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EDITORIAL

Advances in spatial economic data analysis: methods and applications

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ABSTRACT

Spatial economic studies traditionally exploit areal data at the regional or sub-regional level. More recently, scholars have started to exploit spatial data of a different nature and, at the same time, extend the fields of application in economics. Specifically, this special issue contributes to the spatial economic literature by providing empirical evidence on a wide range of phenomena (socio-economic deprivation, land price volatility, electoral competition, real estate market, firm survival and tourism economics) and exploiting data at the municipality, firm, house and even individual level. At the same time, it tackles some of the methodological issues faced by the above-mentioned analyses.

KEYWORDS
spatial economic data, spatial methods, areal data, geocoded data, GPS data

JEL C21, C31, R12, R3
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INTRODUCTION

Spatial analysis in empirical economics is traditionally oriented to explore areal data at the regional or sub-regional level. Typical contexts in which spatial analysis is applied include convergence analysis, agglomeration economies, business demography and labour markets (e.g., Arbia et al., 2008; Espa et al., 2014; Halleck Vega & Elhorst, 2014, 2017; Piacentino et al., 2017a, 2017b).

More recently, the spatial economic literature has extended its investigation to many other fields, driven by the availability of data of a very different nature. Indeed, the big data revolution (Arbia, 2021; Morrissey, 2020) has made available to researchers and practitioners a wide variety of data coming from many unconventional sources, offering previously inconceivable research opportunities with more to follow in the future. Among these it is worth mentioning register data, counter data, crowdsourcing, webscraping, Global Positioning System (GPS), data streaming, satellite and aerial photographs, information obtained through drones, mobile phone data, internet of things, and many others. This new context has the potential to revolutionize spatial economic analysis. Indeed, the availability of new detailed geographical databases now makes it possible to model individuals' economic behaviour in space to gain information about economic trends at a regional or macro-level. In fact, a spatial microeconometric approach, which was

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unconceivable until only few decades ago, is now increasingly feasible due to the increasing availability of very large georeferenced databases in all fields of economic analysis (Arbia et al., 2021).

Examples of this kind can be increasingly found in all branches of economics, including education, health economics, agricultural economics, labour economics, political economy, environmental economics, industrial economics, firm demography, house/land prices, tourism economics, technological diffusion, and many others.

New challenges at the methodological level are typical of the new typologies of data that are becoming available. These range from the treatment of large data sets in spatial models, to the problem of sampling from georeferenced populations (Tillé et al., 2018) and to the presence of measurement errors, missing data, and intentional and unintentional locational errors (Arbia et al., 2016).

THIS ISSUE

This special issue has the ambition to show the potential of novel approaches and techniques that can be introduced to face some of the many important methodological challenges deriving from the new big-data world and from the increasing availability of data for spatial economic researchers. It also introduces some of the novel fields of application which are becoming popular in the economic analysis exploiting the newly available typologies of spatial data.

The first three articles in this special issue (Cartone & Postiglione, 2021, in this issue; Nguyen et al., 2021, in this issue; Sato & Matsuda, 2021, in this issue) exploit areal data at a fine spatial scale. They propose novel methods and approaches to investigate economic phenomena such as price volatility, electoral competitions and socio-economic deprivation.

More specifically, Cartone and Postiglione (2021, in this issue) introduce a novel approach to the principal component analysis (PCA) for spatial data. The approach is based on the use of spatial filtering. The introduction of spatial techniques to multivariate methods such as PCA is particularly important from a policy perspective. These methods allow researchers to obtain composite indicators for multivariate phenomena, and this may substantially support the planning of social and economic policies. If the spatial nature of data are not considered, this kind of analysis may lead to serious misspecification problems and inappropriate interpretation. Cartone and Postiglione apply their empirical approach to the case of socio-economic deprivation in the province of Rome. Through their approach, they show how isolating the spatial components supports the quantification of the magnitude of the neighbourhood component of material deprivation.

