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A REVIEW OF SPATIAL ECONOMETRIC MODELS FOR COUNT DATA

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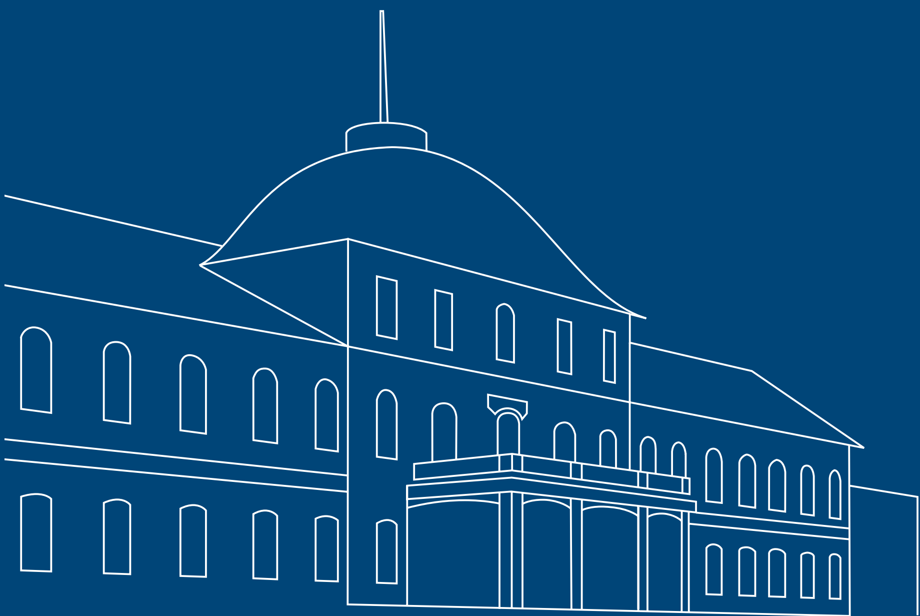

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Abstract

Despite the increasing availability of spatial count data in research areas like technology spillovers, patenting activities, insurance payments, and crime forecasting, specialized models for analysing such data have received little attention in econometric literature so far. The few existing approaches can be broadly classified into observation-driven models, where the random spatial effects enter the moments of the dependent variable directly, and parameter-driven models, where the random spatial effects are unobservable and induced via a latent process. Moreover, within these groups the modelling approaches (and therefore the interpretation) of spatial effects are quite heterogeneous, stemming in part from the nonlinear structure of count data models. The purpose of this survey is to compare and contrast the various approaches for econometric modelling of spatial counts discussed in the literature.

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1 Introduction

Spatial models, at least for continuous dependent variables have found broad application in econometrics during the last 30 to 40 years (for a survey see e.g. Anselin (2010) or Lee and Yu (2009)). With regard to count data analysis the most widely used approach is the modelling of spatial heterogeneity. Spatial autocorrelation (SAR) models for count data, in contrast, are not studied extensively and the propositions of such a model did only seldom find application by others than the authors themselves. The obvious reason for a lack of SAR models for count data is that unlike in classical models for continuous data, there is no direct functional relationship between the dependent variable y and the regressors X. To illustrate this, the general specification of a count data model is given:

$$y|\mu, \theta \sim D(\mu, \theta), \quad \mu = \exp(X\beta) \tag{1}$$

with X being a matrix of exogenous variables and β the corresponding parameter vector. D is generic notation for a distribution suitable for count data with intensity μ and optional further parameters θ. The most common special cases of this class are the Poisson regression model with $y|\mu \sim Po(\mu)$ and the negative binomial regression model with $y|\mu, \alpha \sim NB(\mu, \alpha)$. The negative binomial model deals with a restriction of the Poisson model namely its equidispersion.

The intensity parameter μ, which equals the conditional expectation $E[y|X]$, is a function of the regressors, but there is no direct functional relationship between observations y and regressors X. Because of this peculiarity of count data modelling, a direct transfer of the spatial model types for continuous data is not possible. In the following of this paper, several ways to handle this are reported. Aside from spatial error models, spatially lagged covariate models (SLX) can be used to consider spatial structures without dealing with the problems created by including endogenous spatial terms into the functional form given in Equation (1). Nevertheless, the focus of this literature review are approaches introducing a SAR-like structure into count data models.

