University of Groningen

Raising the bar (16)

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:
[10.1080/17421772.2020.1836818](https://doi.org/10.1080/17421772.2020.1836818)

IMPORTANT NOTE: You are advised to consult the publisher's version (publisher's PDF) if you wish to cite from it. Please check the document version below.

Document Version
Publisher's PDF, also known as Version of record

Publication date:
2020

[Link to publication in University of Groningen/UMCG research database](#)

Citation for published version (APA):

Elhorst, P., Abreu, M., Amaral, P., Bhattacharjee, A., Chasco, C., Corrado, L., Doran, J., Felsenstein, D., Fuerst, F., Le Gallo, J., McCann, P., Monastiriottis, V., Quatraro, F., Temursho, U., & Yu, J. (2020). Raising the bar (16). *Spatial Economic Analysis*, 15(4), 353-358. <https://doi.org/10.1080/17421772.2020.1836818>

Copyright

Other than for strictly personal use, it is not permitted to download or to forward/distribute the text or part of it without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license (like Creative Commons).

The publication may also be distributed here under the terms of Article 25fa of the Dutch Copyright Act, indicated by the "Taverne" license. More information can be found on the University of Groningen website: <https://www.rug.nl/library/open-access/self-archiving-pure/taverne-amendment>.

Take-down policy

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

Downloaded from the University of Groningen/UMCG research database (Pure): <http://www.rug.nl/research/portal>. For technical reasons the number of authors shown on this cover page is limited to 10 maximum.

Raising the bar (16)

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 & Jihai Yu

To cite this article: 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 & Jihai Yu (2020) Raising the bar (16), Spatial Economic Analysis, 15:4, 353-358, DOI: [10.1080/17421772.2020.1836818](https://doi.org/10.1080/17421772.2020.1836818)

To link to this article: <https://doi.org/10.1080/17421772.2020.1836818>

Published online: 17 Dec 2020.

Submit your article to this journal [↗](#)

Article views: 36

View related articles [↗](#)

View Crossmark data [↗](#)

EDITORIAL

Raising the bar (16)

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 15.4 in order to raise the bar in applied spatial economic research and highlight new trends and knowledge. The first paper challenges the standard notion that more growth is better. The second paper challenges macroeconomic models by looking at them from a regional micro-grounded lens, where the effect of productivity shocks depends on the distribution of economic activity and the locations where shocks occur. The third paper investigates the wage-productivity nexus using the latest techniques on cross-sectional dependence. The fourth paper introduces a new method to determine regional price differentials. The fifth paper tests whether economic-theoretical insights obtained from urban economic models apply not only to cities in developed countries but also to those in developing countries. The sixth paper sets out an estimation method for a spatial random coefficients model for clusters of observations. The seventh paper proposes a new method for regionalizing national input–output tables. The final paper focuses on Big Data and its role in regional growth.

KEYWORDS

Shrinkage, spatial differences, prices, wage, productivity, clustering, regionalization

JEL C1, D5, J1, R1

Spatial Economic Analysis is a pioneering journal dedicated to the development of theory and methods in spatial economic analysis. The last issue of this volume contains eight papers contributing to these developments: two opinion papers, one economic-theoretical paper, one paper combining economic theory with empirics, two applied papers, and two methodological papers. The overarching theme is that approaches that take into account spatial differences offer greater insights than aggregated approaches.

This issue opens with Rachel Franklin's (2020) *Spatial Economic Analysis* Annual Lecture given at the Regional Studies Association 2019 Annual Conference in Santiago de Compostela, Spain, with the bold title 'I come to bury (population) growth, not to praise it'. In this contribution, which might be viewed as a logical continuation of the previous special issue of this journal on climate change edited by Batabyal and Folmer (2020), the author opposes the standard notion that more is better.

