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CONTRIBUTIONS TO SPATIAL ECONOMETRICS

Introduction

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Section INTRODUCTION

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Contributions to spatial econometrics: non-linearity, causality and empirical applications

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ABSTRACT: This introduction summarizes the main contributions of the papers selected to be published in this special issue. These papers were presented (among others) in the Fourth Seminar Jean Paelinck hold in Oviedo (Spain) in 2010 and their quality justified the edition of this Special Issue. As members of the organizing committee, we are pleased with the results of this Seminar which it is considered as a reference in the spatial econometric field.

This special issue consists of two types of contributions. On the one hand, papers focus on the development of new methodologies linked to the concept of causality in spatial econometrics and, on the other hand, applied contributions where different economic problems are analyzed from a spatial or spatio-temporal perspective.

JEL Classification: C01-C21-C31.

Keywords: Spatial econometrics, econometric modeling, causality.

Contribuciones a la econometría espacial: no linealidad, causalidad y aplicaciones empíricas

RESUMEN: Esta introducción trata de resumir las principales contribuciones de los artículos que finalmente han sido incluidos en este número especial. Estos trabajos formaron parte (junto con otros) del Fourth Seminar Jean Paelinck celebrado en Oviedo (España) en 2010 y la calidad de los mismos justifica la edición de este número especial de *Investigaciones Regionales.* Nos congratula, como responsables de la organización en Oviedo y como participantes en las ediciones precedentes, que este Seminario se haya convertido en un referente nacional e internacional en el ámbito de la econometría espacial.

Este número especial consta de dos grandes conjuntos de trabajos. Por un lado, trabajos que recogen nuevas propuestas metodológicas vinculadas a la idea de causalidad en econometría espacial y, por otro, trabajos aplicados en los que se analizan diferentes problemas económicos desde una óptica espacial o espacio-temporal.

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Clasificación JEL: C01-C21-C31.

Palabras clave: Econometría espacial, modelos econométricos, causalidad.

In social sciences it is a given that economic agents operate in space and time.The concreteness of economic phenomena binds what happens at a given time to what has happened in the past and, in turn, allows the former to influence the future. Also, what happens in a given location is partly the result of influences from other locations, and generates externalities in them.

That simple fact needs to be included in prospective theoretical and empirical models. Therefore, econometric techniques must also respond to this reality, and achieve in their analyses a necessary, albeit difficult, balance between simplification and fidelity to the facts, that is to say,complex spatial relationships have to be included in the models.

Over the last 30 years, the increase in theoretical and applied research that explicit the spatial phenomenon has led to substantial continuous development in the field of spatial econometrics.

The papers presented at the *Jean Paelinck* seminars have contributed to the said development. The last edition of the seminar, with «Nonlinearity and Causality in Spatial Econometrics» as theme, was held at the University of Oviedo in 2010 (October 22-23). There were presented new methodological approaches and applications to different areas of regional economics.

In this special issue, two groups of contributions may be clearly distinguished: papers which collect new methodological approaches related to causality in spatial econometrics, and applied research papers in which diverse economic issues are studied from a spatial or time-spatial perspective.

The following papers propose new methodologies to overcome the limitations of commonly used techniques in certain contexts (causality, non-linearity, heteroskedasticity, etc.).

The first paper in this special issue, by Professor Jean Paelinck himself, tackles the topic of non-linearity and its measurement by means of a new statistic, the peakiness index. The paper, whose starting point is the «complexity index», presents results related to the former index, and shows the relation between both indices using data from France.

Pinske and Slade (2010) have brought up some of the issues spatial economics may address in the next years, among them the development of non-parameteric and semiparametric alternatives for identifying spatial dependence patterns. Along this line, F. A. López, A. Artal and M. Luz Maté analyze the size and revise the characteristics of three non-parametric tests: Brett and Pinkse (1997), Ku (2009) and SG (2010). Their behavior is compared to that of traditional tests with data having nonlinear spatial structure (Moran), and the authors conclude that the behavior of the former is better than that of the latter.

Angulo and Mur analyze the performance of the common factor likelihood ratio test —a parametric alternative— in the presence of non-ideal conditions.Montecarlo simulations show that the size of the test is quite adequate with the exception of bidirectional causality. In what concerns the power of the test, the results are good when causality is considered. All in all, the test may be deemed useful in the specification of spatial econometric models.

The definition of the spatial weight matrix has been widely discussed in the literature. Fernández's paper follows this line and proposes not to impose the elements of the spatial matrix but estimate them by cross-entropy (CE) econometrics. The results show that maximum entropy estimates outperform classical estimates, especially when the specification of the weights matrix is dissimilar to the actual.

Timo Mitze analyzes the role of globally cointegrated variable relationships using German regional data (NUTS 1 level) for GDP, trade, and FDI activity during the period 1976-2005. A Spatial Panel Error Correction Model (SpECM) for regional output growth is applied to analyze the short and long-run impacts of internationalization activities. The results point out the importance of both direct as well indirect links between variables in the long-run.

Several authors have recently revised the models selection strategies used in spatial econometrics. Along this line, P. Burridge asserts in his paper that the prevailing specific-to-general strategies may be inefficient under certain conditions. Furthermore, the existence of heteroskedasticity in spatial data is usually overlooked, which in turn may cause inefficiency problems. The author proposes a nested spatial regression model which incorporates heteroskedastic shocks, and discusses the hypothesis testing both nested and non-nested cases in a quasi-likelihood framework.

Diverse economic issues are tackled in this special issue using the most up to date spatial econometric techniques. The papers aim to show the usefulness of spatial econometric models beyond the academia, so that they may well be taken into account in the design of economic policies.

P. Suárez, M. Mayor and B. Cueto use local spatial autocorrelation measures so as to analyze whether the accessibility to public employment offices is equitable in Spain according to the distribution of three different types of municipalities: large urban, small urban and non-urban. An empirical model is estimated including spatial regimes apply for the different type of municipalities and allowing simultaneously spatial heterogeneity and spatial autocorrelation. The results suggest a negative relation between accessibility and unemployment rates in non-urban areas.

The relation between accessibility and local development in the Spain-Portugal cross-border area is analyzed by A. Ribeiro and J. Silva. The novelty of their approach lies in the inclusion of spatial effects between neighboring regions belonging to different countries.

The impact of noise on housing prices in Madrid is analyzed by J. M. Montero, R. Mínguez, and G. Fernández. In their paper, they use GIS infrastructure to define acoustic areas, and then estimate the impact of noise on housing prices by means of a traditional hedonic model which takes into account the existence of spatial dependence. The authors have resorted in this case to the spatial Durbin model (SDM), and computed the direct, indirect and total effects following LeSage and Pace (2009). As the authors themselves assert, the hedonic theory is not borne out by the approach, which suggests a design problem in the acoustic areas.

Aliaga *et al.,* consider the possibility of using solely spatial data to detect causal relationships between physical and social factors, and deforestation. They have based their strategy on a sequence of Lagrange multipliers, and the results obtained suggest that the structure of property rights has the greatest causal impact on deforestation.

The dynamic domestic effects of public infrastructures in Spain are estimated using the spatial vector autoregressive (SpVAR) methodology by M. A. Márquez, J. Ramajo and G. J. D. Hewings. The estimated SpVAR is used to calculate impulse responses that provide insights about the effects of shocks to relative regional productive capacity on differentregions.

Angulo *et al.,* revisit the utility of gravity models for analyzing the main determinants of exports. Specifically, the effect of the omitted variables and the dynamics of trade flows are analyzed by means of spatial econometrics techniques in a panel data framework.

Finally, we would like to thank all those who have taken part in the seminar in any of its editions. Thanks also should go to the authors and referees who have contributed to the writing and editing of this special issue, which would not have ever been possible without the devoted support of many others, particularly the editor-in-chief of *Investigaciones Regionales*, Juan R. Cuadrado, and the managing editor, Andrés Maroto. This special issue has also been supported by the Spanish Department of Science and Innovation (ECO2009-07408) and the regional Strategy for Science, Technology and Innovation in the Principality of Asturias (PCTI-FICYT- CNG10-24).

