Contemporary developments in the theory and practice of spatial econometrics

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EDITORIAL

Contemporary developments in the Theory and Practice of Spatial Econometrics

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Abstract

The papers in this special issue cover a wide range of areas in the methodology and application of spatial econometrics. The first develops a Generalised Method of Moments (GMM) estimator for the spatial regression model from a second order approximation to the Maximum Likelihood (ML). The second develops Bayesian estimation in a stochastic frontier model with network dependence in efficiencies, with application to industry dynamics. The third studies cross-country convergence under the Lotka-Volterra model and obtains new insights on spatial spillovers. The penultimate paper develops robust specification tests for the social interactions model under both ML and GMM frameworks. The final paper proposes identification and GMM estimation in a high order spatial autoregressive model with heterogeneity, common factors and spatial error dependence.

Keywords: #
spatial econometrics; panel data; social networks; generalized method of moments (GMM); Bayesian methods; Lotka-Volterra model.

JEL classification: C11; C21; C23; C38; C52.

This Special Issue collects selected papers from the 26th (EC)² Conference on "Theory and Practice of Spatial Econometrics", organised in December 2015 by the Spatial Economics & Econometrics Centre (SEEC), Heriot-Watt University (Edinburgh, Scotland, UK).[1] The conference was a great success, with wide participation and high quality of papers. Subsequently, *Spatial Economic Analysis*, one of the leading field journals in the area, approached the organisers with an invitation to organise a special issue. Unfortunately, the preparation of this Special Issue also happened in the shadow of the loss of

[1] (EC)², *European Conferences of the Econom[etr]ics Community*, is one of the oldest and prestigious scholarly societies in econometrics and, since 1990, has been organising a series of annual international conferences on quantitative economics and econometrics. For the first time, in 2015, the chosen topic was spatial econometrics or allied areas.

two of the leading researchers in the areas of spatial econometrics and regional science: Cem Ertur (1962-2016) and Raymond J. G. M. Florax (1956-2017). Beyond their important roles as leading researchers in the area, they were also dear friends and colleagues to many of us. Though neither Cem nor Raymond were able to attend the conference in person, they both had significant presence intellectually, in the papers presented at the conference, in the literatures that the presented papers contributed to, and likewise in the papers in this issue.

The papers submitted to this Special Issue were subjected to the regular review standards and processes of *Spatial Economic Analysis*. The five selected papers are, individually and collectively, indicative of the high quality of the papers presented at the conference, and cover a wide range of models, applications and approaches of analyses. One of the objectives of the $(EC)^2$ Conference 2015 was to provide a platform to early career researchers, including doctoral students. It is a happy coincidence that this issue also retains the same healthy representation of young researchers.

Each paper is placed below within the context of the current literature in the area. Three important highlights emerge collectively from the papers. First, the three methodological contributions in this issue (Breitung and Widder, 2018; Doğan et al., 2018; and Wang and Lee, 2018) offer exciting new insights into the comparison and contrast between maximum likelihood (ML) and generalized method of moments (GMM) inferences for spatial regression models. Second, the papers also offer interesting contrasts on alternative ways of modelling spatial dependence. While Breitung and Widder (2018) and Carvalho (2018) focus on the spatial error model and Ditzen (2018) on the spatial Durbin model (SDM), Doğan et al. (2018) and Wang and Lee (2018) consider combinations of spatial lag and spatial error models. Further, Ditzen (2018) and Wang and Lee (2018) highlight alternate ways of modelling spatial dependence arising from common factors. Third, peer and social networks constitute one important application area of spatial econometrics (Bhattacharjee and Holly, 2013; Liu et al., 2014) which has received relatively little coverage in *Spatial Economic Analysis* and allied journals. This issue contains two papers, Carvalho (2018) and Doğan et al. (2018), that are directly related to peer networks, while another two, Breitung and Widder (2018) and Wang and Lee (2018) also have connections. We hope that this collection will contribute towards more active research on social networks in the spatial econometrics tradition.