This issue continues with another provocative paper. Beenstock (2020, this issue) surveys spatial general equilibrium theory and its implications for GDP. The main finding is that the

CONTACT

(Corresponding author) j.p.elhorst@rug.nl

effect of productivity shocks depends upon the distribution of economic activity and locations where shocks occur. This has major implications for current macroeconomic models accounting for heterogeneous behaviour of microeconomic agents. Sometimes they also take into account sectoral variation, but only very rarely regional economies; for some departures, see Rokicki and Hewings (2019) and Stimson (2019). This paper provides theoretical arguments to encourage macroeconomics to take into account the sub-national spatial structure, as productivity shocks can have different consequences depending on where they occur. According to the reviewers of this paper, this is a nice and somewhat provocative contribution to the existing literature. The author proves several results that are intuitive and reasonable. To do so, he uses reduced forms for several effects highlighted in new economic geography and urban economics, and presents the mathematics and spatial equilibria in a clear and elegant way. Yet, these results are not necessarily well known and do not immediately come to mind. An empirical application of the analysis of spatial general equilibria accounting for the sub-national spatial structure is available in Beenstock, Felsenstein and Xie (2018).

The objective of the third paper in this issue, by Martini and Giannini (2020, this issue), is to analyse the long-term relationship between wages and labour productivity using data from 21 Italian regions between 1995 and 2015. For this purpose, the authors first specify a theoretical model that takes into account the characteristics of the collective bargaining system in Italy. Next, they test and find empirical evidence in favour of the hypotheses that these two variables are cross-sectionally dependent and cointegrated. Based on this, they estimate a panel error correction model (PECM) accounting for common factors, measured by one, two or three principal components, as well as spatial lags in the left and right-hand side variables of this model. They also compare their estimation results for different types of advanced estimators that have been proposed in the literature. The authors find that labour productivity has a positive effect of 0.28 on nominal wages, and that a change in the productivity of a particular region spills over to both adjacent regions and the neighbours of these adjacent regions. Altogether, this is an interesting paper applying the latest techniques combining both weak and strong cross-sectional dependence. It fits within a series of previous papers on this econometric topic – for example, Carrion-i-Silvestre and Surdeanu (2016), Ditzen (2018), Wang and Lee (2018), and Salvatore et al. (2019).

In addition to spatial differences in growth, productivity and wages, regions are also characterized by price differences. Some regions might seem less attractive from a job perspective, but more attractive given the cost of living (Rokicki & Hewings, 2019). The fourth paper in this issue, by Weinand and Von Auer (2020, this issue), constructs sub-national spatial indices of consumer prices for 295 counties and 107 cities in Germany. The authors refrain from any grouping of products because inaccurate grouping may generate contaminated price data and biased regional price indices. Instead, they estimate micro-founded hedonic price equations based on product and outlet identifying attributes, weighted by their consumption expenditure shares. The analysis is based on 381,983 of consumer price observations for goods, services and rents classified into 650 narrowly defined categories of household consumption expenditures. Munich turns out to be the most expensive city-region in Germany, where prices are about 27% higher than the region with the lowest prices. Neighbouring regions also tend to exhibit similar high/low costs to one another due to spatial autocorrelation in the cost of housing, which typically accounts for two-thirds of subnational CPI.

The fifth paper in this issue, by Lima and Silveira-Neto (2020, this issue), investigates the determinants of urban land use. It focuses on Recife, the most easterly city in Brazil. According to the authors, this fast growing city is different from other Brazilian cities since it does not impose constraints on the allocation of land to particular uses and has unique natural amenities, of which its coastal location is the most important. As we learn from Franklin (2020), however, more is not always better. As explained in the paper, Recife suffers from traffic congestion,

violence and environmental degradation. The authors estimate a conditional parametric spatial multinomial logit model based on 98,198 observations. The terminology ‘multinomial logit’ is explained by the fact that they consider five discrete types of land use. The term ‘parametric’ follows from the fact that the logit model is parameterized. Since the parameters of a logit model do not represent the marginal effects of the explanatory variables, the latter are also derived and analysed. The term ‘spatial’ is added since the authors use a non-parametric kernel function to account for the observation that data points close to each other are spatially correlated. This mix between a non-parameterized kernel function and a parameterized logit model finally explains the term ‘conditional’. One of their main findings is that the patterns of urban land use in Recife do not differ to any great extent from that of North American cities (McMillen & Soppelsa, 2015; Wang, Kockelman & Xiaokun, 2011), and thus that many theoretical insights obtained from urban economic models also apply to cities located in a developing country.

