Raising the bar (15)

Elhorst, Paul; Abreu, Maria; Amaral, Pedro; Bhattacharjee, Arnab; Chasco, Coro; Corrado, Luisa; Doran, Justin; Felsenstein, Daniel; Fuerst, Franz; Le Gallo, Julie

Published in:
Spatial Economic Analysis

DOI:
10.1080/17421772.2020.1756468

EDITORIAL

Raising the bar (15)

Paul Elhorst, Maria Abreu, Pedro Amaral, Arnab Bhattacharjee,
Coro Chasco, Luisa Corrado, Justin Doran, Daniel Felsenstein,
Franz Fuerst, Julie Le Gallo, Philip McCann, Vassilis Monastiriotis,
Francesco Quatraro, Umed Temursho and Jihai Yu

Abstract This editorial summarises the papers published in issue 15.2 so as to raise the bar in applied spatial economic research and highlight new trends. The first paper combines a conditionally autoregressive (CAR) process from the spatial statistics literature with a spatial Durbin error model (SDEM) from the spatial econometrics literature. The second paper feeds a multi-stage and multi-level data envelopment analysis with a microeconomic foundation. The third paper provides empirical evidence that Flegg's location quotient combined with a gravity model produces the most accurate interregional input-output multipliers. The fourth paper investigates the impact of inventor networks on the number of patents per capita in Brazil.

KEYWORDS
Population density, Data Envelopment Analysis, Input-output, Collaboration, Patents

JEL C21, C23, O31, O33, R15

Spatial Economic Analysis is a pioneering journal dedicated to the development of theory and methods in spatial economic analysis. This issue contains four papers contributing to these developments.

The first paper in this issue, by Epifani, Ghiringhelli and Nicolini (2020), is an interesting, consistent and well-documented piece of research; it models spatial dependence while controlling for both local and global heterogeneity within the applied empirical strategy to explain population distribution across space. It is interesting for a series of reasons. First, it adopts a conditionally autoregressive (CAR) rather than a spatial autoregressive (SAR) process. Except for Beręsewicz and Nikulin (2018), *Spatial Economic Analysis* has not published many papers estimating CAR processes. It points to a dichotomy between the spatial econometric and the spatial statistics literatures that apparently is difficult to bridge. Spatial econometricians may read the *Handbook of Spatial Statistics* edited by Gelfland, Diggle, Fuentes, and Guttorp (2010) to appreciate that this is a different world. Fortunately, there also researchers trying to bridge the gap, such as Ver Hoef, Hanks and Hooten (2018), who explain the differences and similarities between CAR and SAR processes.

Second, the paper by Epifani et al. (2020) is quite unique due to its focus on the spatial Durbin error model (SDEM), which is a model containing spatially lagged explanatory variables, a spatially correlated error term (CAR process), but not a spatially lagged dependent variable. Elhorst (2017) has extensively discussed the differences. A SAR model or spatial Durbin model (SDM) causes global spillover effects and a SDEM model local spillover effects. *Spatial Economic Analysis* receives a striking number of submissions only focusing on the SDM model, probably due to the popular textbook by LeSage and Pace (2009), which strongly propagates this model. However, not many researchers ask themselves whether global spillovers really make sense for the problem they have at hand. In many cases, local spillovers are much more likely, requiring the SDEM model. In later work, LeSage (2014) fixed this by developing a Bayesian comparison test that helps to test the SDM with global spillovers and the SDEM with local spillovers against each other. Successful applications of this approach are Rios, Pascuel and Cabases (2017) and Credit (2019). We hope that this new contribution on CAR will further strengthen this tendency, including in the spatial statistics literature.

