Spatial dependence in (origin-destination) air passenger flows

Romain Doucet & Paula Margaretic [1] & Christine Thomas-Agnan [2] & Quentin Villotta

[1] *6 Impasse du Ramier des Catalans, Batiment B, Appt 202, (31000), Toulouse, France et E-mail: paumargaretic@gmail.com.*
[2] *21 Allée de Brienne, 31015 Toulouse Cedex 06, France et E-mail: christine.thomas@tse-fr.eu*

Résumé. Nous explorons l'estimation des flux de passagers aériens, par paires de villes, afin de prendre en compte explicitement l'autocorrélation spatiale. A notre connaissance, nous sommes les premiers á appliquer des modèles économétriques spatiaux et des approches de filtrage spatial au transport aérien. S'appuyant sur un échantillon mondial de 279 villes sur la période de 2010 à 2012, nous trouvons des preuves significatives d' autocorrélation spatiale dans les flux de passagers aériens. Ainsi, et contrairement à la pratique courante, nous devons intégrer la structure spatiale existante dans les données lors de l'estimation des flux de passagers aériens. Il est important de souligner qu'une erreur dans cette démarche peut conduire à des coefficients estimés inefficaces et des biais dans les prédictions.

Mots-clés. Autocorrélation spatiale, modèles économétriques spatiaux, filtrage spatial, flux de passagers aériens

Abstract. We explore the estimation of origin-destination (OD), city-pair, air passenger flows, to explicitly take into account spatial autocorrelation. To our knowledge, we are the first to apply spatial econometric OD flow models and eigenfunction spatial filtering approaches to air transport. Drawing on a world sample of 279 cities over 2010-2012, we find significant evidence of spatial autocorrelation in air passenger flows. Thus, contrary to common practice, we need to incorporate the spatial structure present in the data, when estimating OD air passenger flows. Importantly, failure to do it may lead to inefficient estimated coefficients and prediction bias.

Keywords. Spatial autocorrelation, spatial econometric flow models, eigenfunction spatial filtering, air passenger flows

1 INTRODUCTION

This paper investigates the estimation of origin-destination (OD) air passenger volume. Our interest is to estimate air passenger traffic from one city to another. Among the factors that make a city attractive for passengers, the literature has mainly focused on the size of the city population and its socioeconomic development, as measured, for example, by income per capita. However, much less attention has been given to the spatial dependence among these factors.

Spatial dependence means the co-variation of factors within a geographic space. In our context, this implies that the characteristics at proximal cities may impact air passenger flows, between two cities.[1] Because spatial dependence violates the typical independence assumption made in regression analysis, our aim is to study whether and how spatial dependence plays a role, when estimating OD air passengers. Importantly, failure to properly account for spatial dependence, when it exists, may lead to inefficient estimated coefficients and prediction bias, among others.

Our paper has three main motivations. The first one is empirical: Spatial interaction models focus on OD flow data. Among them, gravity models have been extensively used, with numerous applications in trade, migration and air transportation.[2] The main particularity of gravity models is that they rely on a function of the distance between origin and destination (together with characteristics of both origins and destinations), assuming that distance can effectively eliminate the spatial dependence potentially present in OD flow data.

However, numerous investigations have challenged this assumption, both theoretically and empirically.[3] A prolific strand of literature has emerged, proposing alternative ways to extend spatial gravity models to account for spatial dependence. On the one hand, within the spatial econometric methods, LeSage and Pace (2008) propose to incorporate spatial autoregressive dependence (spatial lag), while Dubin (2003) works with a spatially autocorrelated error term (spatial error).[4] On the other hand, several authors, like Fischer and Griffith (2008 and 2013) and Chun and Griffith (2011) apply eigenfunction spatial filtering methodologies to account for spatial dependence.[5] Our motivation is to contribute to this debate and assess whether these forms of spatial structure play any role, when estimating OD air passenger flows.

Second, from an applied point of view, being able to predict the number of air passengers between two cities at a given point in time is of major importance both for aircraft manufacturers and airlines. Aircraft manufacturers, such as Airbus, rely on this type of

[1] See LeSage and Pace (2008) for a discussion.

[2] Taafe (1962) has been the first to apply a gravity model to analyse air passenger flows. Bhadra and Kee (2008), Doganis (2004), Jorge-Calderon (1997) and Russon and Riley (1993) are other examples of the application of gravity models to air transport. See Grosche *et al.* (2007) for a literature review.