Spatial count data is very common in other disciplines including ecological statistics, biostatistics, and epidemiology for example. Articles from these areas have also been considered in the following if they meet the conditions set for a spatial *econometric* model. First, spatial econometric data is usually given on a (irregular) lattice. Point processes, which are for example common in ecological statistics (plant counts), are therefore excluded from the survey. Second, spatial econometric models usually aim at estimating a parameter of spatial autocorrelation from the data and identifying spatial spillover effects. On the contrary, in spatial statistics the focus often lies on visualizing a spatial process (Kauermann et al., 2012, p. 437). An example is disease mapping which is a very common application for spatial count data modelling (a survey can be found e.g. in Best et al. (2005)). The examined SAR models therefore all include such a parameter. Third and last, econometric modelling is almost always concerned with the effect of covariates on the dependent variable. Because of this, the following models must allow the analysis of the influence of non-spatial covariates as well. Having said that, a natural condition for all models in this review is that they model original count data and do not use linear approximations like log transformed counts or rates of counts.

The following shall give an overview of the literature on spatial autoregressive modelling of count data and the applications for which such models are employed. This review aims at giving a full picture of the approaches for modelling spatial autoregressive effects in count data, comparing the different attempts to overcome the difficulties caused by the non-linearity of count data models. Additionally, Sections 3 and 4 give examples of spatial heterogeneity (SEM) and SLX modelling, respectively. Both model classes are applied in various studies in the econometric literature, but are not in the focus of this review. The models are presented with a focus on the approach of introducing a spatial structure into the model. For all other information regarding more details on model specification, distributional theory, and details on the pursued estimation strategy the reader is referred to the cited articles.

2 Spatial Autocorrelation Models

For continuous data an intuitive approach to incorporate a spatial effect into a model is to include the spatially lagged dependent variable, i.e. the weighted observations of the neighbors. While there are plenty of econometric applications for linear spatial models with spatially lagged dependent variables (a review can be found in Anselin (2010), for example), only few authors use spatial models for count data which include a global spatial autocorrelation parameter. One reason for the lack of a widely applied SAR count model is that there is no direct functional relationship between dependent variable y and regressors X in classical count data models (see for example Equation (1)). A direct transfer of the spatial structure from continuous SAR models is therefore not possible. While the SAR model goes back to Whittle (1954), its adaption to count data modelling took another 20 years until Besag (1974) introduced his auto-Poisson models among others like the auto-Gaussian and auto-binomial models.

In the auto-Poisson model the spatially lagged dependent variable is included in the intensity equation of a regression model in which the dependent variable conditional on its neighbors follows a Poisson distribution: $Y(i)|\{Y(j)\}, j \in N(i) \sim Po(\mu(i))$ where $N(i)$ is the set of all neighbors of i and

$$\mu(i) = \exp\left(\alpha(i) + \sum_{j \in N(i)} \beta_{i,j} y(j)\right) \tag{2}$$

which introduces the spatial effect as a weighted sum of neighboring observations with weights $\beta_{i,j}$. Translated to the nowadays common notation, Besag's weights can be divided into a spatial autocorrelation parameter λ and the element of a spatial weights matrix $w_{i,j}$, i.e. $\beta_{i,j} = \lambda\, w_{i,j}$. The weights satisfy $\beta_{j,i} = 0$ if i and j are not neighbors and $\beta_{i,j} = \beta_{j,i}$, i.e. the relationships are symmetric and no row-standardization of the weight matrix takes place. The remaining, non-spatial regressors are introduced through $\alpha(i)$ (Besag, 1974, p. 202). For estimating the model Besag (1974) proposes a coding technique for which the set of spatial units is divided into mutually independent subsets. For each subset the model is estimated conditional on the other subsets and the results are combined. In a later article Besag (1975) also proposes a pseudo-likelihood estimation for the auto-models which uses the product of the conditional probability functions instead of a full likelihood function.

Besag's auto-Poisson model suffers from a severe limitation. The inclusion of neighboring observations, whose range is infinite, into the exponential function might cause the process to be explosive if $\beta_{i,j} > 0$. This means that only negative spatial dependence can be modelled. This restriction on the spatial correlation is derived from the necessity that the normalizing constant of the joint probability function derived from the conditional model given above is finite (Besag (1974, p. 202). For a summary of the derivation see also Cressie and Chan (1989, pp. 396)).
Nevertheless, Mears and Bhati (2006) use specification (2) in their negative binomial model of the relationship between homicides and resource deprivation in Chicago. The spatially lagged dependent variable is only considered as a control variable and maximum likelihood estimation is carried out as usual. An auto-model specification is also chosen by Andersson et al. (2009), who estimate, among various spatial and non-spatial specifications, the effect of university decentralization on the number of patents by using a spatial panel Poisson and a spatial panel negative binomial model, respectively, with intensity

