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EDITORIAL

Raising the bar (2)

ABSTRACT *In this editorial we summarise and comment on the papers published in issue 11.2 so as to raise the bar in applied spatial economic research and highlight new trends. The first paper analyses which regions in Europe were resilient to the great Recession and which ones were not. The second and the third develop a competing-destinations gravity model to explain respectively which hospitals people go to depending on their residential location and which regions migrants go to on entering Europe. The fourth proposes a Bayesian approach to obtain likely values if data on certain spatial units are missing. Finally, the last paper tries to explain the spreading of people in sprawling cities.*

Titre: Soulever la barre (2)

RÉSUMÉ *dans le présent éditorial, nous récapitulons les communications publiées dans l'édition 11.2, et présentons des commentaires sur celles-ci, dans le but de «hausser la barre» dans la recherche sur l'économie spatiale appliquée, et de souligner les nouvelles tendances. La première communication examine quelles régions d'Europe se sont montrées résilientes à la grande récession, et quelles sont celles qui, au contraire, ne l'ont pas été. La deuxième et la troisième développent un modèle gravitationnel des destinations concurrentes, afin d'expliquer respectivement dans quels hôpitaux se rendent les gens selon le lieu de leur domicile, et dans quelles régions les migrants se rendent lorsqu'ils arrivent en Europe. La quatrième propose une approche bayésienne pour obtenir des valeurs probables lorsqu'il manque des données sur certaines unités spatiales. Enfin, la dernière communication s'efforce d'expliquer le déferlement des gens dans des villes tentaculaires.*

Título: Elevación de las normas (2)

RESUMEN *en este editorial resumimos y comentamos los estudios publicados en la edición 11.2 para elevar las normas en relación con la investigación económica espacial aplicada y destacar las nuevas tendencias. El primer estudio analiza qué regiones de Europa lograron resistir la gran recesión y cuáles no. El segundo y tercer estudio desarrollan un modelo de gravedad de destinos opuestos para explicar respectivamente a qué hospitales va la gente según la ubicación de su residencia y a qué regiones van los migrantes cuando ingresan a Europa. El cuarto estudio propone un enfoque bayesiano para obtener los posibles valores cuando faltan los datos de ciertas unidades espaciales. Por último, el último estudio trata de explicar la distribución de la población en las ciudades desperdigadas.*

标题: 提高标准 (2)

摘要: 这篇编者序言概要介绍和评价了第11.2期中发表的论文, 以此提高应用空间经济学研究领域的标准, 突出最新趋势。第一篇论文分析了欧洲哪些地区在应付经济

大衰退方面具备韧性，哪些地区却并不如此。第二和第三篇论文建立竞争目的地引力模型，分别解释人们选择前往哪家医院视乎其居住地点，以及移民进入欧洲后前往哪些地区。第四篇论文提出使用贝叶斯方法，在某些空间单元数据缺失时，取得估算的数值。最后，最后一篇试图说明居民在不断扩张的许多城市的人口散布情况

KEYWORDS: *Resilience; migration; urban sprawl; hospital choice; missing data*

Spatial Economic Analysis is a pioneering journal dedicated to the development of theory and methods in spatial economic analysis. This issue contains five papers contributing to these theoretical and empirical developments. The first one by Sensier et al. (2015, in this issue) immediately challenges many spatial economists. It describes resilience as a complex, multidimensional concept that is unlikely to be measurable by one simple indicator or composite index alone. Instead of Kernel density functions and nonparametric estimations (McMillen, 2013), which are sometimes difficult to understand, this paper contains maps of Europe subdivided into underlying Nuts 1 or 2 regions to show which ones were hit by the latest economic crisis (Great Recession) and which ones appeared to be resistant, as well as which ones recovered from the crisis in 2011, measured in terms of both employment and GDP (note: results are different), and which ones did not at that time. The regions that did not recover are further subdivided into those that were still turning down in 2011, and regions that experienced at least some recovery. The paper offers an original way of looking at resilience pointing to substantial differences among countries and across regions within countries.

Based on the anonymous reviewer reports, two challenges in this paper are left. First, while it is true that the economic crisis should not be expected to have hit Europe uniformly across space, another question is whether these regions have been exposed to equally strong shocks. If not, then varying reactions might be the result of the varying strengths with which each regional economy has been hit, rather than the outcome of different resilience capabilities. Separating these two effects would be another step forward. Second, while it is correct to treat each region as an individual entity and to consider its response to the Great Recession according to its own unique evolutionary trajectory, it is not true that regions can be treated as independent entities. Resilience in one region might be a function of resilience in neighbouring regions, as has been pointed out by the spatial econometrics literature in general (Anselin, 1988; LeSage & Pace, 2009; Elhorst, 2014; Lee & Yu, 2015), and some previous papers in this journal analysing regions across Europe in particular (De Dominicis, 2014; Paci et al., 2014; Broekel et al., 2015). Hopefully, some researchers are challenged by these two ideas.

Suppose that the population is spread over R residential regions and that this population makes use of services spread over S locations. Which locations are these people then going to? Mello-Sampayo (2015, in this issue) develops a competing-destinations gravity model to answer this question for the case of health supply. The model is estimated using a Poisson maximum likelihood (ML) estimator. This ML estimator is used instead of ordinary least squares to deal with zero flows between several residential region-service region pairs. Zero flows are a problem in many of these studies – see, for example, Burger et al. (2009) for an earlier contribution to this journal.