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ON THEORY AND METHODS

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Section On theory and methods

On Some Analytical Statistics for Geographic Patterns: From Non-linearity to Linearity

Jean H. P. Paelinck *

ABSTRACT: In Getis and Paelinck (*L'Espace Géographique, 2004, No 1*) some analytical indices for geographic patterns were proposed; one of them was a Chaitin conditional complexity index, *c*, based on the observed coordinates. This index was reanalyzed, and showed a large variability as a function of those coordinates. A new index of «peakiness», *p*, is proposed, tested, and applied to French data relating to «upper» employment in 37 areas of the Rhône-Alpes region (centered around Lyons).

JEL Classification: C0, R1.

Keywords: Complexity, concentration, patterns.

Algunos estadísticos para los patrones geográficos: de lo no lineal a lo lineal

RESUMEN: Getis y Paelinck (*L'Espace Géographique, 2004, N.º 1*) proponen algunos indicadores analíticos apropiados para analizar los patrones geográficos. Uno de ellos consiste en un índice de complejidad condicionada tipo «Chaitin» (*c*) basado en las coordenadas geográficas observadas. Este índice ha sido estudiado posteriormente mostrando una gran variabilidad en función de dichas coordenadas. En este artículo se propone un nuevo índice de «*peakiness*» (*p*) y se analiza su comportamiento utilizando para ello las cotas superiores de empleo de 37 áreas de la región francesa de Rhône-Alpes (en los alrededores de Lyon).

Clasificación JEL: C0, R1.

Palabras clave: Complejidad, concentración, estructuras.

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1. Introduction

In Getis and Paelinck (2004) a series of analytical indices for geographic patterns were proposed, i.a. characteristics of spatial statistical distributions, concentration and dispersion indices, geophenograms, cluster indicators.

In this paper one indicator will be taken up again, to wit a conditional complexity index, of which the spatial behavior will be studied; as unexpected characteristics creep up, another index will be developed, which takes into account «peakiness» of geographical space.

Next sections will be devoted to those topics, with conclusions and references following.

2. Conditional complexity analysis

An index of conditional complexity (Chaitin, 1975; Wolfram, 2002, pp. 552 a.f.) can be defined as:

$$c = (t - 1)/(t_{max} - 1) \tag{1}$$

were t is the number of non-zero terms of a polynomial, $p(x,y)$, in coordinates x and y, and t_{max} their maximal number, in fact the number of observations; obviously $0 \leq c \leq 1$.

A special aspect of interest is the presence of a certain number of «peaks», so a case was set up with 25 points randomly scattered (Figure 1 and Table 1); the left hand column lists the abscissae, the right hand one the ordinates.

Figure 1. Coordinates

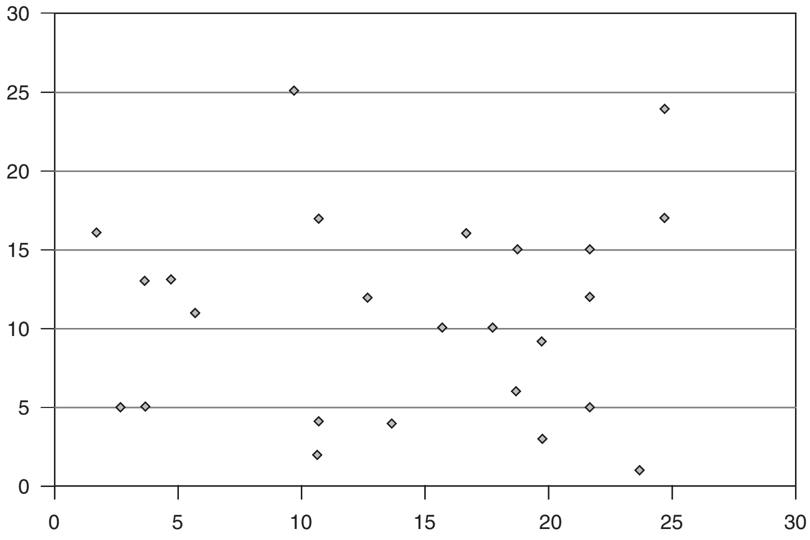

Table 1. Coordinates

x	y
3	5
11	2
13	12
22	15
22	5
20	3
25	24
10	25
22	12
2	16
4	13
25	17
20	9
6	11
17	16
19	6
4	5
24	1
16	10
18	10
19	15
5	13
14	4
11	4
11	17

To compute the complexity index, a system of 25 linear equations has to be solved in order to derive the polynomial coefficients; its degree here is 6. If every location gets the same mass - e.g. 1 - only the constant of the polynomial is non-zero, and $c = 0$; but if the whole mass of 25 is located in one point, the results may differ considerably, as Table 2 shows.

Table 2. Some results

Observation	*t*	*c*
1	2	0.0417
3	25	1
7	17	0.7083
8	15	0.6250
18	18	0.7500

The observation numbers correspond to the rows of Table 1. The diversity in results is due, on the one hand to the values of the coordinates, on the other to the non-linearity of the polynomial; the most curious case is that of observation 1, where a sort of discrete Dirac function could be described by only 2 polynomial terms, hence the search for a complementary indicator for «peaky» landscapes.

3. A new spatial pattern indicator

Indeed, observed spatial patterns are often non-smooth, in the sense that a few extremely high values of the variable analyzed are present at some (random) locations, amidst an overwhelming majority of relatively lower values; Figure 2 further down is an excellent illustration of this fact. It has incited to develop an appropriate indicator for such situations; the proposed indicator is the following one:

$$p = \left[\sum_i m_j^k - n(m/n)^k\right] \big/ \left[m^k - n(m/n)^k\right] \tag{2}$$

where the m_i are different masses, m the total mass, n the number of locations, and $k > 1$, the latter characteristic allowing possibly present peaky masses to dominate smaller ones. Obviously, if the whole mass is concentrated in one point, $p = 1$; in case of a homogeneous spread, $p = 0$. For the case of 25 locations with 5 peaks of 5 units each, and $k = 1.1$, $p = 0.4599$, which still shows a fair degree of «peakiness».

Table 3 shows some «peakiness» indices for different locations, three concentrated and the last one dispersed; peakiness is generally high.

Table 3. Peakiness indices for different «peaky» situations

Observations	*p*
3, 15, 19, 20, 24	1
5, 6, 13, 16, 18	1
10, 11, 14, 22, 25	.7083
1, 7, 8, 12, 18	.7500

The logic of the indicator has been exposed above; the real test of its analytical power resides in its application to empirically observed situations, as will be done hereafter.

4. Application to French data

In Coutrot, Paelinck and Sallez (2009) a spatial econometric study was made of the dynamics of locations of «advanced» employment in urban areas of South-Eastern France, the so-called «Rhone-Alpes» region; the method used was that of potentialized partial finite difference equations. Table 4 reproduces the data, Figure 2 the regions and Table 5 hereafter gives the c- and p-values for three years.

