Chapter 18
Conclusions: The Future of Spatial Interaction Modelling

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18.1 A Reappraisal of the Presented Contributions

The present volume showcased a series of papers related to some of the most recent developments in the field of spatial econometric methods applied to spatial interaction modelling. In particular, this book was motivated by the need to testify, through a collection of methodological and empirical studies, how the various approaches that have been present in this field in the last decades have recently developed, by including tools that are typical of spatial statistics and spatial econometrics, giving birth to a somewhat novel discipline characterized by a body of methods and techniques known under the heading of *spatial econometric interaction models* (LeSage and Pace 2009).

Looking at the contributions reported here, the reader can have a good snapshot of the current state-of-the-art in the field. In particular, from a theoretical point of view, the papers contained in this volume witness the various methodological progress made recently in the analysis of gravity-type modelling (e.g., in the chapters by Griffith and Fischer, Tamesue and Tsutsumi, and Patuellli, Linders, Metulini and Griffith), in the definition of exogenous and endogenous spatial interaction (LeSage and Fischer), in the analysis of the effects of spatial dependence on flow data (Bavaud, as well as Beenstock and Felsenstein), in the Bayesian

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approach to spatial interaction modelling (the chapters by LeSage and Satici, Deng, and LeSage and Llano), and in assessing the effect of scale on spatial interaction model parameters (Arbia and Petrarca). Under the applied point of view this book also provides a good overview of the typical areas of application of spatial econometric interaction models, such as tourism (Patuelli, Mussoni and Candela), transportation (Diaz-Lanchas, Gallego, Llano and de la Mata), social networks (Llano and de la Mata), migration (Mitze), urban development (Lee and Chun) and trade (Mastromarco, Serlenga and Shin).

18.2 Future Roads of Spatial Interaction

If it is certainly true that the progress in the field has been tremendous in the last 50 years or so, starting from the publication of the first prototype gravity-type models (Isard 1960; Tinbergen 1962; Wilson 1970), it is equally fair to recognize that a lot still remains to be done in different directions in order to answer the current and future challenges of the discipline. In particular, the measurement of spatial and network autocorrelation in flow data is still nowadays for the most part based on the typical spatial autocorrelation indices that assume normally distributed random variables. However, flow data are, by definition, non-negative and discrete, which raises the important question of whether the classical spatial correlation measures, like Moran's *I* or Geary's G indices, are the most appropriate ones to characterize the phenomenon. A step forward in this direction could be represented by the use of alternative indices that explicitly account for non-normality in flow data like those reported in Jacqmin-Gadda et al. (1997); Arbia and Lafratta (2005); Lin and Zhang (2007) or Griffith (2010). A further problem of spatial interaction modelling that is often overlooked and needs to be properly considered is represented by the possible presence of heteroskedasticity in the regression disturbances. As it is well known, heteroskedastic disturbances destroy the properties of the estimators and may lead to wrong hypothesis testing decisions. However, spatial units are often characterized by heterogeneity in many important characteristics (e.g., in their size) and hence in most empirical situations the homoscedasticity assumption may not be sustainable. An example of a heteroskedastic spatial interaction modeling of commodity flows can be found in Trang et al. (2016), based on the advances introduced in the literature by Kelejian and Prucha (see Kelejian and Prucha 2007, 2010; and Arbia 2014b, for a review). A typical application of spatial interaction models that could be greatly influenced by the presence of spatial dependence in flow data is the process of interpolation. In this field it is necessary to develop appropriate methods that could help in filling gaps in data while considering autocorrelation issues (as a starting point, see, e.g., Polasek et al. 2012). Furthermore, the spatial econometric interaction modelling literature still appears to be scarcely considering special cases in which the distribution of flow data does not conform to the expected one for Poisson models. A typical example is the case of zero-inflation (Burger et al. 2009), which is indeed very frequent in empirical cases. Regression models that explicitly and separately consider spatial effects in the zero-inflation and count parts (Metulini et al. 2015) should be developed in order to enrich the set of tools available to researchers and practitioners facing challenging data sets. Finally, another field where the introduction of innovation is needed is in the area of efficient visualization especially in the presence of a very large number of origins and destinations.

