Spatial Econometrics: Recent Developments

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Key note prepared for the

V International Scientific Conference

Spatial Econometrics and Regional Economic Analysis

Lodz, Poland

June 14-15, 2018

Point of departure

1. Elhorst J.P. (2014) Spatial Econometrics: From Cross-sectional Data to Spatial Panels. Springer, Heidelberg New York Dordrecht London.
2. Editor-in-Chief Spatial Economic Analysis.
3. Author

Four topics

1. SLX model.
2. Limited dependent variables and spatial econometrics.
3. Controls for common factors.
4. Micro data and spatial econometrics.

1. SLX model

Halleck Vega, S., Elhorst J.P. (2015) The SLX model. Journal of Regional Science 55(3): 339-363.

Elhorst J.P., Halleck Vega S.M, (2017) The SLX model: Extensions and the sensitivity of spatial spillovers to W. Papeles de Economía Española 152: 34-50. (English version available at www.spatial-panels.com)

- There are K spatial lags WX, and only one WY and only one W*error term, so it makes sense to focus on WX variables first.
- Only in the SLX, SDEM, SDM and GNS models can the spatial spillover effects take any value. The SLX model is the simplest one in this family of spatial econometric models.
- In the SLX model W can easily be parameterized (e.g. $\mathrm{w_{ij}} = 1/d_{ij}^{\gamma}$, $\mathrm{w_{ij}} = \exp(-\delta \mathrm{d_{ij}})$, $\mathrm{w_{ij}} = \frac{\mathrm{P_i^{\gamma_1} P_j^{\gamma_2}}}{\mathrm{d_{ij}}^{\gamma_3}}$).

- The spatial weight matrix of every exogenous spatial lag $W_k X_k$ may also be modeled as $\mathrm{w}_{\mathrm{ijk}} = \frac{1}{{\mathrm{d}_{\mathrm{ij}}}^{\gamma_{\mathrm{k}}}}$; why should the distance decay effect be the same for every explanatory variable?
- The estimation of this model also does not cause severe additional econometric problems (no endogeneity, no regularity conditions), provided that the explanatory variables X are exogenous and the functional form of spatial weights matrix W is known and exogenous. An iterative two-step approach is needed since the model is non-linear in the parameters.
- The SLX model also allows the application of standard econometric techniques to test for endogenous explanatory variables.

2. Limited dependent variables and spatial econometrics

Baltagi B.H., LeSage J.P., Pace R.K. (2017) Spatial Econometrics: Qualitative and Limited Dependent Variables, Advances in Econometrics, Volume 37. Bingley (UK), Emerald Group Publishing Limited.

Elhorst J.P., Heijnen P., Samarina H., Jacobs J.P.A.M. (2017) State transfers at different moments in time: a spatial probit approach. Journal of Applied Econometrics 32(2): 422-439.

- Improved maximum likelihood estimation procedures for binary dependent (spatial probit) and count variables, which outperform the Bayesian and GMM procedures that have been developed in the past, see Elhorst et al. (2017). These routines have been developed by Roman Liesenfeld, Jean-Francois Richard, and Jan Vogler, see chapter 3 of Baltagi et al. (2017).

In Elhorst et al. (2017) a SAR model is applied. In an upcoming paper, SDM is applied so as to account for flexible spillovers.

Heijnen, P., Elhorst, J.P. (2018) The diffusion of local differentiated waste disposal taxes in the Netherlands. *De Economist*, doi.org/10.1007/s10645-018-9321-3.

3. Controls for common factors

Fourth generation of spatial econometric models (1=Cross-sectional spatial econometric models, 2=Static spatial panel econometric models, 3= Dynamic spatial panel econometric models, 4= Dynamic spatial panel econometric models with common factors).

Common factors can be modeled by cross-sectional averages (CA) of the dependent and/or independent variables OR by principal components (PC). Both generalize time dummies. Two main examples of both:

Halleck Vega S., Elhorst J.P. (2016) A regional unemployment model simultaneously accounting for serial dynamics, spatial dependence and common factors. Regional Science and Urban Economics 60 (2016) 85-95.

Shi, W., and L.-f. Lee (2017) Spatial dynamic panel data model with interactive fixed effects. Journal of Econometrics 197: 323-347.

They generalize time dummies since a time dummy has the same impact on every unit in the sample, while CA or PC have unit-specific parameters, as a result of the which, for example, business cycle effects may hit one unit harder than another unit.

