Special Session Proposal

Spatial trends, spatial unit roots, spurious spatial regressions, and Regional Science

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Abstract

There are two general approaches to analyzing spatial data (Bruna, 2024, 2025).

In geostatistics and spatial statistics, a *global-to-local* perspective is typically adopted: global spatial trends are first modeled over the entire sample, and any remaining local spatial dependence is subsequently captured through the structure of the residuals.

In contrast, spatial analysis in the social sciences often follows a *local-to-global* logic. Economic or social theory (Fujita et al., 1999; Brakman et al., 2009) is assumed to account for the global spatial pattern, while residual local dependence is modeled using spatial econometric processes, which, in turn, might create global spillovers.

A key limitation of this latter approach is that it may overlook the presence of global non-stationarities in the spatial distribution of the data. When, for instance, the mean of the variable varies systematically across space, global spatial trends may arise. Ignoring such trends can lead to spurious regression results, in a manner analogous to what is well known in time series analysis.

Recent econometric contributions have explicitly addressed these issues (Fingleton, 1999; Mur & Trívez, 2003; Ezcurra et al., 2007; McMillen, 2010; Lauridsen & Kosfeld, 2011; Yu et al., 2012; Arbia et al., 2013; Montero Lorenzo et al., 2012; Elhorst et al., 2013; Basile et al., 2014; Chasco & Le Gallo, 2015; Guastella & van Oort, 2015; García-Córdoba et al., 2019; Mínguez et al., 2020; Makeienko & Matilla-García, 2024; Müller & Watson, 2024; Baltagi & Shu, 2024). These developments, however, have yet to be systematically incorporated into the standard empirical toolbox of regional and spatial studies.

Extending the notion of spurious regression from time series to spatial or spatiotemporal settings entails a substantial increase in both theoretical and empirical complexity. Unlike time series, areal socio-economic data are not observed at equidistant locations, and spatial dependence unfolds along multiple directions

rather than along a single temporal dimension. Moreover, spatial stationarity involves not only homogeneity in means and variances, but also homogeneity in spatial dependence across directions, that is, isotropy.

This session aims to open a structured discussion on the problem of spurious spatial regressions in Regional Studies, fostering the exchange of ideas on appropriate testing strategies, model specification, and valid inference in the presence of global spatial non-stationarities.

We invite both empirical and theoretical contributions addressing, among others, the following topics:

- Exploratory spatial data analysis with spatial and spatiotemporal non-stationarity
- Case studies about misleading conclusions if non-stationarity is ignored
- Spatial unit root tests: theory, tests, and empirical applications
- Spatial first-differencing and spatial cointegration approaches
- Disentangling spatial autocorrelation and spatial heterogeneity from the perspective of spatial non-stationarity
- Applications using cross-sectional and panel data models, both static and dynamic
- Testing economic and social theories in the presence of global spatial trends
- Modeling strategies for spatial and spatiotemporal non-stationarity
- Semiparametric and geoadditive models
- Software tools for detecting and modeling spatial non-stationarities
- Methodological discussions on the implications of non-stationarity for:
    - estimation of long- and short-run effects in space and time,
    - issues related to MAUP and the change-of-support problem,
    - interactions between data aggregation and non-stationarity
- Links between these topics and influential contributions or ongoing debates in Regional Studies

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