Table 4. «Upper» urban employment of *37 French urban areas, employment in 1982, 1990 and 1999; longitudes and latitudes*

French urban areas	*1982*	*1990*	*1999*	*Long*	*Lat*
Lyon	43,364	65,004	75,935	4.84	45.75815
Grenoble	15,891	22,612	28,202	5.72046	45.18487
Saint-Etienne	5,284	7,228	8,084	4.42236	45.42559
Genève(CH)-Annemasse	981	2,640	2,933	6.24884	46.18764
Valence	3,033	4,328	5,008	4.91851	44.92424
Chambéry	2,656	3,520	4,149	5.91044	45.58507
Roanne	1,440	1,664	1,688	4.08665	46.04374
Saint-Chamond	875	996	1,192	4.51223	45.46843
Thonon-les-Bains	690	1,036	1,037	6.49760	46.37112
Romans-sur-Isère	689	816	1,114	5.04985	45.05926
Villefranche-sur-Saône	1,038	1,408	1,602	4.73478	45.98457
Cluses	925	1,392	1,626	6.58466	46.06109
Montélimar	638	840	955	4.74990	44.55462
Vienne	672	932	1,130	4.88886	45.52256
Saint-Juste-Saint-Rambert	443	688	846	4.25215	45.49209
Voiron	395	636	848	5.58996	45.38055
Sallanges	317	528	604	6.60885	45.93178
Aubenas	365	536	445	4.39640	44.60769
Aix-les-bains	522	780	855	5.91287	45.69171
Annonay	328	464	603	4.6468	45.24522
Roussillon	362	504	430	4.82239	45.38275
Albertville	274	472	471	6.41332	45.66381
Bourgon-Jallieu	497	688	735	5.27602	45.60308

Table 4. *(Continue)*

French urban areas	*1982*	*1990*	*1999*	*Long*	*Lat*
Montbrison	242	368	407	4.07652	45.60295
Privas	249	352	374	4.60051	44.7193
Tournon-sur-Rhône	204	332	270	4.81975	45.0534
Tarare	213	244	343	4.42655	45.90881
Livron-sur-Drôme	98	136	130	4.83280	44.79212
Rumilly	146	204	333	5.94732	45.85452
Saint-Marcellin	172	192	197	5.31961	45.15225
Chamonix-Mont-Blanc	91	160	192	6.93263	45.92758
Saint-Jean-de Maurienne	118	144	239	6.35145	45.27329
La-Tour-du-Pin	116	152	223	5.45322	45.57263
Pierrelatte	539	740	595	4.69467	44.36283
Feurs	167	192	176	4.23356	45.73358
Bourg-Saint-Maurice	85	132	134	6.76867	45.66473

Figure 2. The Rhone-Alpes region and its main urban centers

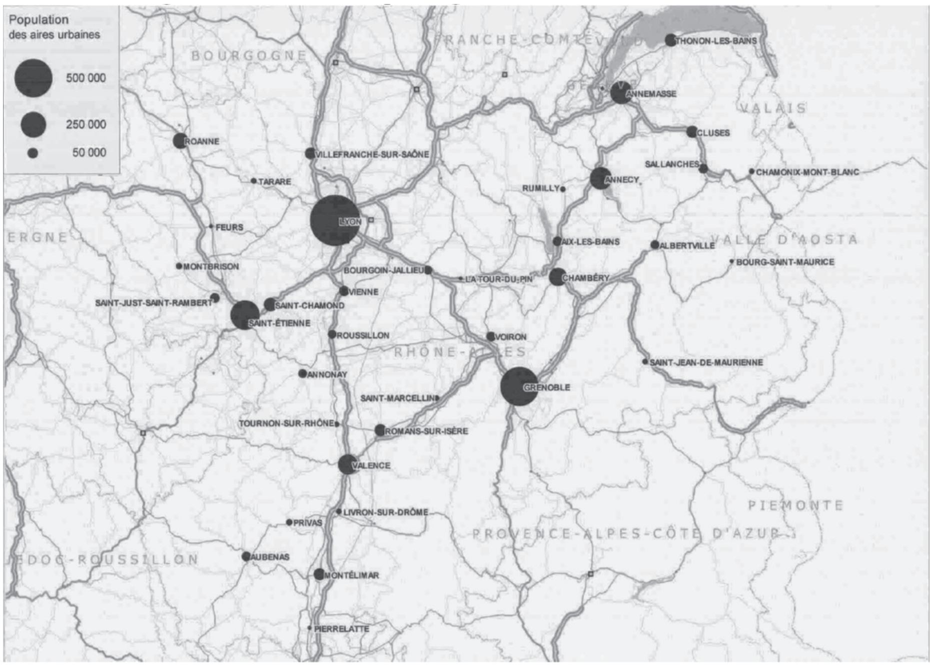

Table 5. *C*- and p-values for the French data

Years	*p*	*c*
1982	0.4411	0.9117
1990	0.4478	0.9117
1999	0.4547	0.8611

One notices a slight increase in the *p*-values, to be compared, for their order of magnitude, with the result shown at the end of section 3; as to the *c*-values, they are systematically high, with a decrease in 1999. These latter values should be compared to the results obtained in section 5 hereafter.

5. An alternative to polynomial complexity

As has been said before, results on complexity are i.a. influenced by the non-linearity of the polynomial; this leads to the idea of investigating a linear variant, and as geographical space is involved, coordinates of the own area and its nearest neighbors in decreasing order could be considered.

That this would not immediately solve the problem can be shown as follows. Translate both coordinates by a same amount, instead of a system matrix **A** one would now have to consider a system:

$$(\mathbf{A} + \lambda \mathbf{J})\mathbf{x} = \mathbf{b}^* \tag{3}$$

where *J* is a full square unit matrix; the solution to the system is now:

$$\mathbf{x} = (\mathbf{I} - \lambda \mathbf{A}^{-1}\mathbf{J}^{-1})\mathbf{A}^{-1}\,\mathbf{b}^* \tag{4}$$

which reduces to the original solution for $\lambda = 0$. So an additional transformation might be to take the values of the deviations to the center of gravity, to generate a quasi-symmetry.

The idea was applied to observations 1, 2, 3, 10, 11 of Table 1 with the following results, total mass having been allocated successively to those observations.

Table 6. Linear complexity analysis

Observation	*c_l: original data*	*c_l: deviations from c.g.*
1	1	1
2	0.6	1
3	1	1
10	1	1
11	0.6	1

One will notice that indeed the deviation method conserves the 0 – 1 complexity. This phenomenon was tested on the data of table 1, and the result was the same for complete concentration in one spot, i.e $c = 1$; that result could be easily inferred from the complete inverse matrix of expression (4), which did not contain a single zero.

Applied to the French data the value of c for the successive years 1982, 1990 and 1999 was invariably 0.9444, showing a higher degree of complexity than the one obtained polynomially (Table 4), which confirms the dominant position of the three major cities: Lyons, Grenoble and Saint-Etienne.

6. Conclusions

The exercises presented concern an additional set of indicators, to be used in a geophenogram manner, as was mentioned earlier.

Linearity and non-linearity problems have been recognized at an early stage in spatial econometric analysis (see e.g. Paelinck and Klaassen, 1979, pp. 6-9); there is some parallel with the ex ante – ex post distinction (ex ante behavioral relations in spatial econometrics are more often than not non-linear, or even non-convex – see for instance the generalized Weber location problem – while ex post resulting flows – e.g. transport flows – can be modeled linearly.

In the present exercise the approach is about what can be called «analytical descriptions»; in some cases they should have a strong non-linear character (see the peakiness index of section 3), while in others linear transformations might be in order (as was the case in section 5).

The real issue is to derive a specification that matches the problem at hand; in the present study it has been tried to demonstrate how analytical descriptions can be appropriately defined as a function of the spatial patterns to be analyzed.

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Section On theory and methods

Identifying nonlinear spatial dependence patterns by using non-parametric tests: Evidence for the European Union

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ABSTRACT: Accounting for spatial structures in econometric studies is becoming an issue of special interest, given the presence of spatial dependence and spatial heterogeneity problems arising in data. Generally, researchers have been employing parametric tests for detecting spatial dependence structures: Moran's I and LM tests in spatial regressions are the most popular approaches employed in literature.However, this approach remains misleading in the presence of nonlinear spatial structures, inducing important biases in the estimation of the parameters of the model. In this paper we illustrate that issue by applying three non-parametrical proposals when testing for spatial structure in data. Empirical findings for the regions of the European Union show important failures of traditional parametric tests if nonlinearities characterise geo-referenced data. Our results clearly recommend employing new families of tests, beyond parametrical ones, when working in such environments.