So far the interest in spatial interaction models have been motivated by the need to explain the aggregated flows of individual agents, goods, or information occurring between discrete partitions of space. In this book, as an example, all papers refer to flows as they are observed between, cities, metropolitan areas, provinces, regions or states. However, the big data revolution that we are currently experiencing has the potential to revolutionize our current approach to the analysis of flows providing detailed datasets describing the movements of individuals over space and their interacting behavior. New and alternative methods of data collection (such as crowd sourcing, GPS positioning devices, cell phones data, drones, satellite images and many others) will more and more be able to provide detailed information about the movements of economic agents, of goods and information over geographical space. For example, in many instances data are already available sourced from sample information obtained through cell phone movements; furthermore, satellite images provide data on flows proxied by the remotely sensed quantity of lighting on the earth; drones can acquire information about the movement of people; sensors located on individuals can perfectly describe their daily commuting trip. These are only a few examples of how the process of data acquisition is changing dramatically in these days. This huge amount of information about individual flows made available to researcher and practitioners, while solving at its very root the modifiable areal unit problem (MAUP; see the chapter by Arbia and Petrarca), also raises entirely new problems of method and interpretation under many different points of view. Some of them are not of direct interest to spatial econometrics (such as the confidentiality and ethical issues connected with the process of automatic data acquisition), some are potentially very relevant (such as the computational issues raised by analyzing with the current techniques very large sample sizes; see, e.g., LeSage and Pace 2007; Arbia 2014a; Arbia et al. 2015), but some of them will definitely constitute the big challenge faced by all researchers involved in this field in the next few years. The big data revolution is already manifesting itself in many scientific fields, and the ability of the scientific community to answer to these questions will determine the future of the spatial econometrics of spatial interaction.

References

Arbia G (2014a) Pairwise likelihood inference for spatial regressions estimated on very large datasets. Spat Stat 7:21–39

Arbia G (2014b) A primer for spatial econometrics: with applications in R. Palgrave Macmillan, New York

Arbia G, Lafratta G (2005) Exploring nonlinear spatial dependence in the tails. Geogr Anal 37(4):423–437

Arbia G, Bee M, Espa G, Santi F (2015) Fitting spatial econometric models through the unilateral approximation. DEM Discussion Papers 2014/08, University of Trento, Trento

Burger M, van Oort F, Linders GJ (2009) On the specification of the gravity model of trade: zeros, excess zeros and zero-inflated estimation. Spat Econ Anal 4(2):167–190

Griffith DA (2010) The Moran coefficient for non-normal data. J Stat Plann Inference 140(11):2980–2990

Isard W (1960) Methods of regional analysis. MIT Press, Cambridge

Jacqmin-Gadda H, Commenges D, Nejjari C, Dartigues JF (1997) Tests of geographical correlation with adjustment for explanatory variables: an application to dyspnoea in the elderly. Stat Med 16(11):1283–1297

Kelejian HH, Prucha IR (2007) HAC estimation in a spatial framework. J Econom 140(1):131–154

Kelejian HH, Prucha IR (2010) Specification and estimation of spatial autoregressive models with autoregressive and heteroskedastic disturbances. J Econom 157(1):53–67

LeSage JP, Kelley Pace R (2007) A matrix exponential spatial specification. J Econom 140(1):190–214

LeSage JP, Pace RK (2009) Introduction to spatial econometrics. CRC Press, Boca Raton

Lin G, Zhang T (2007) Loglinear residual tests of Moran's *I* autocorrelation and their applications to Kentucky breast cancer data. Geogr Anal 39(3):293–310

Metulini R, Patuelli R, Griffith DA (2015) Estimating a spatial filtering gravity model for bilateral trade: functional specifications and estimation challenges. Paper presented at the European Trade Study Group 2015, Paris

Polasek W, Llano C, Sellner R (2012) Bayesian methods for completing data in spatial models. Rev Econ Anal 2(2):192–214

Tinbergen J (1962) Shaping the world economy: suggestions for an international economic policy. Twentieth Century Fund, New York

Trang HTT, Arbia G, Miyata Y (2016) The analysis of commodity flows in San-En-Nanshin region (Japan) with heteroskedastic spatial interaction models. Mimeo

Wilson AG (1970) Entropy in urban and regional modelling. Pion, London