$$\mu_{it} = \exp\left(\lambda \sum_{i \neq j} w_{ij} y_{jt} + \beta X_{it} + \sum_{j=1}^{n} \alpha_j \mathbb{I}_j + \sum_{t=1}^{T} \gamma_t \mathbb{I}_t\right) \tag{3}$$

where X_{it} is a set of regressors, $\alpha_j, \quad j = 1, \ldots n$, represent entity fixed effects, $\gamma_t, \quad t = 1, \ldots T$, time fixed effects and $\mathbb{I}$ dummy variables for entity and year. The model is estimated using the not amplified Bayesian methods of "Geobugs". Both papers do not consider any restrictions to ensure the non-positiveness of the spatial autocorrelation parameter.

Several suggestions have been made on how to overcome the shortcomings of the auto-Poisson model, but none of them have found broad, if any, application in the empirical analysis of count data: Cressie and Chan (1989) use auto-Gaussian models as an approximation for modelling transformed sudden infant death syndrome (SIDS) counts from North Carolina. Griffith (2006, p. 163) and Kaiser and Cressie (1997, p. 423) point out that the auto-Poisson model can be approximated with an auto-binomial model, which is able to capture positive spatial autocorrelation, by choosing an artificially large n for the binomial distribution. Ferrandiz et al. (1995) model cancer mortality data from Valencia, Spain, by restricting their dependent variable to a finite range so that the auto-Poisson model can also model positive spatial correlation and propose maximum pseudo-likelihood or Monte Carlo scoring for estimation. Kaiser and Cressie (1997) use Winsorization ($Z = Y\ \mathbb{I}(Y \leq R) + R\ \mathbb{I}(Y > R)$) where the largest values are replaced by the truncation value R and therefore the range of the dependent variable is no longer infinite. In their paper, Kaiser and Cressie provide a simulated example with $n = 6$ which they estimate via maximum likelihood. Due to the form of the normalizing constant of the joint winsorized distribution, the maximum likelihood estimation of this model becomes infeasible for large n (Augustin et al., 2006). Augustin et al. (2006) employ a truncated auto-Poisson model as a practical alternative to the winsorized Poisson model to investigate the spatial correlation in leaf and seed counts, respectively. They also run a small simulation study to compare the results from coding, maximum pseudo-likelihood and Monte Carlo maximum likelihood finding that the maximum pseudo-likelihood estimation leads in their setting on average to the smallest bias in parameter estimation but also to asymptotic standard errors that are too small (Augustin et al., 2006, pp. 13).

Analogous to the time series literature for counts, the classification of Cox (1981) can be adopted for spatial autoregressive models as well. He distinguishes between 'parameter-driven' models in which the (spatial) correlation stems from a random process and 'observation-driven' models in which the correlation is driven by actual observations. Therefore, the auto-models and their variants described above all count to the observation-driven models because the observable spatially lagged dependent variable drives the spatial correlation.

For the sake of completeness, the spatial autocorrelation filtering for count data is mentioned, even though this approach does not fulfill the requirements for spatial econometric models described in the introduction. It has been proposed by Griffith (2002, 2003) as an alternative to the auto-Poisson model. He runs a Poisson regression on eigenvectors of the matrix $(I - \mathbf{1}\mathbf{1}^T/n)W(I - \mathbf{1}\mathbf{1}^T/n)$, where I is the identity matrix, $\mathbf{1}$ denotes a vector of ones, and W is a spatial connectivity matrix. Doing this, he obtains data without spatial autocorrelation which can then be analysed using non-spatial models. Empirical examples are given using several plant count data sets. In an empirical comparison of the Winsorized auto-Poisson model and their spatial filtering model using Irish drumlin counts, Griffith (2006) points out the higher flexibility of his spatial modelling structure which allows for several spatial autocorrelation parameters and gives a more detailed picture of the underlying spatial dependence than a model with one spatial parameter. Other applications of spatial filtering can be found in Haining et al. (2009) for offend counts in Sheffield, England, in Chun (2014) for vehicle burglary incidents in Plano, Texas, and in Tevie et al. (2014) for human West Nile virus counts in California and Colorado.

The auto-models and the mentioned variants thereof all try to model spatial dependence by including the spatially lagged dependent variable in the intensity equation of a

Poisson regression or other standard count data distributions. This approach bears the problem that a reduced form of that model cannot be obtained. Specifically, it is not possible to use a Leontief inverse $(I - \lambda W)^{-1}$ to obtain a reduced form, like in the linear SAR model, which can be estimated by full maximum likelihood:

$$\begin{aligned} y &= \lambda W y + X\beta + \epsilon \Leftrightarrow \\ y &= (I - \lambda W)^{-1} X\beta + (I - \lambda W)^{-1}\epsilon \end{aligned} \tag{4}$$

where λ is the parameter of spatial autocorrelation in the dependent variable and ϵ_i is i.i.d.