[3] Curry (1972) has been the first to argue that spatial autocorrelation effects are confounded with distance decay effects during the estimation of gravity model parameters. In turn, using journey-to-work data, Griffith and Jones in 1980 show that spatial autocorrelation matters. Tiefelsdorf in 2003 arrives to the same conclusion, using migration flow data.

[4] See also Dubin (2004) and LeSage and Pace (2004 and 2010).

[5] Eigenfunction spatial filtering relies on a spectral decomposition of a spatial weight matrix into eigenvalues and eigenvectors and then uses a subset of these eigenvectors as additional explanatory variables in the model specifications. See also Chun (2008) and Griffith (2009), among others. Section 2 provides more details.

modeling to assess the future demand for civil passenger and freighter aircraft, which in turn, steer them towards innovation. Airlines also need these models to decide whether to open new routes, offer more frequencies and/or increase aircraft capacity.

Finally, from a policy standpoint, better predicting OD air passengers can also be useful for airport planners, government and non-government agencies and air transport and economic policy-makers world-wide. As an illustration, since the 1979 Airline Act Deregulation in the US, there has been a global trend towards liberalisation of air travel in Europe, Asia and Latin America. There is now a strong need to evaluate the impact of these regional measures on air traffic. Properly accounting for spatial interactions can help us better evaluate the effect of these policies.

Drawing on a sample of 279 cities around the world over the period $2010 - 2012$, we first apply the traditional gravity model to estimate air passenger flows. Interestingly, we consider both the log-normal additive and the Poisson gravity model. Second, inspired by LeSage and Pace (2008) and Fischer and Griffith (2008), we apply the spatial autoregressive and the eigenfunction spatial filtering approach and modify the gravity model to account for spatial dependence.

To our knowledge, we are the first to apply these two effective approaches that account for spatial dependence to air transport.[6] Another virtue of our application is that the dataset is global, that is, the 279 cities belong to the five continents.

We estimate five spatial specifications. Based on likelihood ratio tests and informational criteria, we conclude that any of the spatial specifications considered here is better than the gravity model specification assuming independence. Crucially, this conclusion holds both for the log-normal additive and the Poisson gravity model.

This result has two key implications. First, we need to incorporate the spatial patterns of the geographical phenomena, when analysing OD air passengers. Second, despite the common practice, least-square estimates and inferences that ignore this spatial dependence in air transport seem not to be justified.

The paper closest to ours are LeSage and Pace (2008) and Fischer and Griffith (2008). The former proposes a way to incorporate spatial autoregressive dependence to the traditional gravity model. We apply their technical results to air transport and conclude that spatial dependence matters when estimating air passenger flows. Fischer and Griffith (2008), in turn, outline and compare the spatial econometric and the eigenfunction spatial filtering approach, as we do; but instead of focusing on spatial autoregressive dependence, they work with a spatially auto-correlated error term. They illustrate the comparison with patent citation flow data.

[6] By calibrating a gravity model for 100 American cities in 1970, Fotheringham (1981) shows evidence of the relationship between distance decay parameters and the size and configuration of origins and destinations. Boros *et. al* in 1993 test the presence of spatial autocorrelation, using data on daily flights for nine main airlines operating in US domestic market in 1992.