JEL Classification: C-14, C-63, O-32, R-12.

Keywords: Nonlinear processes, non-parametric tests, spatial dependence, spatial filters, EU regions.

Identificando estructuras espaciales no lineales utilizando test no paramétricos: Evidencias para las Regiones Europeas

RESUMEN: Es cada vez mas frecuente evaluar la presencia de estructuras de dependencia espacial en estudios econométricos cuando se analizan datos de corte

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transversal. La práctica habitual de los investigadores es utilizar tests paramétricos para identificar este tipo de estructuras en los datos y, con diferencia, los dos contrastes más populares son el test de la I de Moran (IM) y el basado en los Multiplicadores de Lagrange (LM). Sin embargo, este enfoque puede ser engañoso cuando en nuestros datos están presentes estructuras de dependencia espacial no lineales. En este trabajo ilustramos esta problemática presentando tres contrastes no paramétricos, alternativos a los clásicos que presentan un mejor comportamiento en presencia de no-linealidades. Una aplicación utilizando diversas variables económicas y filtros espaciales en las Regiones Europeas recomiendan, claramente, utilizar estos contrastes no paramétricos.

Clasificación JEL: C-14, C-63, O-32, R-12.

Palabras clave: Procesos no lineales, contrastes no paramétricos, dependencia espacial, filtros espaciales, Regiones Europeas.

1. Introduction

Spatial models are becoming an important tool in economics, as economists have been rediscovering that geography matters (Anselin, 2010). Research in this area used to begin by applying simple statistics, as Moran's I for example (Moran, 1948), in order to find the presence of a clear spatial pattern in data, and then accounting for it in the subsequent estimation procedure. Nevertheless, traditional parametric statistics, although easy to implement and available in most of the spatial packages, could fail in identifying such correlation patterns in the presence of more complex structures of spatial dependence. As an example, this could be the case when one departs from the linear world, accounting for nonlinear spatial dependence relationships.

Some fields of research have been pioneers in developing nonlinear modeling and accounting for nonlinear relationships in data, given the relevance of obtaining good predictions. Forecasting of exchange rates evolution is one main field in economics where there has been a development of nonlinear methods [1]. The extension of financial crisis is undoubtedly a matter of concern for economists, since the Asian and Latin American turbulences of the 90's, while in recent years has acquired a prominent role fueled by the global financial crisis, which has turned into a sovereign debt crisis. Contagion of financial pressures in the global economy has then become a hot topic in research papers, including nonlinear contagion of financial turbulences leading to national solvency crisis. However, we have just only starting to understand transmission mechanisms of financial and real shocks, and how it affects global financial stability. Extensions of these issues appear of pivotal interest for example for integrated monetary unions as the EU, given that the recent Eurocrisis has unveiled the tough effects that asymmetries between partners can inflict to these areas in case of world financial instability.

Notwithstanding the relevance of the exchange rates topic, the most prominent field of research where we assist to the surge of methodological innovations and de-

[1] See, for example, the early paper of Meese and Rose (1990) on the topic.

partures from the linear world is that one leading with performance of stock markets. Studies focusing in disentangling the presence of nonlinear dependencies in stock returns are becoming very usual in the literature (see, i.e., Hinich and Patterson, 1985). In this field, standard tests of nonlinear dependence have shown strong evidence on the presence of nonlinearities in raw stock returns (Solibakke, 2005). Alternatively, other prominent researchers have been contributing by developing new methods for dealing with nonlinearities in time-series and cross-section modeling, together with neural networks analysis or chaos theory, that have been applied to the study of financial assets behaviour and price formation. As a result, all of these advances have been spilling over the whole profession'smethodological tool-kit, improving our understanding of spatial analysis for socio-economic processes (Lee, White and Granger, 1993).

In this regard,the focus on developing nonlinear models emerges as a clear example of how econometrics is responding to current challenges in data analysis, with new developments arising in the field of spatial econometrics [2]. Some pioneer contributions sharing this focus include those of renamed authors as Arbia *et al.* (2010), Basile (2009), Basile and Girardi (2010) or Osland (2010), that have been showing how non-parametric and semi-parametric techniques can render better results than traditional parametric ones in evaluating nonlinear spatial dependence patterns for cross-sectional data, (López *et al.,* 2010). In summary, employing new proposals better suited for dealing with nonlinearities and the resource to non-parametric and semi-parametric proposals for identifying spatial dependence patterns would surely conform part of the research agenda of spatial econometrics in the near future (Pinkse and Slade, 2010).

In this sense, this paper continues extending that incipient literature: First, we present three types of tests designed for checking for spatial dependence patterns in the presence of nonlinearities: BP test (Brett and Pinske, 1997), Ku test (Kulldorff and Nagarwalla, 1995), and the recently proposed SG test (López et al, 2010). Second, we apply those three proposals on relevant data for the EU regions, as unemployment levels, GDP per capita, etc., in order to empirically capture the emergence of nonlinear spatial structures along that geographical space. And finally, we check for the power of new test against traditional parametric tests (MI) when nonlinearities arise in data analysis. Anticipating some of the results, the failure of the traditional MI test is highlighted in nearly all of the empirical exercises of the investigation. In contrast, non-parametric proposals show greater power in detecting spatial structures in the presence of nonlinearities. In that sense, our results clearly recommend the need of employing new tests in the presence of nonlinearities, given low power of traditional ones.

The remainder of the paper is as follows. In section 2 we make a description of the non-parametric and semi-parametric spatial dependence tests we will apply further in our study. In section 3, we present an empirical application for testing the power of those tests in a nonlinear world. We also include here a discussion of the main findings of the investigation. Finally, section 4 concludes.

[2] As an example, consult the monographic number that the *Journal of Econometrics* has recently devoted to the topic (*JoE*, vol. 157 (2010), Elsevier).

2. Non-parametric approach when testing for spatial dependence

In this section, we briefly describe the three non-parametric tests to be employed in the following empirical exercise, commenting on the pros and cons associated to every one of the proposals. We also detail the characteristics of the well-known Moran's I test for novel readers. Further, we evaluate the size dimension of the tests through permutation techniques. All tests are presented in the chronological order they appeared in the literature.

2.1. Four proposals for testing spatial dependence

The most popular test to contrast spatial correlation is Moran's I Test (Moran, 1948) which is widely employed in the first stages of many exploratory and spatial econometrics studies. Moran's I test for a variable x measures if the values of this variable, at different locations (x_i and x_j with $i, j = 1,2, ..., n$ and $i \neq j$), are associated. Formally, Moran's I test follows the expression (1) which is asymptotically distributed as a normal:

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}(x_i - \bar{x})w_{ij}(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{1}$$

where $\bar{x}$ is the sample mean for the variable x, w_{ij} is the (i, j) -element of the known Weight matrix (W) which quantifies the different intensities among spatial locations in function of their proximity. Finally, S_0 is the sum of all W elements and n is the number of observations.

$$S_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} \tag{2}$$

The second test we present is the Brett and Pinkse proposal (Brett and Pinkse, 1997), that unless appeared more than a decade ago, it is still not so much generalised. This is a non-parametric test which is built considering the properties of the characteristic functions. Specifically, it is based on the property that if two variables (in our case, X and his spatial lag $X^N = WX$) are independent, the joint characteristic function must factorize into the product of their marginal characteristic functions. To compute the test, a f practitioner-chosen density function with infinite support is considered with $h(x) = \int e^{iux} f(u)du$ its Fourier transform. Let $\{X_t\}$ and $\{X_t^N\}$ independent with

X_t^N be the average of proximate observations of X_t. We also define $h_{ts} = h(X_t - X_s)$, $h_{ts}^{NN} = h(X_t^N - X_s^N)$ and, $\eta_{n1} = n^{-2} \sum_{s,t} h_{ts} h_{ts}^{NN}$, $\eta_{n2} = n^{-3} \sum_{s,t,u} h_{ts} h_{tu}^{NN}$ $\eta_{n3} = n^{-4} \sum_{s,t,u,v} h_{ts} h_{uv}^{NN}$, with n the number of observations. Let

$$\eta_n = (\eta_{n1} - \eta_{n2})^2 (\eta_{n2} - \eta_{n3})^2 \tag{3}$$

and

$$\upsilon_n = (\gamma_n - \mu_n^2)^2 n^{-1} \sum_t n_t^{-1} (I(n_t > 0) + \sum_s n_s^{-1} (I(s \in N_t) I(t \in N_s)) \tag{4}$$

where $\mu_n = n^{-2} \sum_{t,s} h_{ts}$, $\gamma_n = n^{-3} \sum_{t,s,u} h_{ts} h_{tu}$, N_t the set of proximate observations of point t and n_t, that is, the cardinal of set N_t.