Dynamic spatial panel econometric models with common factors specified are extremely simple to run, also in Stata, see following example

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//Dynamic Spatial Panel Data model + CF

xsmle depvar [indepvar] depvarCA_1 … depvarCA_N wmat(W) model(sar) dlag(3) fe type(ind) effects nsim(1000)
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depvarCA_1 … depvarCA_N may be treated as exogenous since contribution of dependent variable of a single unit to cross-sectional average is negligible if N is large.

Only include unit fixed effects and not time dummies since they are perfectly multicollinear with depvarCA_1 … depvarCA_N.

Testing for common-factors: CD-test and exponent α-estimator

Elhorst, J.P., Gross M., Tereanu E. (2018) Spillovers in space and time: where spatial econometrics and Global VAR models meet. European Central Bank, Frankfurt. Working Paper Series No 2134. https://www.ecb.europa.eu/pub/pdf/scpwps/ecb.wp2134.en.pdf?b33bf8d0dc4c5addae515ce126b98b7d.

Interplay between cross-section dependence, CF, weight structure and estimation

α can be estimated consistently only for $1/2 < \alpha \leq 1$. Use Pesaran's CD test to find out whether α is smaller or greater than ½.

α	**Cross section dependence**	**Weight structure**	**Estimation**
$0<\alpha<0.5$	weak	sparse: local, mutually dominant units	ML/IV/GMM
$0.5<\alpha<0.75$	moderate	still quite sparse	
$0.75<\alpha<1$	quite strong	dense	OLS sufficient
1	strong	CS averages or PC (no weights involved)	

Observable common factors and quadratic regressors

Elhorst, J.P., Madre, J.P. Pirotte, A. (2018) Car Traffic, Habit Persistence, Cross-Sectional Dependence, and Spatial Heterogeneity: Some Insights on French Regional Data.

- Applies principal components of Shi and Lee (2017).
- Dependent variable: Regional traffic per light vehicle at the NUTS3 level in France over the period 1990-2009. Independent variables: Population density, real household income per capita, car fleet per capita, and real price of gasoline.
- The last variable may be treated as an observable common factor!
- A quadratic functional form is used for the first three variables, as a result of which the marginal effects are not constant but may change over space and time since they are dependent on other variables in the model. For example, the derivative of $\frac{1}{2}\beta_1 X_1^2 + \frac{1}{2}\beta_2 X_2^2 + \beta_3 X_1 X_2$ with respect to X_1 is $\beta_1 X_1 + \beta_3 X_2$, as a result of which the researcher also know due to which factors marginal effects change over space and time, information that is not obtained when using a non-parametric approach.
- No evidence in favor of spatial dependence (WY and WX) which is understandable from an economic-theoretical viewpoint (see critique of spatial econometrics raised in a special theme issue of the Journal of Regional Science (Volume 52, Issue 2).

4. Micro data and spatial econometrics

Elhorst, J.P., Duran, N. (2017) Testing for spatial dependence and common factors in unbalanced panels: an application to individual housing prices.

The explanation of housing prices is a reoccurring topic in the regional science literature. The Journal of Regional Science (JRS) published eight studies dealing with this topic over the last five years. An important trend is that more and more studies use micro data. Whereas three studies use aggregated data, five use micro data.

- This paper extends the cross-sectional dependence (CD) test of Pesaran (2004, 2015a) and the estimator for the degree of cross-sectional dependence of Bailey et al. (2016b) to micro data sets with varying numbers of observations in the time and cross-sectional domains.

- Gibbons and Overman (2012) argue that spatial econometric models may suffer from misspecification since the weight matrix which is central to those models is constructed in an ad-hoc manner. However, one issue often overlooked here is that weight matrices when explaining housing prices can only be constructed in a meaningful way when employing data on individual houses. Many non-spatial but also spatial hedonic studies in the literature employ data aggregated at some spatio-temporal scale (e.g., average prices per municipality, zip-code, or neighborhood, on a monthly, quarterly, or yearly basis). However, as every house is sold within a specific spatial and temporal context, each focal house's submarket defined by similar nearby and previously sold houses needs to be accounted for. If this type of heterogeneity is or cannot be accounted for, for example due to using aggregated data, any spatial econometric approach is indeed doomed to fail.