Accordingly, several spatial autocorrelation models have been proposed which promise a more comfortable handling than the previously discussed approaches. Two of them are especially notably, i.e. the spatial autoregressive Poisson model (P-SAR) of Lambert et al. (2010) which is observation-driven and the spatial autoregressive lagged dependent variable (SAL) Poisson model of Liesenfeld et al. (2016b) which employs an parameter-driven approach. By introducing the spatially lagged conditional expectation μ into the intensity equation – instead of the spatially lagged dependent variable – the Leontief inverse can be used in both models to obtain a reduced form. Also, these models do not suffer from the limitation to negative spatial dependence which applies to the auto-Poisson model.

The P-SAR model in its reduced form is given by

$$y|\mu \sim Po(\mu) \tag{5}$$

$$\log \mu = \lambda W \log \mu + X\beta$$

$$\Leftrightarrow \log \mu = (I - \lambda W)^{-1} X\beta \tag{6}$$

where W is a $(n \times n)$ row-standardized spatial weight matrix and λ the spatial autocorrelation parameter. y denotes the observed counts, X is a matrix of exogenous variables, and β denotes the corresponding parameter vector. The reduced form of the P-SAR model makes it obvious that this way of introducing spatial dependence only allows for spatial dependence in the regressors, not in the unexplained part of the observations, since only X enters Equation (6). This is a severe limitation, as it implies that all spatial dependency in the data must be covered by the observed covariates. Obviously, it would be preferable to also capture the unexplained part of spatial correlation in many applications. However, this model does not count to the SLX models in which only local spillover effects (i.e. a change in unit i only affects the proximate neighbors of unit i) are modelled. Here, a change in the regressors of one unit affects all other units via the Leontief inverse which relates all units to each other (Anselin, 2003, p. 156). Therefore, the model entails global spatial effects. For estimation Lambert et al. (2010) suggest a two-step limited information maximum likelihood approach. A full information maximum likelihood approach is also derived but reported to be numerically infeasible. Although the spatial correlation is introduced by the spatially lagged intensity μ, the reduced form of the P-SAR model clarifies that μ itself is a function of the observed explanatory variables X and does not contain any other random processes. Hence, the model can be classified as observation-driven.

An earlier approach to include spatial correlation by Bhati (2008) also belongs to the class of observation-driven models. He uses the relationship in Equation (6) to obtain a spatial generalized cross-entropy model by replacing the original independent variables in the model with $\tilde{X} = (I - \lambda W)^{-1}X$. By inserting the Leontief inverse into his model, Bhati allows for global spillover effects as it is the case in the P-SAR model. This cross-sectional model has been applied to homicide counts for Chicago.

In a working paper, Hays and Franzese (2009) introduce their observation-driven "S-Poisson" model, which is similar to Lambert's P-SAR model but assumes an additive structure:

$$y \;=\; \mu + u, \quad \text{with } \log(\mu) = \lambda W \log(\mu) + X\beta \tag{7}$$

where μ is a vector of the conditional means of $y = [y_1, \ldots, y_n]'$, and the errors $u_i,\ i = 1 \ldots n$ are independently and heteroskedastically distributed. For estimating this model they propose two estimators, a nonlinear least-squares and a generalized method-of-moments estimator, and illustrate this with simulated data.

Two other implementations of an observation-driven spatial count data model have been published: Beger (2012) uses a negative binomial regression model to estimate counts of civilian deaths in the Bosnian war. To account for spatial dependence he includes the spatially lagged dependent variable with an exponentiated coefficient into the intensity equation:

$$\mu_i = (y_{s,i})^{\lambda} \exp(x_i\beta) p_i \tag{8}$$

with $y_{s,i}$ being the average number of counts in the neighbor units of unit i, λ a parameter measuring the strength of the spatial diffusion, and p_i the population of unit i used as an offset variable. By including the parameter of the spatial lag as an exponent the author aims at allowing for positive and negative spatial diffusion while ensuring the positiveness of the intensity at the same time (Beger, 2012, pp. 36). The model is estimated using MCMC methods.