Then, under the null of independence, the Brett and Pinkse statistic (*BP*)

$$BP = \frac{n\eta_n}{2\upsilon_n} \tag{5}$$

is asymptotically χ_1^2 distributed.

The third alternative is a very popular test in epidemiology (Kulldorff and Nagarwalla, 1995), which has also been employed in economics in its spatial-temporal version (Kang, 2010). In its last definition, due to Kulldorff *et al.* (2009), the Ku test is defined for the case of an underlying Normal distribution, and can be viewed as a semi-parametric test. This proposal, under the null hypothesis, assumes equality of mean values for the variable under study in all locations included in the geo-data set. The alternative hypothesis relies on the existence of a spatial cluster where mean values differ from those of the rest of the sample. In this case where the variable presents spatial structure, and according to the Tobler law, Ku test would reject the null of equidistribution.

Formally, Ku test defines the following null hypothesis,

$$H_0 : X_i \equiv N(\mu,\sigma)\ (\forall i)\ i.i.d.$$

versus the alternative of,

$$H_1 : X_i \equiv N(\mu_Z,\sigma)\ (i \in Z) \text{ and } X_i \equiv N(\lambda_Z,\sigma)\ (i \notin Z) \text{ with } \mu_Z \neq \lambda_Z.$$

where Z is a spatial cluster of connected regions. The new specification of the Ku test allows its generalisation for the analysis of topics related to economics and regional science, widening in that way the scope of research fields where to be applied.

Basically, the Ku test identifies regional clusters where the variable of interest shows significant different behaviour. To define the clusters the test employs «windows» (Z) of different size and shape, then comparing the mean value of the observations lying inside the window with those staying outside it. The «window» (Z) also moves across the entire map, changing its size and shape while searching for identifying the maximum differential existing between the spatial clusters defined in the sample. Once the window with the maximum differential is identified, it is evaluated by checking if that difference appears to be statistically significant. So, under the null hypothesis, the log likelihood of $(X_1, ..., X_n)$ is defined as,

$$\ln L_0 = -n\ln(\sqrt{2\pi}) - n\ln(\sigma) - \sum_i \frac{(x_i-\mu)^2}{2\sigma^2} \tag{6}$$

Under the alternative hypothesis, we first calculate the maximum likelihood estimators that are specific to each circle z, which is $\mu_z = x_z/n_z$ with $x_z = \sum_{s\in z} x_s$ and $n_z = \sum_{s\in z} x_n$ for the mean inside the circle, and $\lambda_z = (X - x_z)/(n - n_z)$ with $x_z = \sum_{s\in z} x_s$ for the mean outside the circle. The maximum likelihood estimate for the common variance is,

$$\sigma_z^2 = \frac{1}{n}\left(\sum_{i\in z} x_i^2 - 2x_z\mu_z + n_z\mu_z^2 + \sum_{i\notin z} x_i^2 - 2(X - x_z)\lambda_z + (n - n_z)\lambda_z^2\right) \tag{7}$$

The log likelihood for the alternative hypothesis

$$\ln L_z = -n\ln(\sqrt{2\pi}) - n\ln(\sqrt{\sigma_z^2}) - n/2 \tag{8}$$

Then the Ku statistic is defined as

$$Ku = \max_z(\ln L_z - \ln L_0) = \max_z\left(n\ln(\sigma) + \sum_i \frac{(x_i-\mu)^2}{2\sigma^2} - n/2 - n\ln(\sqrt{\sigma_z^2})\right) \tag{9}$$

Only the last term depends on z, so from this formula it can be seen that the most likely cluster selected is the one that minimizes the variance under the alternative hypothesis, what is intuitive. The p-value is obtained through Monte Carlo hypothesis testing (Dwass, 1957), by comparing the rank of the maximum likelihood from the real data set with the maximum likelihoods from the random data sets. If this rank is r, then the p-value = r/(1 + # simulations). By repeating this procedure and eliminating the selected window we can detect secondary clusters. There is also available a free software to run the Kulldroff test called SatScan, that can be downloaded from *www.satscan.org.*

The final of the proposed tests in our exercise is characterized by a pure non-parametric approach. In comparison with the other two proposals, it does not use the theoretical distribution of observations in its computation. This test, called the SG test, has been proposed recently by one of the authors (López *et al.,* 2010) and builds on the concept of symbolic entropy when defining a measure of cross-sectional spatial dependence. Applying the concept of symbolic entropy for spatial econometrics has been appearing as a feasible tool for dealing with important questions still to be solved in the field (Ruiz *et al.,* 2010; Herrera, 2011).

We explain how to compute the SG test. Given the spatial process $\{X_s\}$with $s \in S$, where S is a set of spatial coordinates, then embedded in an m-dimensional space ($m \geq 2$) as follows:

$$X_m(s_0) = (X_{s_0}, X_{s_1}, \ldots, X_{s_{m-1}}) \tag{10}$$

where s_1, s_2, ..., s_{m-1} are the $m - 1$ closer neighbours to s_0, which are ordered from leaser to greater Euclidean distance with respect to the location s_0. The term $X_m(s)$ is called the m – surroundings of s. The next step in the definition of this test is to encode all the m – surroundings into symbols. To get this purpose, a set of h symbols $\Gamma = \{\sigma_1, \sigma_2, ..., \sigma_h\}$ is defined. Then, the spatial process is symbolised through a symbolization map f with:

$$f : \mathbb{R}^m \to \Gamma \tag{11}$$

such that $f\,[X_m(\mathrm{s})] = \sigma_{j_s}$ with $j_s \in \{1, 2, ..., h\}$. The set of spatial observations $s \in S$ is of σ_i -type if and only if $f\,[X_m(\mathrm{s})] = \sigma_i$.

Based on the symbolization map, the cardinality of the subset S, composed by all the elements of σ_i -type, is defined us $l_{\sigma_i} = \#\{s \in S \,|\, f\,[X_m(s)] = \sigma_i\}$. Besides, the relative frequency of a symbol $\sigma \in \Gamma$ is computed by:

$$p(\sigma) := p_\sigma = \frac{\#\left\{s \in S \mid s \text{ is of } \sigma - \text{type}\right\}}{|S|} \tag{12}$$

where $|S|$ denote the cardinality of the set S.

Under this setting, the symbolic entropy of the spatial process $\{X_s\}$ with $s \in S$ for an embedding dimension is defined as a Shanon's entropy of the h different symbols as follows:

$$q(m) = -\sum_{\sigma \in \Gamma} p_\sigma Ln(p_\sigma) \tag{13}$$

$q(m)$ is the information contained in comparing the m-surroundings generated by the spatial process.

Taking into account previous concepts, the SG test on the spatial process $\{X_s\}$ with $s \in S$ is defined as follows:

$$SG(m) = 2|S|\left[Ln(h) - q(m)\right] \tag{14}$$

This test is asymptotically distributed as a χ_k^2 where k refers to the number of unknown parameters under the alternative hypothesis minus the number of unknown parameters under the null hypothesis.