A similar model is applied in Wang et al. (2015, in this issue), except that R and S are replaced by I and J. When migrants originating from I countries enter Europe, which destinations do they choose from J (Nuts 1) regions? According to the authors, this depends on cultural diversity and cultural distance, among many other control variables. The first cultural variable is measured by a simple index of fractionalization, while the second cultural variable is derived from a questionnaire among 1,935 migrants composed of 116 questions, which are first reduced to 29 principal components and then used to measure the cultural distance between the countries of origin and the regions of destination. Full details of the applied formulas are in the paper. The authors were also so kind as to make the Matlab code of their routines available. There are available in an online appendix. The estimation model consists of two stages. In the first stage the destination region chosen by each migrant is explained by a multidimensional logit model, where the attractiveness of a region is modelled as function of the two mentioned cultural variables. Since these variables might be endogenous, they are instrumented in the second stage, not in the usual way but by an artificial approach taken from Bayer et al. (2004). One concern is that the work of Bayer et al. has not been published in a peer-reviewed journal, but only appeared as an NBER paper. Fortunately, the authors also carried out tests to show that their instruments are valid (relevant and exogenous) and that the application of IV significantly affects the estimation results. All in all, this is a highly relevant paper, since migration is high on the political agenda at the moment due to the recent influx of migrants from Syria and 'neighbouring' countries.

Missing data is a problem in many empirical studies, especially in spatial econometric studies, since the impact of spatial interaction effects can only be estimated if all spatial units are in the sample. If spatial units are missing, the specification of the spatial weights matrix describing the arrangement of the units in the sample is often meaningless. Panzera et al. (2015, in this issue) propose a Bayesian approach to obtain likely values for missing data using Besag's (1974) conditional autoregressive (CAR) model. Their argument for adopting this model is that it does not entail any loss of generality because any Gaussian distribution on a finite set of sites can be expressed as a CAR process. They present both a univariate and multivariate version of this model. Unfortunately, they do not clearly point out whether their Bayesian approach can be used for both randomly and non-randomly missing data. From their empirical illustration of Verdoorn's law, however, it appears that their proposed method not only works in the first case but may also work in the second case.

To judge the performance of the Bayesian approach, Panzera et al. do not make the mistake of focusing only on the parameter estimates. They consider the direct and indirect effects estimates. If the parameter of the spatially lagged dependent variable is over or underestimated, the parameter estimates of the independent variables (X) and of the spatially lagged independent variables (WX) may compensate for this, such that the direct and indirect effects, which are composed of these underlying parameters, are still close to their true values. This is a new insight that has only recently been documented by LeSage & Pace (2015). Just like Wang et al., Panzera et al. were so kind as to make their data and software code of their routines available. This is a new policy of *Spatial Economic Analysis*; authors are encouraged to submit supplemental data and programming sources for online-only publication alongside their article.

The final paper by Gomez-Antonio et al. (2015, in this issue) is a perfect illustration of the difficult relationship between economic theory and the theory behind spatial econometrics on the one hand and applied empirical research on the other. The topic of this paper is urban sprawl. Thanks to new and advanced data, the authors are able to measure urban sprawl as the percentage of open space in the square kilometre surrounding each average residential development. Next, they discuss an economic-theoretical model explaining the urban expansion of cities which, due to supposed strategic interaction among cities, results in a spatial lag model; that is, a linear regression model extended to contain a spatially lagged dependent variable (WY). To test whether the empirical specification derived from the theoretical model might be different from the true model, the authors initially consider a spatial Durbin model; that is, a linear regression model extended to contain a spatially lagged dependent variable (WY) and spatially lagged independent variables (WX). The advantage of this model is that the indirect effects (read: spatial spillover effects) can take any value, whereas this flexibility gets lost when adopting the simpler spatial lag model. In the latter model, the ratio between the indirect and direct effects is the same for every explanatory variable (Halleck Vega & Elhorst, 2015). This can be clearly seen from Table A1 in the appendix of the paper by Gomez-Antonio et al. The ratio between the indirect and direct effects respectively reported in the lower and the upper panels of column 3a all amount to approximately 0.5. In addition, ten variables turn out to produce significant spatial spillover effects. This picture changes completely when considering column 5a and the ratios between the indirect and direct effects are flexible. In this case six variables turn out to produce significant spatial spillover effects. More than that, only three variables in both columns overlap each other. Seven variables producing significant spillovers in the spatial lag model do not in the spatial Durbin model. Conversely, three variables producing significant spillovers in the spatial Durbin model do not in the spatial lag model. Apparently, the choice of model is a crucial issue. The authors eventually reject the spatial Durbin model estimated by maximum likelihood (ML) in favour of the spatial lag model estimated by generalized spatial two stage least squares based on the arguments that ‘the structuring of generalized spatial two stage least squares makes it effectively impossible to fit a spatial Durbin model’ and that ‘this estimator has significant advantages over ML estimation since it does not require any distribution-related assumptions and often turns out to be less sensitive to model misspecification’. See here the tension between theory and practice. We leave it to the readers to determine their preference.

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