Held et al. (2005) propose to use the sum of the observed counts in neighboring units of unit i ($j \sim i$) in the intensity equation of their space-time model. The intensity of their

Poisson or negative binomial model is given by

$$\mu_{it} = \lambda y_{i,t-1} + \phi \sum_{j \sim i} y_{j,t-1} + \eta_{it}\nu_{it} \tag{9}$$

where η_{it} are population counts of unit i and ν_{it} is an exponential function of all remaining regressors, including a trend. They estimate their model using maximum likelihood and apply it to measles case counts for Lower Saxony.

Liesenfeld et al. (2016b) turn away from observation-driven modelling of spatial counts and adopt the parameter-driven models for time series of counts by Zeger (1988) with their SAL-Poisson model. Their resulting spatial parameter-driven model for the i-th observed count is given as

$$y_i|\mu_i \sim Po(\mu_i) \quad \text{with} \quad E[y_i|\mu_i] = \exp(\mu_i) \tag{10}$$

Collecting all the μ_i's in the latent state vector μ, the structure of the model can be written as

$$\mu = \lambda W\mu + X\beta + \epsilon \tag{11}$$

$$\Rightarrow \mu = (I - \lambda W)^{-1}X\beta + (I - \lambda W)^{-1}\epsilon \tag{12}$$

Due to the error term $\epsilon \sim N(0, \sigma^2 I)$ the model allows for spatial dependence in the unexplained part of the variation in the data, too. In that sense it is more flexible and closer to the continuous SAR model specification than the P-SAR model. The SAL-model cannot be estimated via standard maximum likelihood methods as the likelihood contains an n-dimensional integral. Liesenfeld et al. (2016b) propose an efficient importance sampling (EIS) procedure to evaluate the integral and obtain the likelihood function.

A panel data version of the SAL model is proposed in Liesenfeld et al. (2016a) by generalizing the model and the EIS procedure to allow for temporal dependency and unobserved heterogeneity (by including random effects). Equation (11) then becomes:

$$\mu_t \quad = \quad \kappa\mu_{t-1} + \lambda W\mu_t + X_t\beta + \epsilon_t \tag{13}$$

where μ_t denotes the $(n-1)\times 1$ vector of latent state variables in period t and the error term follows a Gaussian random-effect specification:

$$\epsilon_t = \tau + e_t, \quad \text{with } e_t|X_t \sim N_N(0, \sigma_e^2 I_N), \quad \tau|X_t \sim N_N(o, \sigma_\tau^2 I_N) \tag{14}$$

The model is used to estimate and forecast crime counts for the U.S. cities Pittsburgh and Rochester.

Besides the model of Liesenfeld et al. (2016a), two other parameter-driven specifications are available. In the framework of generalized ordered-response probit (GORP) models Castro et al. (2012) implement a Poisson model as a special case. It contains spatial dependence of the underlying latent continuous variable y_{it}^*:

$$\begin{aligned} y_{it}^* &= \delta\sum_{j=1}^{n} w_{ij}y_{jt}^* + \beta_i x_{it} + \epsilon_{it} \\ y_{it} = m_{it} &\text{ if } \psi_{i,m_{it}-1,t} < y_{it}^* < \psi_{i,m_{it},t} \end{aligned} \tag{15}$$

The error term ϵ_{it} is supposed to be standard normally distributed and uncorrelated across observation unit i but to have a temporal first-order autoregressive structure. The latent variable y_{it}^* is mapped to the observed counts by the thresholds $\psi_{i,m_{it},t}$ (for details on their form see p. 258). The model is applied to crash frequencies at urban intersections in Arlington, Texas, and is estimated using pairwise composite marginal likelihood.

A variation of the model has been introduced by Bhat et al. (2014), who model the number of new businesses in the counties of Texas for 11 different sectors in a multivariate setting. They allow the error terms ϵ_{is} to be correlated over the sectors $s = 1, \ldots, S$. Additionally, they add spatial lags of the K explanatory variables to the model, leading to the following latent process

$$y^*_{is} = \delta_s \sum_{j=1}^{n} w_{ij} y^*_{js} + \beta_s x_i + \sum_{k=1}^{K} \pi_{sk} \sum_{j=1}^{n} w_{ij} x_{jk} + \epsilon_{is} \tag{16}$$

Estimation is again carried out using composite marginal likelihood.