2.2. Some brief considerations on the characteristics of the spatial tests

In this subsection we briefly review the main features of every defined test, in order to better characterise every one of them. So, the BP test appears to be useful in determining the existence of spatial dependence structures when the underlying spatial process is clearly a nonlinear one (López *et al.,* 2010). In contrast, one of the cons of this test is related to its underlying assumptions, given that the test could fail when the analysed process is a non-stationary one or it does not follow a Normal distribution. So, in the BP-test the spatial process has to be stationary and strongly mixing. In that sense, the BP test requires ex-ante the choice of the function f, with different choices leading to different values of the statistic. In the original paper of Brett and Pinkse, the standard Gaussian density was used for defining the underlying f. In this paper the authors decide to employ the same function according to simulation experiments previously run on a similar time series context by Pinkse (1998), where the author shows any strong sensitivity of the results to the choice of the observations. Also we must note that this aspect of the test has been never explored,neither in its spatial version, nor in its spatio-temporal one (see, i.e, López *et al.,* 2011).

In what respects to the definition of the Kulldorff test, we must note that it does not require any spatial dependence structure information ex-ante, derived from the related weight matrix**.** On the negative side, the Kulldorff test assumes the null hypothesis of *iid*, following a Normal distribution with the same mean value for every cluster or observation in the sample. This is perhaps its more restrictive assumption, with the lack of normality being perhaps responsible in some cases of the rejection of the null of spatial independence. Finally, when implementing the statistic, the researcher must decide the shape of the window and the maximum number of cases that any given window can cover. With the current software available, analysis can be done using circular or elliptical windows (see *www.satscan.com*). The power of the contrast is then related to two factors: (i) The shape of the window Z employed (circular, elliptical or flexible) (ii) The maximum number of elements included in Z. Regarding the first factor, the shape of the window Z used to be defined as a circular window, although employing flexible (computer-defined) shape of windows used to improve the power of the Ku-test (Tango and Takahashi, 2005; Yiannakoulias *et al.,* 2007). In what affects the second factor, it is recommended that the maximum number of cases entering any given window does not exceed 50% of all available cases. In the case that the identified cluster shows a very irregular shape, it is recommended to reduce the number of cases entering the exercise does not surpass 5% or 10% of total available cases. In this paper we follow both recommendations, employing circular windows with a number of cases not accounting for more than 50% of total cases.

In the case of the SG test, its main advantage is related to the fact that it does not require the specification of a pre-determined weight matrix in order to define the neighbouring observations or the underlying spatial structure in data. This is an interesting positive feature of this proposal, but at the same time it does not provide the necessary flexibility to the researcher for testing for the effects of several spatial structures in data. On the negative side, this test renders better results with large than with small samples. Moreover, the SG test present overlapping problems induced by the building of the m-surroundings, which could turn of importance in small samples. Finally, for the SG-test all locations have the same number of neighbours while this not happens for the other two tests.

2.3. Exploring size's tests by employing permutationtechnique

Some properties of the selected tests are described in this subsection, such as the values of the BP test change depending on the chosen *f* function, as well as on the scaling made on observations. The test also presents some problems with the normality assumption if dropped (López *et al.,* 2010). The SG test could also show some size problems in small samples and when using irregular lattices, given overlapping problems. In general, and although it is possible to recover *p-values* from these tests by using asymptotic theory, it seems reasonable to evaluate their behavior by simple permutational test. By doing so, in this subsection we explore the size's characteristics of the proposed test by employing permutation bootstrapping, together with those of the MI test in order to have a reference of a parametrical test. Results on tests' power are not included here for space restrictions, but they are available on request to the authors as usual.

The evaluation of the significance of the coefficients is analysed through the permutation tests. Specifically, for the MI, the Brett and Pinkse and the SG tests a bootstrapping permutation is applied, while for the Kulldorff test a Monte Carlo bootstrapping is undertaken to get the *p-values*. For the BP test we use the proposed transformation suggested by Brett and Pinkse (1997) to drop out scale problems in the variables. To get this purpose, while computing the BP test values, the observations were normalized by first subtracting the median, and subsequently dividing by the median of the absolute values of resulting sequence divided by 0.675 as those authors propose.

Table 1 shows the size values of the considered tests for several sample sizes and distributions. We consider that the observations are distributed on irregular lattices. To compute the MI and BP tests we employ a four nearest neighbour weight matrix. For the SG test, we consider the m-surroundings of size three. The Kuldorff test is built by applying circular windows.

In all cases, independently of the sample lattice or underlying distribution, the sizes appear in the expected range. Therefore, the permutation technique appears

Table 1. Empirical Size. Pseudo *p-value* in irregular lattice

		MI	*BP*	*Ku*	*SG*
N(0,1)	R = 49	0.041	0.055	0.065	0.059
	R = 100	0.054	0.055	0.054	0.051
	R = 225	0.064	0.064	0.064	0.055
U(0,1)	R = 49	0.070	0.054	0.049	0.048
	R = 100	0.060	0.060	0.055	0.067
	R = 225	0.065	0.069	0.065	0.062
$\beta(\frac{1}{2},\frac{1}{2})$	R = 49	0.050	0.040	0.050	0.040
	R = 100	0.055	0.040	0.055	0.040
	R = 225	0.050	0.060	0.050	0.065
χ^2_1	R = 49	0.060	0,045	0.070	0.070
	R = 100	0.065	0.055	0.045	0.050
	R = 225	0.045	0.050	0.065	0.055

to render good results. Regarding the power of tests, there are some published results that analyze its behaviour in linear and nonlinear processes, using permutation techniques and/or asymptotic theory. Detailed results on the power characteristics for Moran's I, BP, SBDS and SG tests in nonlinear environments can be consulted in López *et al.* (2010), that employ asymptotic theory. A comparison for Moran's I, BP, SG, and Ku tests can be found in López *et al.,* 2011, where the authors employ permutation tests.

3. Nonlinear spatial structures in economic variables: Analysing the case for the European Union

This section undertakes an empirical application to evaluate the behaviour of the previously presented spatial dependence tests under nonlinear process in comparison with the traditional techniques. To get this purpose, we consider as a representative traditional spatial dependence test the MI test of Moran. Because of its simplicity, the Moran's I (MI) test has been widely applied in different research areas. But, the MI test is in strict terms an autocorrelation index, therefore, it not appears as the perfect candidate to evaluate the presence of nonlinear spatial structures in data. The different non-parametric and semi-parametric spatial dependence tests introduced in the previous section could be an interesting alternative to MI for detecting such nonlinear structures in socio-economic variables. The goal of this section is to provide an empirical exercise that illustrates the adequacy of applying alternative non-parametric or semi-parametric spatial dependence tests when we presume the existence of nonlinear spatial dependence structures in the data.

In our empirical exercise, we will use both the Cambridge Econometrics and REGIO databanks. From these databases, we focus our analysis on a total of 261 regions, NUTS II level, from the 27 countries that are currently members of the European Union (EU-27). For different reasons, various regions have been excluded, among them the Canary Islands, Ceuta, Melilla and the Portuguese archipelagos of the Azores and Madeira. With the aim of providing more robustness to our results, we develop our analysis for three years (1991, 2000 and 2010). We focus our attention on four classic variables computed for the European Regions because of their importance as economic indicators. These are: the unemployment rate (UR), the percentage of active population in the agriculture sector over the total population (EAr), the R & D expenditure per capita (RDpc) and the gross domestic product per capita (GDPpc).