Breitung and Wigger (2018, in this issue) make a significant contribution to spatial econometric methodology and philosophy of estimation. Equally importantly, the paper clearly highlights the link between GMM and ML estimation of spatial regression models. In this sense, and following on from Elhorst (2010), this article places different estimation methodologies on the same platform and encourages the reader to think carefully about the underlying estimation philosophies and their implications for theory and applied research in spatial econometrics.

Specifically, and first, the paper considers the spatial error model and shows that, similar moment conditions as those proposed by Kelejian and Prucha (1999) can be obtained from a second order approximation of the ML first order conditions. There is a commonly held notion that the "GMM estimator approximates the ML score", but this specific approach to derive the moment conditions from a second order expansion of the scores clearly expresses a sense in which the above notion can be justified. The moment conditions and corresponding estimator thus derived are new to the literature.

Second, the paper considers another new and simple moment estimator, based on the first order approximation, that performs almost as well as the much more demanding GMM estimators based on the second order approximations.

Third, the paper proposes a computationally simple way to obtain the optimal GMM estimator based on rewriting the moment conditions in the form of a martingale difference sequence. Heteroscedasticity robust versions of all the estimators are also proposed.

Finally, the paper also considers extensions to the spatial autoregressive (SAR) and spatial Durbin models (SDM) and highlights issues of identification and estimation using similar principles under these alternate models. The paper does not in itself include any application, but it draws extensively upon the empirical literature on regional spillovers and peer effects to highlight implications of the research in this paper for applied work; see, for example, Ertur and Koch (2007), Fingleton (2008), de Dominicis et al. (2013) and Liu et al. (2014).

The second paper by Carvalho (2018, in this issue) is innovative in the choice of model, estimation methodology and application, and develops fascinating new insights into spatial econometric modeling in the context of error components models. This paper links to Breitung and Wigger (2018, in this issue) in their common focus on the spatial error model. Specifically, this paper develops Bayesian inference for a spatial random effects stochastic frontier model with spatial dependence in the efficiency error component, which handles unobserved heterogeneity and allows for spillovers between the units. Also, the paper focuses on small sample performance and proposes a Guided Walk Metropolis method as an alternative to rejection sampling techniques. The proposed model and methodology are applied to a sample of 27 New Zealand electricity distribution firms to evaluate the impact of an ownership unbundling policy that induced a vertical separation of the electricity supply industry with respect to ownership.

This paper makes several important contributions to the spatial economics and econometrics literature. First, it considers a very useful but relatively less researched econometric model: the stochastic frontier model. There is a small but influential spatial econometric literature for this model; for recent contributions, see, among others, Areal et al. (2012), Glass et al. (2016) and Filippini et al. (2018).

Second, and further, while a substantial part of this literature builds the spatial structure using the spatial lag, this paper assumes a spatial error model. This renders identification and inference particularly significant and challenging because the stochastic frontier model has an error components structure that is identified by shape (distributional) restrictions on the error components.

Third, the paper places adequate emphasis on structural understanding of spatial regression models. In the absence of strong theory, structural interpretations are challenging in spatial econometrics (Elhorst, 2010). One standard approach for practitioners is to take a reduced form general-to-specific approach; however, this generates only limited structural interpretation. The other approach is to use carefully conducted specification tests to aid model selection (Florax et al., 2003). By contrast, this paper uses a compelling application context to motivate structural interpretation of spatial dependence in the spatial error form. In this paper, this objective is achieved by focusing on network interactions in cost efficiency.

Fourth, the paper reports careful Bayesian analysis placing special attention to identification, drawing upon the Generalized True Random Effects model of Greene (2005) and the subsequent literature, and finite sample performance using a carefully planned Monte Carlo study.