The sixth paper in this issue, by Ma, Xue and Hu (2020, this issue), develops a Bayesian clustered coefficients linear regression model with spatial random effects to capture heterogeneity of regression coefficients. This is quite a mouthful for a model that is relatively easy to position in the existing literature. One way to make a standard linear regression model spatial is to add a variable intercept representing the effect of omitted variables that are peculiar to each spatial unit or observation considered. This variable intercept may be fixed or random; the authors of this paper choose the latter. Although the random effects model accommodates spatial heterogeneity to a certain extent, the problem remains as to whether the data in such a model are pooled correctly. A natural generalization is to let the slope parameters of the covariates vary as well. An overview of all these model options is provided by Elhorst (2014). A problem, however, is that the number of parameters to be estimated might grow large relative to the number of observations. Only if the number of observations in the time domain remains large relative to the number of observations in the cross-sectional domain can one estimate a single model for each individual cross-sectional unit. See, for example, the recent contribution of Aquaro et al. (2020) and an application of this model by Autant-Bernard and LeSage (2019). An alternative is to cluster the observations in different groups based on background characteristics and/or the mutual distance between the cross-sectional units. This is the method proposed in this paper, operationalised using Bayesian techniques. As an application, the authors analyse monthly housing costs in 159 counties of Georgia. Their most important finding is that counties belonging to one cluster do not need to be direct neighbours of each other. The overlap with the fourth paper in this issue (Weinand & Von Auer, 2020), especially the evidence of spatial autocorrelation of the cost of living, means that it would be interesting to apply this technique to their data as well.

The seventh paper in this issue, by Pereira-López, Carrascal-Incera and Fernández-Fernández (2020, this issue), fits within a series of papers on input-output (IO) analysis. A major issue in this literature is the regionalization of national IO tables if corresponding regional data are unavailable. The authors propose a new non-survey technique for regionalizing IO tables from an observable national IO table. The standard procedure for regionalizing IO tables is the correction of national IO coefficients by a location quotient. Anthony Flegg’s augmented location coefficient (AFLQ), according to the authors the most sophisticated and advanced LQ currently available, is taken as the point of departure. The modification proposed offers a bi-dimensional correction of the national IO coefficients, depending on two parameters: the degree of regional productive specialization and the size of purchasing industries. To analyse the accuracy of the obtained estimates relative to AFLQ, the authors use Eurostat’s IO database of 2005 for six European countries and 59 sectors. Flegg in the meantime has also been busy further improving his LQ-based method, which resulted in the paper by Jahn, Flegg and Tohmo (2020) that appeared in the previous issue of this journal. Readers interested in this topic can find a more detailed overview of LQ-based methods and its theoretical background in the latter paper.

Table 1. Papers recently published based on relatively large data microeconomic data sets

Papers	Issue	Topic	# observations*
Weinand & Von Auer (2020)	15.4	Regional price differentials	382,000
Lima & Silveira-Neto (2020)	15.4	Urban land use	98,000
Zhu, He & Hu (2020)	15.1	Productivity	50,000 – 75,000
Huang & Zhang (2020)	15.1	Spillover impacts of FDI	41,000
Corrado, Distanto & Joxhe (2019)	14.4	Body mass index	15,000
Sarrias (2019)	14.1	Subjective well-being	16,000
Storm & Heckelevi (2019)	13.4	Omitted-variable bias	30,000 – 32,000
Dubé, Legros & Thanos (2018)	13.1	House prices	18,000
Hermannsson, Lecca & Swales (2017)	12.4	Education	32,000
Bhattacharjee, Cai & Maiti (2017)	12.2-3	House prices	12,000
Haapanen & Böckermann (2017)	12.1	Education on migration	234,000