Bibliographie

[1] Anselin L (1988) *Spatial Econometrics: Methods and Models.* Kluwer Academic Publishers, Dordrecht.
[2] Anselin L, Arribas-Bel D (2013) Spatial fixed-effects and spatial dependence in a single cross-section. *Papers in Regional Science* 92 (1): 3-17.
[3] Beer C, Riedl A (2012) Modelling spatial externalities in panel data: The Spatial Durbin model revisited. *Papers in Regional Science* 91 (2): 299-318.
[4] Bhadra D, Kee J (2008) Structure and dynamics of the core US air travel markets: A basic empirical analysis of domestic passenger demand. *Journal of Air Transport Management* 14 (1): 27-39.
[5] Boros A, Lee J, Shaw S L (1993) Analysis of network structure for US domestic airline networks. *Papers and Proceedings of Applied Geography Conference* 16: 136-143.
[6] Chun Y (2008) Modeling network autocorrelation within migration flows by eigenvector spatial filtering. *Journal of Geographical Systems* 10 (4): 317-344.
[7] Chun Y, Griffith DA (2011) Modeling network autocorrelation in space-time migration flow data: an eigenvector spatial filtering approach. *Annals of the Association of American Geographers* 101 (3): 523-536.
[8] Curry L (1972) Spatial analysis of gravity flows. *Regional Studies* 6: 131-147.
[9] Doganis R (2004) *Flying Off Course: The economics of international airlines.* Routledge, London, New York.
[10] Dubin R (2003) Robustness of spatial autocorrelation specifications: some Monte Carlo evidence. *Journal of Regional Science* 43 (2): 221-248.
[11] Dubin R (2004) Spatial lags and spatial errors revisited: Some Monte Carlo evidence. *Advances in Econometrics* 18: 75-98.
[12] Fischer M M, Griffith D A (2008) Modeling spatial autocorrelation in spatial interaction data: an application to patent citation data in the European Union. *Journal of Regional Science* 48 (5): 969-989.
[13] Fischer M M, Griffith D A (2013) Constrained variants of the gravity model and spatial dependence: model specification and estimation issues. *Journal of Geographical Systems* 15 (3): 291-317.
[14] Fischer M, LeSage J (2010) Spatial econometric methods for modeling origin-destination flows. In: Fischer M, Getis A (eds) *Handbook of applied spatial analysis: Software tools, methods and applications.* Springer-Verlag Berlin Heidelberg.
[15] Flowerdew R, Aitkin M (1982) A Method of Fitting the Gravity Model Based on the Poisson Distribution. *Journal of Regional Science* 22 (2): 191-202.
[16] Fotheringham S (1981) Spatial structure and distance-decay parameters. *Annals of the Association of American Geographers* 71 (3): 425-436.
[17] Garrow L (2010) *Discrete choice modelling and air travel demand: theory and applications.* Ashgate Publishing Limited, England, and Ashgate Publishing Company, USA.

[18] Goulard M, Laurent T, Thomas-Agnan C (2013) About predictions in spatial autoregressive models: Optimal and almost optimal strategies. *Toulouse School of Economics Working Paper* 13 (452).
[19] Griffith D A, Jones K G (1980) Explorations into the relationship between spatial structure and spatial interaction. *Environment and Planning A* 12 (2): 187-201.
[20] Griffith D A (2007) Spatial structure and spatial interaction: 25 Years Later. *The Review of Regional Studies* 37(1): 28-38.
[21] Griffith D A (2009) Modeling spatial autocorrelation in spatial interaction data: empirical evidence from 2002 Germany journey-to-work flows. *Journal of Geographical Systems* 11 (2): 117-140.
[22] Grosche T, Rothlauf F, Heinzl A (2007) Gravity models for airline passenger volume estimation. *Journal of Air Transport Management* 13: 175-183.
[23] Jorge-Calderon J D (1997) A demand model for scheduled airline services on international European routes. *Journal of Air Transport Management* 3 (1): 23-35.
[24] Kockelman K M, Wang X, Wang Y (2013) Understanding spatial filtering for analysis of land use-transport data. *Journal of Transport Geography* 31: 123-131.
[25] LeSage J P, Pace R K (2004) Spatial and spatiotemporal econometrics. *Advances in econometrics* 18: 1-32.
[26] LeSage J P, Pace R K (2008) Spatial econometric modeling of origin-destination flows. *Journal of Regional Science* 48 (5): 941-67.
[27] LeSage J P, Pace R K (2009) *Introduction to spatial econometrics.* CRC Press.
[28] LeSage J P, Pace R K (2010) Spatial econometric models. In: Fischer M, Getis A (eds) *Handbook of applied spatial analysis: Software tools, methods and applications.* Springer-Verlag Berlin Heidelberg.
[29] LeSage J P, Thomas-Agnan C (2014) Spatial econometric origin-destination flow models. In: Fischer M, Nijkamp P (eds) *Handbook of Regional Science.* Springer: 1653-1673.
[30] Patuelli R, Griffith D, Tiefelsdorf M, Nijkamp P (2011) Spatial Filtering and Eigenvector Stability: Space-Time Models for German Unemployment Data. *International Regional Science Review* 34 (2): 253-280.
[31] Taaffe E (1962) The Urban Hierarchy: An Air Passenger Definition. *Economic Geography* 38 (1): 1-14.
[32] Tiefelsdorf M (2003) Misspecifications in interaction model distance decay relations: A spatial structure effect. *Journal of Geographical Systems* 5: 25-50.
[33] Tiefelsdorf M, Griffith D A (2007) Semiparametric filtering of spatial autocorrelation: the eigenvector approach. *Environment and Planning* 39 (5): 1193-1221.