Finally, the paper develops important insights on the measurement of efficiency and its policy implications. Given the nature of the problem, the technical details are somewhat unusual for a spatial econometrics audience, but careful reading is very rewarding. We feel that the capacity of identification of network structure in spatially dependent efficiencies is a significant finding, and has the potential to generate further research, possibly in the estimation of network dependence or inferring stability of network structures; for related literatures, see Bhattacharjee and Jensen-Butler (2013), Bhattacharjee and Holly (2013) and Angulo et al. (2017).

Ditzen (2018, in this issue) provides an excellent application of growth empirics embedded in economic theory and current best practise of spatial econometrics. Specifically, this paper uses a general Lotka-Volterra model to infer on convergence for 93 countries over the period 1960 to 2007. The paper makes several important innovations, and in doing so, carves out a niche within an area with a large empirical and theoretical research.

First, the paper expertly places itself within the existing literature, both theoretical and empirical. Thereby, it provides an excellent introduction and current review of the growth empirics and growth theory literature in a way that is accessible to a general audience. It starts from the seminal contributions of Fingleton and López-Bazo (2006) and Ertur and Koch (2007, 2011) estimating the rate of convergence in the context of spatial Solow and spatial Schumpeterian growth models. Then, it discusses a distinct literature (Arbia and Paelinck, 2003a,b) estimating regional convergence, focusing on stability, using a Lotka-Volterra approach popular in mathematical biology. The paper places these two approaches together, highlighting similarities and differences in the empirical specifications, but also builds in links to a large literature surrounding the two models. Notable contributions along the way include, among others, Abreu et al. (2004), Koch (2008), Lesage and Fisher (2008) and Le Gallo and Fingleton (2014). This provides an excellent new, easily approachable and encyclopaedic synthesis that, in our view, is a significant highlight of the paper.

Second, the paper motivates the use of a time-space recursive model (Anselin, 2001; Elhorst, 2001) which includes a spatial time lag rather than a spatial lag. A theoretical motivation for this modelling choice arises from the Lotka-Volterra model and the objective of studying stability conditions. Empirical motivations come from a concern for analysing endogenous spatial weights.

Third, the paper takes a very thorough and state-of-the-art approach to factor structure and heterogeneity. The combination of spatial dependence and common factors has recently received attention in the literature and was summarised in Elhorst et al. (2016); see Bhattacharjee and Holly (2011, 2013), Bailey et al. (2016) and Ertur and Musolesi (2017) for important current contributions to the literature. The estimated model includes common factors and potentially heterogeneous slopes and dynamics in a way that is well-motivated by the theoretical model and the current spatial econometrics literature. Estimation and inferences are based on the dynamic common correlated effects estimator (Chudik and Pesaran, 2015) in a way that is new to the growth empirics literature. Stata code for the implementation is also made available by the author; please see the paper for further details.

Finally, the paper also considers multiple potential channels for cross-country spillovers captured by the spatial time lag. Here, the possible channels considered are: trade, related to specialisation; foreign direct investment capturing technology diffusion that can affect the accumulation of capital; and high skilled migration in the form of human capital producing more knowledge. After controlling for global spillovers using common factors, foreign direct investment and migration are found to produce the strongest effects on spatial interactions. The consideration of alternate channels of local and global spillovers is a major innovation in the paper and has the potential for generating further research. For example, new theory will be useful for explaining why trade does not provide an equally potent interaction channel, or indeed why migration is so important in a cross-country growth context.

The final two papers in the issue make a significant methodological contribution to the current spatial econometrics literature. The penultimate paper, by Doğan et al. (2018, in this issue), is a major contribution to specification testing under a very general social interactions model; see, for example, Liu et al. (2014). In addition to unobserved group fixed effects, the model admits possible endogenous effects (spatial lag), contextual effects (exogenous interactions through spatial Durbin terms), and correlated effects (correlation of unobservables through a spatial error term). Then, this paper develops several notable advances to the literature.