In the framework of generalized linear modelling Melo et al. (2015) introduce a generalized linear space-time autoregressive model with space-time autoregressive disturbances (GLSTARAR) for discrete and binary data. The model is applied to a count data set on armed actions of guerillas in Columbia.

$$\begin{aligned} \eta_{it} = \log E[y_{it}|x_{it,\epsilon_{it}}] = \beta_0 + x'_{it}\beta_t + \pi_t \sum_{j=1}^{n} w^{(1)}_{ij} \eta_{jt} + \epsilon_{it} \\ \epsilon_{it} = \psi_t \sum_{j=1}^{n} w^{(2)}_{ij} \epsilon_{jt} + e_{it} \end{aligned} \tag{17}$$

where the coefficients of the explanatory variables β_t as well as the spatial autocorrelation parameter π_t and the spatial autocorrelation parameter of the error term ψ_t are allowed to vary over time. e_{it} is assumed to be i.i.d. normally distributed with zero mean, $E(e_{it}, e_{is}) = \sigma_{ts}\ \forall i, t, s$ and $E(e_{it}, e_{jt}) = 0\ \forall i, j, t$. The number of armed actions y_{it} is supposed to be independently Poisson distributed given the explanatory variables and the unobserved space-time process ϵ_{it}, which is a spatial error term. Additionally, the model can contain a second vector of explanatory variables which are time-invariant. For estimation they propose space-time generalised estimation equations.

At the end of this section a class of models is described which has been developed from an entirely different viewpoint. While all previous models try to incorporate the SAR component of the continuous world into count models, the following ones start from the perspective of the observations-driven integer-valued autoregressive (INAR) model (McKenzie, 1985) and extend its structure to model spatial dependency. Ghodsi et al. (2012) propose a first-order spatial integer-valued autoregressive (SINAR(1,1)) model on a two-dimensional regular lattice. In a regular lattice each observation is characterized by its position on the lattice denoted by i, j and neighbors of unit (i, j) are for example the units $(i, j-1)$, $(i+1, j)$ or $(i-1, j-1)$, i.e. all eight rectangles around unit (i, j). In the SINAR(1,1) a unilateral spatial structure is assumed, i.e. spatial spillovers are considered to move in one direction across the lattice. The SINAR(1,1) model is given by

$$y_{ij} = \alpha_1 \circ y_{i-1,j} + \alpha_2 \circ y_{i,j-1} + \alpha_3 \circ y_{i-1,j-1} + \epsilon_{i,j} \tag{18}$$

where $\circ$ is the binomial thinning operator with $\alpha_1 \circ y_{i-1,j} = \sum_{k=1}^{y_{i-1,j}} Z_k$ and $Z_k \sim Ber(\alpha_1)$. $\alpha_1, \alpha_2, \alpha_3 \in [0, 1)$ and $\alpha_1 + \alpha_2 + \alpha_3 < 1$ ensure the positivity of the mean of y. $\epsilon_{i,j}$ is a sequence of i.i.d. integer-valued random variables. The model is estimated using Yule-Walker estimators and applied to Student's classic yeast cell count data set. In a later article, a conditional maximum likelihood estimator is proposed for the SINAR(1,1) model (Ghodsi, 2015).

The design of the SINAR(1,1) model stems from a different viewpoint than the previous models and does not fit into the idea of a spatial econometric model with a spatial autocorrelation parameter and explanatory variables. But it accounts very well for the count nature of the data and its application to an economic problem with a spatial process that has one source from which it spreads is not implausible. Brännäs (2013, 2014) propose a more general extension of the INAR model with their simultaneous integer-valued autoregressive model of order one (SINAR(1)) which also includes explanatory variables and models the spatial structure with one or two parameters:

$$y_t = A \circ y_t + B \circ y_{t-1} + \epsilon_t \tag{19}$$

where y_t is a $n \times 1$ vector of counts. The elements of the matrices A and B, α_{ij} and β_{ij}, are parameters which are interpreted as probabilities ($\alpha_{ij} \in [0, 1]$, $\beta_{ij} \in [0, 1]$). Also the elements on the principal diagonal of A (i.e. $\alpha_{ii} \forall i$) are equal to zero. The elements in A and B can contain covariates, e.g. in a logistic form (Brännäs, 1995): $a_{ij,t} = 1/(1 + \exp(x_{ij,t}\theta))$. Similarly, they can contain the spatial distance of units in the form $a_{ij,t} = 1/(1 + \exp(\alpha_1 w_{ij}))$, $i \neq j$ (Brännäs, 2013, p. 8) or $a_{ij,t} = 1/(1 + \exp(\alpha_0 + \alpha_1 w_{ij}))$, $i \neq j$ (Brännäs, 2014, p. 6) where w_{ij} is the respective element of a spatial inverse distance matrix W. The inclusion of a spatial distance measure in this way reduces the number of unknown parameters from n^2 in A to one or two (α_0 and α_1), respectively (Brännäs, 2013, p. 6). The authors do not give an empirical application but make some comments on IV and GMM estimation.

