**–19.0418 (11.4263)* **	–15.8561 (0.1972)
i.wage	–0.2229 (1.5791)	**0.9812 (0.9898)**	0.5027 (0.6354)
i.jobs	–0.1596 (0.1605)	**–0.1622 (0.1004)**	–0.1360 (0.2069)
i.unempl	0.7539 (0.6895)	**0.5700 (0.4303)**	0.6043 (0.1918)
i.y_unempl	1.6765 (1.2754)	**2.0904 (0.7893)*** **	1.9044 (0.0262)**
i.EAP	1.4755 (2.7367)	**2.4903 (1.6994)**	2.8184 (0.1251)
i.flats	0.0307 (0.2781)	**0.0402 (0.1735)**	0.0049 (0.9790)
i.empl	0.1315 (0.4713)	**–0.3596 (0.2947)**	–0.3032 (0.3380)
i.dens	–0.2482 (0.2376)	**–0.1021 (0.1494)**	–0.0962 (0.5465)
D	–0.4119 (0.0135)***	**–1.6210 (0.1264)*** **	0.0152 (0.1319)
lam/rho		**0.9922 (0.0000)*** **	0.9392 (0.0000)***
Log-lik		**–5938**	–6003
AIC	15 687	**11935**	12064

Notes: S.E. estimates in parentheses

Conclusion

The study presents partial results on modelling internal migration by means of spatial econometric interaction models. Empirical illustration is based on Slovak data at LAU-1 territorial level. Spatial error model and first-order spatial autoregression model specifications and three ways of handling the intraregional flows are used, and the results are compared to OLS estimates and model estimated without any special treatment of intraregional flows.

In most cases different models offer similar estimates, however few differences can be observed: certain regression coefficients are not statistically significant in all models, or only some of the models identify them as statistically significant and in few cases even the signs of coefficients differ. There may be several explanations such as: explanatory variables are not spatially lagged in any of the investigated models; only one common spatial weights matrix is used, and hence it might not have been properly distinguished between origin-based, destination-based and origin-to-destination based spatial dependence. These issues can be considered as limitations of the study and will be addressed in our future research.

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