First, specification testing for spatial regression models is challenging at the same time as it is very important (Elhorst, 2010). For cross-sectional spatial econometric models, Florax et al. (2003) and Florax et al. (2006) show that a specification search that starts with the most general model performs relatively poorly in terms of leading to the true data generating process. Hence, these studies suggest that, in the absence of well developed theory to motivate the nature of spatial dependence, or even for validating such theory, the use of test statistics is invaluable. Anselin et al. (1996) made a seminal contribution to this literature by developing LM tests that are very popular and useful. Doğan et al. (2018) takes a similar approach to social interaction models, developing new tests together with asymptotic results and extensive Monte Carlo study to evaluate finite sample performance.

Second, and very importantly, this paper considers perhaps the most general form of the social interactions model, including endogenous effects, contextual effects and correlated effects, and develops specification tests for each of these effects. Then, gradient based robust LM tests are developed based on both GMM and ML estimators, where robustness is achieved with respect to local parametric misspecifications. It turns out that the Anselin et al. (1996) LM test is closely related to the ML test developed here, but asymptotic theory for that test was not previously available. Furthermore, the Anselin et al. (1996) test is itself not valid in this current context, because in the presence of group fixed effects, conventional estimation approach for the cross-sectional spatial regression models cannot be directly applied. Nevertheless, the general intuition from Anselin et al. (1996) are confirmed by asymptotic theory and the size and power properties investigated through an extensive Monte Carlo study. Specifically, two-directional test statistics are not useful for detecting the exact source of misspecification. Similarly, the standard one directional test statistics are not reliable as they are not robust to the local parametric misspecification. However, the robust LM tests developed in this paper have good finite sample properties and can be useful for the detection of the source of dependence in social interaction models.

Third, in the process of developing the tests, this paper also offers very interesting contrast between the ML and GMM approaches, particularly in terms of identification. This complements the paper by Breitung and Wigger (2018). The identification conditions for the social interactions model include important restrictions on the spatial weights matrix. Specifically, row normalised weights matrices are necessary for ML, and further for both ML and GMM, a rank condition needs to be satisfied. These conditions are stated and discussed informally in this paper in the context of specification testing. However, the reader is encouraged to read this paper together with more extensive discussions in Lee et al. (2010) in the ML framework and Liu and Lee (2010) for 2SLS and GMM estimation. Another important feature of this paper is a clear discussion of the reflection problem. Specifically, in addition to the above conditions, group size variation is required for mitigating against identification issues connected to the reflection problem.

Finally, a very nice feature of the paper is a very extensive Monte Carlo study, including endogenous, correlated and contextual effects, but also the Spatial Lag of X (SLX) model of Halleck Vega and Elhorst (2015). This Monte Carlo design can provide a good framework for future studies. Several interesting and open problems emerge from the paper. The first is about extension of the methods for more general structures of weights matrices, particularly for the ML framework, but also potentially to models with latent spatial weights (Bhattacharjee and Holly, 2013; Bhattacharjee and Jensen-Butler, 2013; Bailey et al., 2016). Also, the paper highlights that in certain cases the asymptotic distribution of score functions may not be centred around zero even though the estimator itself is consistent, and this results in the LM test statistics being invalid. In such situations, it is possible to adjust the score functions to render valid LM test statistics; one important case for future study may be the case of heteroskedastic errors.

Wang and Lee (2018, in this issue), the final paper in this special issue, provides a methodological contribution and develops identification and GMM estimation for a spatial regression model, with high order spatial lags and high order spatial error dependence, in the presence of heterogeneity, common factors and space time dependence. The model considered here is very general, and in many features is related to Ditzen (2018), but is in addition enriched with high order spatial lags. The paper has several distinguishing features.