Third, this submission caused a fascinating discussion between the authors and one of the reviewers about the existence of a spatial unit root problem in the outcomes. Yu, De Jong and Lee (2012) set out what needs to be understood by a spatial unit root from an econometric-theoretical viewpoint, while Elhorst, Zandberg and De Haan (2013) extensively discuss its empirical implications. Epifani et al. (2020) follow a different approach. They change the prior density function used to generate the spatial autocorrelation coefficient of the error term in their Bayesian estimator such that this parameter is less close to unity. Nevertheless, they still find values ranging from 0.763 to 0.842 for this spatial parameter (α_t in their Table 6). To justify this outcome, they refer to several other studies that also found high values, which almost all appeared in the journal *Spatial Statistics*. We leave the judgement of this alternative approach to the reader, though not without the warning that one potential reason for high values of spatial dependence thwarting many empirical studies is the lack of controls for time period fixed effects. Lee and Yu (2010) show, using Monte Carlo simulation experiments, that ignoring time-period fixed effects may lead to large upward biases (up to 0.45) of the spatial dependence parameter.

The second paper in this issue, by Ribeiro, Varum and Daniel (2019, this issue), deals with multi-stage and multi-level data envelopment analysis (DEA). DEA is a widely used non-parametric or deterministic technique to measure the efficiency of decision-making units (DMUs). According to Nijkamp and Suzuki (2009), it has become an established benchmark tool to develop efficiency strategies in both the public and the private sectors. A multi-stage extension of DEA offers the opportunity to split up the process to be analysed in different stages. In their empirical illustration, the authors consider the production and commercialisation stages of regional innovation systems in Portugal. Similarly, a multi-level approach offers the opportunity to distinguish DMUs at different levels of scale. In their empirical application, the authors distinguish municipalities (sub-DMUs) within the 25 NUTS-3 regions in Portugal. In addition, the authors consider cases with constant and increasing returns to scale. A mathematical overview of these different models and cases are provided in the first part of paper, while an appendix with supplemental material (data, supporting files, mathematical details, and proofs of the claims made in the paper) is available online. The objective of the paper is to feed DEA with a microeconomic foundation by introducing the Spence distortion principle, perhaps better known as the average-based pricing principle, as the pillar for the proper evaluation of efficiency scores in multi-level and multi-stage systems. According to one of the reviewers, this setup is groundbreaking, while the empirical application illustrates the most important ideas.

The third paper by Jahn, Flegg and Tohmo (2020, this issue) fits within a series of papers on input-output analysis, see the editorial to issue 15.1 for more details (Elhorst et al., 2020). The regionalization of national input–output tables is a major issue in regional science as corresponding regional data are often unavailable. Recently, Jahn (2017) developed a framework to estimate intra- and interregional input–output tables. The intraregional estimates are based on Flegg's Location Quotient (FLQ), while the interregional estimates are constructed using gravity modelling. Jahn illustrated this methodology for German regions; in this paper it is illustrated for South Korean regions. However, the authors make several additional steps forward. First, as Jahn did not have the necessary survey-based regional data for the 16 federal states in Germany to test the proposed methodology, his empirical work was entirely illustrative. Second, the gravity model employed to produce the estimates for Germany was estimated using Eurostat data on international trade, while the Korean dataset in this study also contains data on inter-regional trade. Due to this lack of data, Jahn was unable to generate estimates of the optimal values of the δ parameter in the FLQ formula, which is a major research topic in this interesting methodological contribution to the input-output literature. Finally, for the same reason, he could not assess the relative merits of gravity and simple trade models, which is a key aspect of this study.

The fourth paper in this issue, by Gonçalves, Medeiros de Oliveira and Almeida (2019, this issue), investigates the impact of inventor networks on the output of economically useful technological knowledge measured by the number of patents per capita. The authors consider four network-related explanatory variables: intra- and inter-regional collaborative inventor network characteristics, network density, and international network characteristics. Their theoretical background explanation results in four testable hypotheses, while their empirical model is estimated using data of 558 micro-regions in Brazil over a period of twelve years, 2000-2011. This econometric model takes the form of a spatial autoregressive (SAR) model with regional fixed effects and quadratic terms in some of the explanatory variables to test for nonlinearity. The authors find that intra-regional collaboration is beneficial and inter-regional collaboration only above a certain threshold. In backward regions, international collaborative links sometimes compensate this lack of benefits. Finally, network density turns out to have a negative effect.