* Rounded

The final paper in this issue is based on Karyn Morrissey's (2020, this issue) annual lecture plenary talk at the Cambridge Meetings of the Regional Science Association International British and Irish Section in 2019. It focuses on the knowledge that may be created from Big Data, and especially addresses its role in regional economic growth enriched with evidence from Great Britain. Today, Big Data is better known as 'Data Science' or 'Data Analytics'. It inspired the editorial board of *Spatial Economic Analysis* to look up all papers that appeared in the last four volumes whose analyses are based on relatively large microeconomic data sets. Table 1 lists these papers. We stress that large microeconomic data sets are not synonymous with Big Data. This table nonetheless illustrates that the popularity of spatial economic studies based on microeconomic data sets is increasing. Since we would like to encourage this tendency, we welcome researchers active in this field to consider *Spatial Economic Analysis* as an outlet for their research.

REFERENCES

- Aquaro, M., Bailey, N., & Pesaran, M.H. (2020). Estimation and inference for spatial models with heterogeneous coefficients: an application to U.S. house prices. *Journal of Applied Econometrics*. <https://doi.org/10.1002/jae.2792>.
- Autant-Bernard, C., & LeSage, J.P. (2019). A heterogeneous coefficient approach to the knowledge production function. *Spatial Economic Analysis*, 14(2), 196–218. <https://doi.org/10.1080/17421772.2019.1562201>
- Batabyal, A.A., & Folmer, H. (2020). Spatial economic aspects of climate change. *Spatial Economic Analysis*, 15 (3), 209–218. <https://doi.org/10.1080/17421772.2020.1788221>
- Beenstock, M. (2020). Aggregate supply in spatial general equilibrium theory. *Spatial Economic Analysis*. <https://doi.org/10.1080/17421772.2020.1742928>
- Beenstock, M., Felsenstein, D., & Xie, D. (2018). Spatial econometric analysis of spatial general equilibrium. *Spatial Economic Analysis*, 13(3), 358–378. <https://doi.org/10.1080/17421772.2018.1403645>
- Bhattacharjee, A., Cai, L., & Maiti, T. (2017). Functional regression over irregular domains: variation in the shadow price of living space. *Spatial Economic Analysis*, 12(2-3), 182–201. <https://doi.org/10.1080/17421772.2017.1286374>
- Carrion-i-Silvestre, J.L., & Surdeanu, L. (2016). Productivity, infrastructure and human capital in the Spanish regions. *Spatial Economic Analysis*, 11(4), 365–391. <https://doi.org/10.1080/17421772.2016.1189089>