First, it is an excellent contribution to the growing literature on higher order spatial autoregressive models; see, for example, Lee and Liu (2010), Elhorst et al. (2012), Badinger and Egger (2015), Gupta and Robinson (2015) and Han et al. (2017). As highlighted by this paper, one of the main reasons for the growing importance of models with high order spatial dependence is that, there is often a question of choice between several potential spatial weights matrices reflecting different drivers of spillover or diffusion; see Ditzen (2018) for an example. Further, there is also a subtle connection with social interaction models like those discussed by Doğan et al. (2018). As discussed above, there are strong structural restrictions on the network structure of spatial weights matrices that need to be made in such models (Lee et al., 2010; Liu and Lee, 2010; Doğan et al., 2018). One way of getting around such structural constraints is through higher order spatial lags, because higher order spatial autoregressive models can accommodate farmer-district type structures where the parameter space increases with sample size (Gupta and Robinson, 2015). This suggests that higher order spatial lags may be useful in models of social networks as in Bhattacharjee and Holly (2013) or Liu et al. (2014).

Second, the model considered here is very rich and has some interesting features. In addition to high order spatial lags, it admits common factors. There is now a substantial literature modelling both weak dependence using spatial weights and strong dependence using common factors at the same time; see, for example, Holly et al. (2010), Bhattacharjee and Holly (2011, 2013), Bailey et al. (2016), Carrion-i-Silvestre and Surdeanu (2016), Elhorst et al. (2016), Ertur and Musolesi (2017) and Ditzen (2018). However, the way common factors are modelled in this paper is different from the large N large T setting that is more standard in the literature. Here, the sampling setting is finite T and large N, and therefore common correlated effects are not applicable. Then, the time factors are modeled as a finite number of parameters and their loadings as random effects.

Third, the modelling of the error term (u_t) is also rich. Following Elhorst (2012), the paper allows what it calls interactive space and time dynamics, which implies inclusion of spatial lags (Mu_t), temporal lags (u_{t-1}) as well as space-time lags (Mu_{t-1}) in the error model, where M is the spatial error weights matrix. In addition, higher order spatial lags are allowed in the error term as well.

Fourth, estimation is by GMM based on first and second order moment conditions. One implication of the use of second order moment conditions is that higher order moment assumptions for the factor loading random effects and the errors are needed for applying the Central Limit Theorem (CLT). Nonstochastic regressors with uniform bounds are assumed, but this assumption can be replaced with finite higher order moments. There are no major restrictions on the spatial weights beyond the standard uniform boundedness conditions. Under the above assumptions, conditions for identification are developed, and standard large N asymptotics delivers consistency and asymptotic normality of the proposed optimum feasible GMM estimator based on first and second order moment conditions. With Gaussian errors, the optimal weighting matrix is easily estimated, but estimation may be more complicated in non-Gaussian settings.

Fifth, a best GMM estimator is also developed. ML estimation of this model is computationally challenging, and as discussed above, may also place strong restrictions on the weights matrices. However, the best GMM moments and the score functions have very similar form, which indicates that the best GMM estimator may be almost equally efficient. Indeed, asymptotic efficiency is established under Gaussian errors, and the estimator also has standard asymptotic properties with non-Gaussian errors.

Finally, the paper includes an illuminating Monte Carlo study. The proposed optimum feasible GMM and best GMM estimators have good finite sample properties. However, the more significant finding is that, finite sample estimates of the error space time dynamics are relatively poor. Further, presence of error dynamics reduces the accuracy of estimates of spatial lag parameters in finite samples, while estimates of coefficients for exogenous regressors are not affected much. On the other hand, presence of multiple common factors or higher order spatial lags do not impact efficiency substantially. The authors provide the following intuition: "[t]his could be due to their nonlinearity in the GMM estimation" in the presence of error dynamics which require filtering. Overall, this is a significant piece of work that substantially enhances the literature, and makes very exciting reading.

In our view, the five papers in this issue make a significant contribution to the current literature. We believe that reading this issue will be intellectually challenging and enriching. The papers also highlight several fruitful directions for future research.

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