References

Beręsewicz, M., & Nikulin, D. (2018). Informal employment in Poland: an empirical spatial analysis. *Spatial Economic Analysis*, 13(3), 338-355.

Credit, K. (2019). Transitive properties: a spatial econometric analysis of new business creation around transit. *Spatial Economic Analysis*, 14(1), 26-52.

Elhorst, J.P. (2017). Spatial Panel Data Analysis. In S. Shekhar, H. Xiong, & X. Zhou (Eds.) *Encyclopedia of GIS*, 2nd edition (pp. 2050-2058). Cham: Springer.

Elhorst, P., Abreu, M., Amaral, P., Bhattacharjee, A., Chasco, C., Corrado, L., Doran, J., Felsenstein, D., Fuerst, F., Le Gallo, J., McCann, P., Monastiriotis, V., Quatraro, F., Temursho, U., & Yu, J. (2020). Raising the bar (14). *Spatial Economic Analysis*, 15(1), 60-61.

Elhorst, P., Zandberg, E., & Haan, J. de (2013). The Impact of interaction effects among neighbouring countries on financial liberalization and reform: A dynamic spatial panel data approach. *Spatial Economic Analysis*, 8: 293–313.

Epifani, I., Ghiringhelli, C., & Nicolini, R. (2020). Population distribution over time: modelling local spatial dependence with a CAR process. *Spatial Economic Analysis*, 1-25. doi:10.1080/17421772.2020.1708442

Gelfland, A.E., Diggle, P.J., Fuentes, M., & Guttorp, F. (2010). *Handbook of Spatial Statistics*. Boca Raton: CRC Press.

Gonçalves, E., Medeiros de Oliveira, P. & Almeida, E. (2019). Spatial determinants of inventive capacity in Brazil: the role of inventor networks. *Spatial Economic Analysis*, 1-22. doi:10.1080/17421772.2019.1637532

Jahn, M. (2017). Extending the FLQ formula: a location quotient-based interregional input–output framework. *Regional Studies*, 51, 1518–1529.

Jahn, M., Flegg, A.T., & Tohmo, T. (2020). Testing and implementing a new approach to estimating interregional output multipliers using input–output data for South Korean regions. *Spatial Economic Analysis*, 1-21. doi:10.1080/17421772.2020.1720918

Lee L.F., & Yu, J. (2010). Some recent developments in spatial panel data models. *Regional Science and Urban Economics*, 40, 255-271.

LeSage, J.P. (2014). Spatial econometric panel data model specification: A Bayesian approach. *Spatial Statistics*, 9, 122–145.

LeSage, J.P., & Pace, R.K. (2009). *Introduction to Spatial Econometrics*. Boca Raton: Chapman & Hall/CRC Press.

Nijkamp, P., & Suzuki, S. (2009). A generalized goals-achievement model in data envelopment analysis: an application to efficiency improvement in local government finance in Japan. *Spatial Economic Analysis*, 4(3), 249-274.

Ribeiro, V.M., Varum, C. & Daniel, A.D. (2019). Introducing microeconomic foundation in DEA: the average-based approach. *Spatial Economic Analysis*, 1-20. doi:10.1080/17421772.2020.1701701

Rios, V., Pascual, P., & Cabases, F. (2017). What drives local government spending in Spain? A dynamic spatial panel approach. *Spatial Economic Analysis*, 12(2-3), 230-250.

Ver Hoef, J.M., Hanks, E.M., & Hooten, M.B. (2018). On the relationship between conditional (CAR) and simultaneous (SAR) autoregressive models. *Spatial Statistics*, 25, 68–85.

Yu, J., de Jong, R., & Lee, L.F. (2012). Estimation for spatial dynamic panel data with fixed effects: The case of spatial cointegration. *Journal of Econometrics*, 167: 16–37.