- Corrado, L., Distante, R., & Joxhe, M. (2019). Body mass index and social interactions from adolescence to adulthood. *Spatial Economic Analysis*, 14(4), 425–445. <https://doi.org/10.1080/17421772.2019.1626020>
- Ditzen, J. (2018). Cross-country convergence in a general Lotka–Volterra model. *Spatial Economic Analysis*, 13(2), 191–211. <https://doi.org/10.1080/17421772.2018.1397285>
- Dubé, J., Legros, D. & Thanos, S. (2017). Past price ‘memory’ in the housing market: testing the performance of different spatiotemporal specifications. *Spatial Economic Analysis*, 13(1), 118–138. <https://doi.org/10.1080/17421772.2018.1395063>
- Elhorst, J.P. (2014). *Spatial Econometrics: From Cross-Sectional Data to Spatial Panels*. Berlin: Springer.
- Franklin, R.S. (2020). I come to bury (population) growth, not to praise it. *Spatial Economic Analysis*. <https://doi.org/10.1080/17421772.2020.1802056>
- Haapanen, M., & Böckerman, P. (2016). More educated, more mobile? Evidence from post-secondary education reform. *Spatial Economic Analysis*, 12(1), 8–26. <https://doi.org/10.1080/17421772.2017.1244610>
- Hermannsson, K., Lecca, P., & Kim Swales, J. (2017) How much does a single graduation cohort from further education colleges contribute to an open regional economy? *Spatial Economic Analysis*, 12(4), 429–451. <https://doi.org/10.1080/17421772.2017.1316417>
- Huang Y., & Zhang, Y. (2020). The innovation spillovers from outward and inward foreign direct investment: a firm-level spatial analysis. *Spatial Economic Analysis*, 15:1, 43–59. <https://doi.org/10.1080/17421772.2019.1618484>
- Jahn, M., Flegg, A.T., & Tohmo, T. (2020). Testing and implementing a new approach to estimating inter-regional output multipliers using input–output data for South Korean regions. *Spatial Economic Analysis*, 15 (2), 165–185. <https://doi.org/10.1080/17421772.2020.1720918>
- Lima, R.C. de A., & Silveira-Neto, R. (2020). Patterns of urban land use in a developing country: the role of transport infrastructure and natural amenities in Brazil. *Spatial Economic Analysis*. <https://doi.org/10.1080/17421772.2020.1749336>
- Ma, Z., Xue, Y., & Hu, G. (2020). Heterogeneous regression models for clusters of spatial dependent data. *Spatial Economic Analysis*. <https://doi.org/10.1080/17421772.2020.1784989>
- Martini, B. & Giannini, M. (2020). Regional wage and productivity in Italy: a spatio-temporal analysis. *Spatial Economic Analysis*. <https://doi.org/10.1080/17421772.2020.1769169>
- McMillen, D., & Soppelsa, M. E. (2015). A conditionally parametric probit model of microdata land use in Chicago. *Journal of Regional Science*, 55(3), 391–415. <https://doi.org/10.1111/jors.12174>
- Morrissey, K. (2020). Big Data and its potential role in regional growth: evidence from Great Britain. *Spatial Economic Analysis*. <https://doi.org/10.1080/17421772.2020.1825783>
- Pereira-López, X., Carrascal-Incera, A., & Fernández-Fernández, M. (2020). A bidimensional reformulation of location quotients for generating input–output tables. *Spatial Economic Analysis*. <https://doi.org/10.1080/17421772.2020.1729996>
- Rokicki, B., & Hewings, G.J.D. (2019). Regional price deflators in Poland: evidence from NUTS-2 and NUTS-3 regions. *Spatial Economic Analysis* 14(1), 1–18. <https://doi.org/10.1080/17421772.2018.1503705>
- Salvatore, C., Marcella, D.U., Cristiana, F., & Oreste, N. (2019) Spatial asymmetries in monetary policy effectiveness in Italian regions. *Spatial Economic Analysis*. <https://doi.org/10.1080/17421772.2020.1673899>
- Sarrias, M. (2018). Do monetary subjective well-being evaluations vary across space? Comparing continuous and discrete spatial heterogeneity. *Spatial Economic Analysis*, 14(1), 53–87. <https://doi.org/10.1080/17421772.2018.1485968>
- Stimson, R.J. (2019). Challenges for regional science research: Past and present. *Spatial Economic Analysis*, 14(2), 133–152. <https://doi.org/10.1080/17421772.2019.1558275>
- Storm, H., & Heckelei, T. (2018). Reducing omitted-variable bias in spatial-interaction models by considering multiple neighbourhoods. *Spatial Economic Analysis*, 13(4), 457–472. <https://doi.org/10.1080/17421772.2018.1468571>
- Wang, W., & Lee, L.-f. (2018). GMM estimation of spatial panel data models with common factors and a general space–time filter. *Spatial Economic Analysis*, 13(2), 247–269. <https://doi.org/10.1080/17421772.2017.1353128>

- Wang, Y., Kockelman, K. M., & Xiaokun, W. (2011). Anticipation of land use change through use of geographically weighted regression models for discrete response. *Transportation Research Record*, 2245(1), 111–123. <https://doi.org/10.3141/2245-14>
- Weinand, S., & Auer, L. von (2020). Anatomy of regional price differentials: evidence from micro-price data. *Spatial Economic Analysis*. <https://doi.org/10.1080/17421772.2020.1729998>
- Zhu, S., He, C., & Hu, X. (2020). Change your identity and fit in: an empirical examination of ownership structure change, firm performance and local knowledge spillovers in China. *Spatial Economic Analysis*, 15(1), 24–42, <https://doi.org/10.1080/17421772.2019.1623418>