3 Spatially Lagged Covariates Models

Instead of modelling a spatial autoregressive process, like it is done with the models of the previous section, an easier way to model spatial effects can be chosen by incorporating a spatial structure of the covariates. This way, spatially lagged or otherwise spatial regressors can be computed before the actual regression is performed and be treated the same way as the non-spatial ones. In the following, two examples of the use of spatially lagged covariates in a count data setting are described as an introduction to the topic without going into detail regarding the actual models employed.

Buczkowska and de Lapparent (2014) use an SLX model for the location choices of new establishments in the Paris metropolitan area. They investigate different industry sectors and check several count data models. The results of a Poisson hurdle model with spatial spillover effects are reported in the article. The spillover effects are calculated prior to the estimation as a regressor (p. 76):

$$X_{l,s} = \log(\sum_{j=1}^{L} e^{-d_{l,j}} z_{j,s}) \tag{20}$$

where $j = 1, \ldots, L$ are the spatial units in the data set, $d_{l,j}$ is the distance between the centroid of unit l and j and $z_{j,s}$ is an attribute of unit j that applies to industry sector s, e.g. the number of pre-existing establishments. The inclusion of $X_{l,s}$ into the intensity equation of the model therefore introduces a spatial effect. But due to its predetermined nature, it does not have any consequences on the estimation of the model, which is still done using conventional estimation strategies for non-spatial models.

A different approach of using spatially lagged regressors for counts is employed by Abdelmoula and Bresson (2005, 2007). They use a panel linear feedback model for count data (introduced by Blundell et al. (1995)) to model spillover effects of R&D expenditures on patent activity. In their linear model equation, which is estimated with quasi-differenced generalized method of moments (GMM) (Blundell et al., 2002), the number of patents is a function of the R&D expenditures of the other regions. The R&D expenditures of the other regions are summarized into K geographical distance classes, each with its own elasticity parameter λ_k. The resulting spatial term is

$$\sum_{k=1}^{K} \lambda_k \log R_{t-1,k} \tag{21}$$

where $R_{t-1,k}$ denotes the R&D expenditure in period $t-1$ and geographical distance class k. In a second application they transfer this approach to classes of technological instead of geographical proximity.

Other applications of spatially lagged covariates models for firm location and firm births, respectively, can be found in Alañón Pardo et al. (2007), Arauzo-Carod and Manjón-Antolín (2012), Arzaghi and Henderson (2008), Bonaccorsi et al. (2013), Buczkowska et al. (2014), Martinez Ibañez et al. (2013), Liviano and Arauzo-Carod (2013), and Stuart and Sorenson (2003). Patent data and SLX models are also used by Acosta et al. (2012) and Corsatea and Jayet (2014). Other economic applications include U.S. crime data (Bhati (2005) and Payton et al. (2015)), foreign direct investment (Castellani et al., 2016), terrorist attacks in countries eligible for foreign aid (Savun and Hays, 2011), and traffic accidents (Chiou et al. (2014), and Cai et al. (2016)).[1]

On the one hand, SLX models are very compelling because of the straightforward implementation especially in the context of count data, but on the other hand they only allow for spatial dependence in the covariates, i.e. only local spillovers are obtained (Anselin, 2003, p. 161). Also, they do not consider any spatial structure in the unexplained part of the dependent variable, which might not be plausible in applications, for which not all relevant factors can be observed. The next spatial model class employs the opposite approach and accounts solemnly for spatial correlation in the error terms, i.e. spatial heterogeneity. This solves the limitations just outlined but also means that the spatial structure is a mere nuisance and not of interest by itself.

4 Spatial Error Models

Spatial error or spatial heterogeneity models include spatial correlation into the error term of a regression model. Other than in the SLX model, where local spillover effects of a change in X are present, and in the SAR models, where global spillover effects of a change

[1]Different approaches, in which not the outcomes of the regressors vary depending on the neighbors and the spatial location but the coefficients, are the geographical weighted regression, applied for example to industrial investments in Indiana by Lambert et al. (2006) and car ownership in Florida by Nowrouzian and Srinivasan (2014), or the smooth transition count model of Brown and Lambert (2014, 2016) applied to location decisions in the U.S. natural gas industry.

in X are considered, the expectation of y in a SEM model remains unchanged compared to the one of a non-spatial model. Besides the simultaneous autoregressive scheme of the linear SEM which is given by

$$\begin{aligned} y &= X\beta + \epsilon \qquad (22) \\ \epsilon &= \rho W \epsilon + u \Leftrightarrow \epsilon = (I - \rho W)^{-1} u \qquad (23) \end{aligned}$$

where the vector u contains i.i.d. error terms, a widely used approach in count data modelling is the conditional autoregressive (CAR) scheme introduced by Besag (1974). The standard CAR scheme assumes that the spatial errors in Equation (23) conditional on the neighboring errors are independent and normally distributed i.e.