3.1. Spatial dependence structure in the original raw data

Figure 1 shows the Box Plot of the analysed variables for the last year of the sample, 2010. In all cases we observe a clear spatial dependence structure: For ex-

Figure 1. Quartile Map for original variables (year 2010)

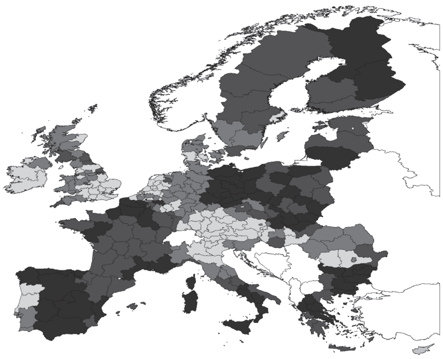

Figure 1a. Unemployment rate

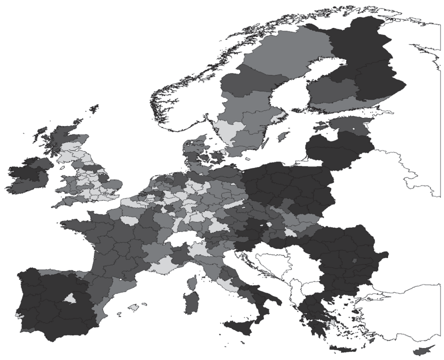

Figure 1b. Agricultural employment rate

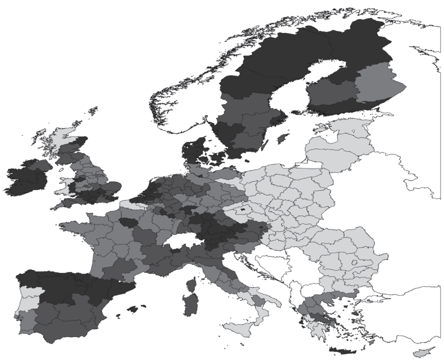

Figure 1c. R&Dpc

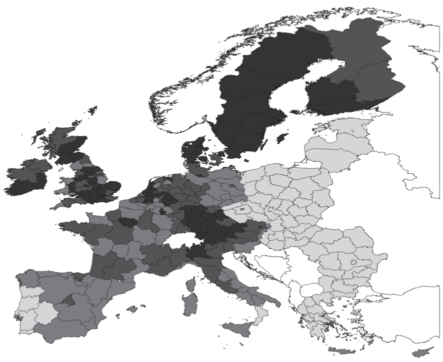

Figure 1d. GDPpc

ample, for the unemployment rate (UR) variable, the highest values correspond to the periphery regions of the Eastern Europe, together with some southern EU regions in Spain, Greece, Italy, of the former Yugoslavia. Agricultural employment (AEr) rate is also higher than the EU average in southern and eastern regions, showing the structural socio-economic changes that these territories are still facing. In terms of R&D expenditures and GDP per capita, the figure shows the contrary situation, with regions in Scandinavian countries (Finland, Denmark and Sweden, particularly) showing the highest rate of investments and living standards or purchasing power. Other European regions in Germany, United Kingdom or France (Ille-de-France) also occupy an important position in that ranking, showing a clear spatial dependence structure along the EU space for all of the chosen variables.

Table 2 shows the values for the different spatial dependence tests and their pseudo p-values. Again for all cases, the statistical values appear very high, leading to a rejection of the null hypothesis about a random pattern in the spatial distribution of data.

Table 2. Test of Diagnostic for spatial dependence on the original data (y)

	MI	*p-value*	*SG*	*p-value*	*BP*	*p-value*	*Ku*	*p-value*
UR 1991	11.12	0.000	188.3	0.000	707.2	0.000	19.6	0.004
UR 2000	12.16	0.000	202.4	0.000	868.0	0.000	22.1	0.003
UR 2010	15.29	0.000	159.5	0.000	941.8	0.000	46.4	0.000
AEr 1991	16.57	0.000	107.8	0.000	1,089.5	0.000	89.5	0.000
AEr 2000	17.43	0.000	129.7	0.000	832.9	0.000	99.6	0.000
AEr 2010	17.03	0.000	94.9	0.000	736.9	0.000	94.7	0.000
RDpc 1991	17.45	0.000	292.8	0.000	3,270.9	0.000	81.9	0.000
RDpc 2000	16.71	0.000	226.9	0.000	2,266.4	0.000	86.6	0.000
RDpc 2010	14.62	0.000	181.1	0.000	1,546.8	0.000	66.6	0.000
GDPpc 1991	18.22	0.000	289.5	0.000	5,400.9	0.000	90.9	0.000
GDPpc 2000	17.38	0.000	213.2	0.000	4,509.2	0.000	93.2	0.000
GDPpc 2010	16.25	0.000	187.7	0.000	3,307.8	0.000	76.1	0.000

p-value = p-seudo value obtain test by permutational bootstrapping. 999 iterations.

The next step in our empirical application is now dropping from these variables the linear spatial dependence structure. In order to do so, we apply the filtering technique usually employed in the spatial econometrics literature, namely the Getis (1990, 1995) proposal [3].

[3] Equivalent results are obtained by authors when filtering data using simple spatial autoregressive model estimation. To use this technique we estimate a simple spatial autoregressive model for each of the empirical variables. Therefore, the residuals of this estimation should not contain any spatial dependence structure. Results are available upon request as usually.

3.2. Applying the filter of Getis

Among the most commonly applied spatial filtering techniques we find the Getis (1990, 1995) proposal, as well as the Griffith (1996, 2003) eigenvector spatial filtering approach. A recent empirical comparison of that two filtering techniques, spatial lag regression and Getis filtred, has shown that both approaches are almost equally equipped for removing the spatial effects from geographically organized variables (Getis and Griffith, 2002). Given their similar empirical performance, for the remainder of the paper we rely on the Getis approach, which has been applied in a variety of empirical research contexts (see e.g. Badinger *et al.,* 2004; Battisti and Di Vaio, 2008; Mayor and López, 2008). Moreover, as Getis and Griffith (2002) argue, the advantage of the Getis approach compared to the eigenvector filtering relies in its simplicity.

To derive the set of spatially «cleaned» variables, the Getis approach uses the local statistic $G_i(d)$ (Getis and Ord, 1992). So, the new filtered variable is defined as in (5)

$$y_i{**} = \frac{y_i\left(W_i/R-1\right)}{G_i(d)} \tag{15}$$

where $G_i(d)$ is the local statistic of Getis and Ord and W_i is the sum of the i- row of the contiguity W matrix. The transformation procedure depends on identifying an appropriate distance d within which nearby areal units are spatially dependent. There have been suggestions for identifying this magnitude d. One of which requires that the statistic $G_i(d)$ be evaluated at a series of increasing distances until no further spatial autocorrelation is evident.

With the aim of filtering data we choose a weight matrix based on the Euclidean distance. Nevertheless, some of the European regions in our sample are located at a long distance from the others. This regional disposition breaks with the symmetry in the weight matrix and needed for computing the local index. To overcome this situation, we connect the furthest regions with the two closers locations independently of the Euclidean distance.

$$w_{ij} = \begin{cases} 1 \text{ if } & d_{ij} < d \text{ or } j \in NN(i,2) \\ 0 & \text{in other case} \end{cases} \tag{16}$$

where NN(i,2) is the set of two nearest neighbors to «i». Figure 2 shows the Box Plots for the filtered variables (y**) by applying the previously described procedure. In this case, results seem to be clearer than for the previous analysis, with the other filtering technique: There is not graphical evidence about the existence of spatial dependence structures.