Sato and Matsuda (2021, in this issue) propose a spatial version of the GARCH model (S-GARCH) to describe volatility behaviour in spatial data. The S-GARCH model can assess volatility clusters and spatial spillovers across geographical units. The authors adopt a two-step procedure based on quasi-likelihood functions to avoid biased estimates. From an economic analysis point of view, this model could be particularly useful for exploring price data and the spatial impact of potential shocks. Indeed, the authors apply their methodological proposal to land-price data in areas of Tokyo and evaluate the impact of the 2011 Tohoku earthquake and tsunami. Two particularly interesting features emerge from this application. First, some spatial volatility clusters are found. Second, the tsunami shock from the earthquake has generated high volatility in regions located far from the coast.

Next, Nguyen et al. (2021, in this issue) introduce a simultaneous autoregressive model for spatial compositional data. They adopt an estimation procedure based on two-stage (S2SLS) and three-stage (S3SLS) least squares which controls for both spatial correlation and correlations across equations. These models can be applied to several fields where data are expressed by shares observed across space (e.g., land use, geochemistry, etc.). The authors apply their model to the field of political economics, exploring the vote share data of the 2015 French departmental election. They find that spatial dependence is significantly present in the electoral competition under study.

The last three articles in this issue (Abbruzzo et al., 2021, in this issue; Piacentino et al., 2021, in this issue; Santi et al., 2021, in this issue) exploit spatial microdata to investigate other phenomena such as agglomeration economies and firm performance, real estate market and tourism demand. Like the previous articles, some novel approaches and techniques are proposed to overcome problems that may influence the spatial analysis of microeconomic phenomena.

Piacentino et al. (2021, in this issue) provide an application on the survival of accommodation businesses in Sicily. The nature of microdata makes it possible to explore in detail the role of agglomeration economies and geography on the survival probability of firms. In the specific case of the island region of Sicily, the geography is expected to assume a strategic role. Indeed, it is found that the risk of exit from the market increases for those firms located farther than 2 km from the coast. Spatial data at firm level also allows researchers to construct accurate measures of both localization and diversification economies. The empirical results show a negative impact of localization (i.e., the spatial concentration of firms operating in the same economic activity) due to, as the authors suggest, a 'congestion effect', and a positive impact of diversification (i.e., the spatial concentration of related industries) on the survival of accommodation businesses.

Santi et al. (2021, in this issue) propose an empirical approach to treat spatial dependence in regression residuals when no information is available about the locations of the units of observations. Consequently, it is impossible to construct any spatial weight matrix, which may bias the estimates based on regression analysis. This situation can occur when spatial micro-data are employed and the locations of units are not available for privacy reasons. The authors provide a practical example based on data from the real estate market in Beijing.

Finally, Abbruzzo et al. (2021, in this issue) explore data extracted from GPS, providing some methodological solutions to the presence of outliers and missing values. This type of spatial data is particularly relevant when investigating social and economic behaviours in local areas. The authors not only propose novel methods for the pre-processing of GPS data, but also a clustering approach to recover the main points of interest and, finally, a weighted-direct network analysis to detect relevant trajectories at an aggregate level. They apply this framework of analysis to tourism economics by exploring three case studies relating to cruise passengers' trajectories in the cities of Palermo, Dubrovnik and Copenhagen.

CONCLUSIONS

Recently, scholars started to exploit new types of spatial economic data providing empirical evidence on a wide range of novel fields of application. Of course, this has brought new challenges at a methodological level. This special issue contributes to the literature with the introduction of some novel economic applications that exploit spatial data at the municipality, firm, house and even individual level. The nature of these data is different not only with respect to the units of observation, but also to the data-collection process (areal, register and GPS data). The economic applications introduced in this special issue range from price volatility to electoral competitions, to real estate market, socio-economic deprivation and tourism economics. Several methodological advancements are also introduced in the articles collected here. The range of novel applications, data, models and methods reported is obviously not exhaustive and many other opportunities and challenges are on the agenda for the spatial economic research community. Among them, effective use of new big-data sources in spatial economic analysis certainly represents one of the most important challenges that both theoretical and applied research will have to face in the near future.

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DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

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