$$\epsilon_i | \epsilon_{(-i)} \sim N(\rho \sum_{j=1}^{n} w_{ij} \epsilon_j, \sigma_i^2) \qquad (24)$$

where $\epsilon_{(-i)}$ denotes the errors of all neighbors of unit i, ρ the spatial correlation parameter of the errors, and σ_i^2 their conditional variance. This leads to the joint distribution of ϵ (see Besag (1974), for a summary of the derivation see also Cressie and Chan (1989, pp. 396)):

$$\epsilon \sim N(0, (I_n - \rho W)^{-1} \Sigma) \qquad (25)$$

with $\epsilon = [\epsilon_1, \ldots, \epsilon_n]'$ and $\Sigma = diag(\sigma_1^2, \sigma_2^2, \ldots, \sigma_n^2)$. This means the error terms follow an auto-Gaussian process. An intrinsic variant (ICAR) has been introduced by Besag and Kooperberg (1995) and an extension to the multivariate case (MCAR) can be found in e.g. Carlin and Banerjee (2003) and Gelfand and Vounatsou (2003). Banerjee et al. (2004) and more recently Czado et al. (2014) give an overview of the different CAR models.

Spatial errors following the CAR scheme are included in count data models which are typically estimated using Bayesian Markov chain Monte Carlo (MCMC) and applied to a wide range of data, e.g. traffic crash data (Aguero-Valverde and Jovanis, 2006; Buddhavarapu et al., 2016; Li et al., 2007; Miaou et al., 2003; Quddus, 2008; Truong et al., 2016), pedestrian casuality counts (Graham et al., 2013; Wang and Kockelman, 2013), crime counts (Jones-Webb et al., 2008; Haining et al., 2009), emergency department visits (Neelon et al., 2013), commuting patterns (Chakraborty et al., 2013), claim numbers on insurances (Czado et al., 2014; Dimakos and Rattalma, 2002; Gschlößl and Czado, 2007, 2008), and firm births (Liviano and Arauzo-Carod, 2014). The CAR approach for modelling spatial heterogeneity is also very popular in biometrics, e.g. for cancer counts (Bernardinelli and Montomoli, 1992; Torabi, 2016; Waller et al., 1997; Xia et al., 1997; Xia and Carlin, 1998; Wakefield, 2007), diabetes mellitus cases (Bernardinelli and Clayton, 1995; Bernardinelli et al., 1997), or Malaria counts (Briet, 2009; Villalta et al., 2012). Various other specifications of spatial error models for count data are applied in the literature as well: LeSage et al. (2007) use a simultaneous autoregressive scheme to model European patent data, Jiang et al. (2013) multiply two different spatial random effects in their Poisson temporal-spatial random effect model for traffic crashes in Florida, and Basile et al. (2013) employ a geoadditive negative binomial model for greenfield investments in the European Union, which includes a bivariate smooth term of latitude and longitude, to name a few.

As mentioned earlier, this way of dealing with spatial association in the data lays emphasis on efficiency but not on explicitly modelling the spatial autocorrelation of the observations and therefore is useful for different applications than the approaches described in the previous two sections.

5 Conclusion

This review summarizes the approaches to model spatial effects in econometric count data. Of the three types of spatial dependency, spatial autoregression, spatial heterogeneity, and spatially lagged regressors, the first one is only seldom addressed in spatial count data analyses. In contrast, spatial heterogeneity is often employed, especially in connection with Bayesian hierarchical models and a conditional autoregressive structure for the error term. Also, spatially lagged regressors are used regularly, in part because of the straightforward inclusion into any non-spatial model without the need of further adjustments of the estimation method.

Most probably, the main reason for the lack of literature on spatial autoregression models lies in the special structure of count data models compared to the linear models for continuous data. Count data models typically do not establish a direct connection between the regressors and the dependent variable. Instead, the regressors are included in an equation modelling the intensity parameter, which equals the conditional expectation of the dependent variable. Therefore, a direct transfer of the spatial autoregressive structure from linear models is not possible. Although several ways of including a similar structure into count data models have been proposed, none of them found broad reception so far. Causes can be found in the fact that many approaches either impose unrealistic restrictions on the spatial autocorrelation parameter, demand for notable (computational) effort when estimating them, or estimate a spatial autocorrelation parameter which is not intuitively interpretable.

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