Figure 2. Quartile Map for Getis Filter variable (y**) (year 2010)

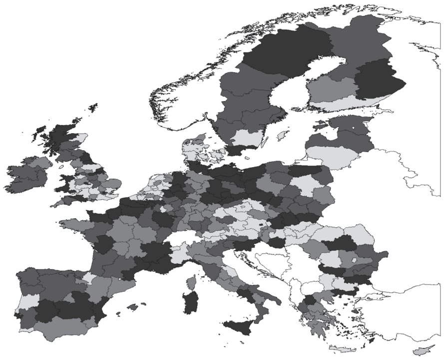

Figure 2a. Unemployment rate

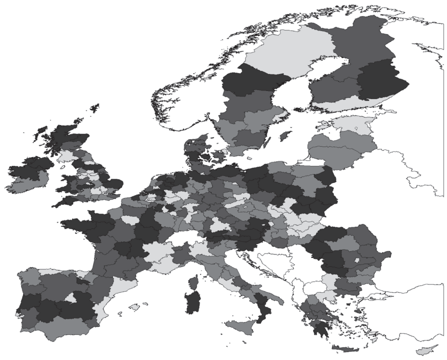

Figure 2b. Agricultural employment rate

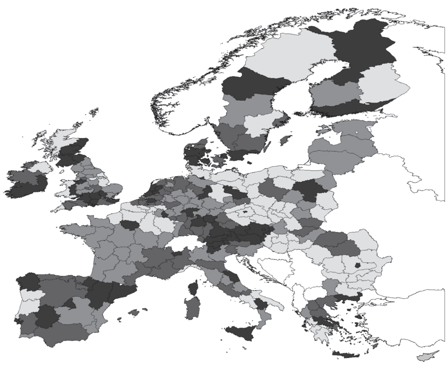

Figure 2c. R&Dpc

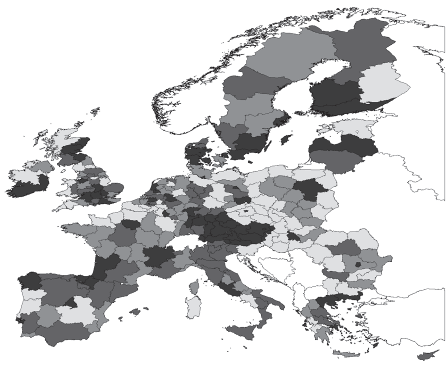

Figure 2d. GDPpc

Table 3 presents the statistical results for our four spatial dependence tests on the filtered variable (y**). For each variable, the shorter distance (*d* in kilometers) is selected in order to drop the spatial dependence structure according to the Getis filter.

Table 3. Test of diagnostic spatial dependence on Getis filtered variables (y**)

	d	*MI*	*p-value*	*SG*	*p-value*	*BP*	*p-value*	*Ku*	*p-value*
UR 1991	280	–1.39	0.150	3.2	0.510	35.3	0.002	9.0	0.604
UR 2000	260	–1.60	0.091	2.5	0.593	40.4	0.000	7.4	0.995
UR 2010	260	–1.11	0.248	2.6	0.557	26.1	0.004	7.4	0.966
AEr 1991	480	–1.17	0.207	3.7	0.390	0.6	0.520	8.1	0.319
AEr 2000	420	–1.04	0.292	6.6	0.167	0.3	0.691	12.5	0.153
AEr 2010	420	–1.35	0.144	7.3	0.135	1.3	0.303	6.5	0.594
RDpc 1991	340	–1.00	0.301	8.5	0.090	25.1	0.007	19.4	0.036

Table 3. *(Continue)*

	d	*MI*	*p-value*	*SG*	*p-value*	*BP*	*p-value*	*Ku*	*p-value*
RDpc 2000	400	–1.11	0.253	32.5	0.000	39.4	0.002	13.0	0.235
RDpc 2010	380	–1.34	0.151	19.2	0.006	2.8	0.242	10.8	0.213
GDPpc 1991	360	–0.73	0.432	25.0	0.001	14.5	0.024	32.1	0.024
GDPpc 2000	380	–1.20	0.210	32.4	0.000	8.9	0.048	23.8	0.048
GDPpc 2010	400	–1.16	0.214	35.3	0.000	7.2	0.079	13.0	0.240

d= distance in Km to compute W(d). p-value = pseudo p-value obtained by permutational bootstrapping (999 iterations).

According to the results of the Moran test, no one of the selected variables would present further spatial dependence signs. On the other hand, the non-parametric tests allows us to observe still the presence of spatial structures in data, with pseudo *p-values* higher than 0.05, what lead to the rejection of the null hypothesis of independence. In that way, for this filtering technique we observe similar conclusions than those obtained after applying the spatial lag filter, once we apply the non-parametric or semi-parametric contrasts. In summary, the resource to such new proposals has allowed us to unequivocally detect the spatial dependence structure underlying our socio-economic variables from a nonlinear perspective. The behavior of the non-parametric and semi-parametric tests in comparison to the traditional spatial dependence tests (Moran's I) highlights the relevance of their application in the initial steps of every spatial dependence analysis with traces of nonlinear spatial structures. The absence of this battery of tests in the researcher's tool kit could obviously generate negative effects in her/his posterior econometric estimation process (Le Sage and Pace, 2009), as we have been able to show in this paper.

Analyzing the results for each variable, we get that for the Agricultural Employment rate (AEr) the spatial dependence structure is completely dropped through the Getis filtering technique. In this sense, all spatial dependence tests accept the null hypothesis of independence. This result is not similar for the other studied variables, particularly, in the case of the RDpc and GDPpc variables where tests reject the null of independence for the years 1991 and 2000. In these cases, the proposed non-parametric and semi-parametric tests are able to capture the presence of spatial structures in a nonlinear fashion. A similar conclusion is found for the Unemployment rate (UR) when the BP test is employed. All of these render important conclusions for the spatial econometrics literature, particularly in the presence of nonlinearities.

4. Conclusions

The interaction relationships among spatial units are complex in empirics. Identifying those linkages is not always a simple matter and, because of that, specifying spatial structures through linear models is not always the best modeling option. The fact that some tests, for example the Moran's I test, have become popular among researchers because of its simplicity and the availability of friendly software to run the computing process, should be complemented with other alternative tests, given the low power characterizing that simple spatial correlation test. Therefore, there is a need in the literature of spreading knowledge on alternative tools useful for evaluating the presence of spatial dependence structures in geo-data.

In this paper, we have tested the improvements that several non-parametric tests can provide to empirical analysis when nonlinear dependence structures could be present in data, this being the pivotal contribution of the investigation. This is an important point, given that some renamed authors as Anselin and Florax (1995) insist in what MI test is a general specification contrast, although they do not really address its weakness in a nonlinear world. Given that Moran's I could fail in detecting spatial association when we depart from simple dependence structures, as we have shown along the empirical part of the paper, we have proposed to employ three new tests recently developed, namely Kulldorff, BP and SG tests. All of them have shown to be well endowed for detecting spatial structures in the presence of nonlinearities. However, we have also shown that everyone performs better under particular circumstances, depending on the distributional characteristics of the process to be analyzed.

In summary, our investigation has shown the importance of following new proposals when testing for spatial correlation if one wants to depart from the linear world. On the contrary, results of econometric modeling could induce important biases when estimating parametersof interest, taking to potential misleading results in policy terms, and a waste of scarce public funds, something very important in a period of hard budgetary constrains as this is.

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Section On theory and methods

Investigaciones Regionales

The Likelihood Ratio Test of Common Factors under Non-Ideal Conditions

Ana M. Angulo *, Jesús Mur **

ABSTRACT: The Spatial Durbin model occupies an interesting position in Spatial Econometrics. It is the reduced form of a model with cross-sectional dependence in the errors and it may be used as the nesting equation in a more general approach of model selection. Specifically, in this equation we can obtain the Likelihood Ratio test of Common Factors (LR_{COM}). This test has good properties if the model is correctly specified, as shown in Mur and Angulo (2006). However, as far as we know, there is no literature in relation to the behaviour of the test under non-ideal conditions, which is the purpose of the paper. Specifically, we study the performance of the test in the case of heteroscedasticity, non-normality, endogeneity, dense weighting matrices and non-linearity. Our results offer a positive view of the Likelihood Ratio test of Common Factors, which appears to be a useful technique in the toolbox of spatial econometrics.

JEL Classification: C21, C50, R15.

Keywords: Likelihood Ratio Test of Common Factor, Heteroscedasticity, Non-normality, Endogeneity, Non-linearity.

El Ratio de Verosimilitudes de Factores Comunes bajo condiciones no ideales

RESUMEN: El modelo espacial de Durbin ocupa una posición interesante en econometría espacial. Es la forma reducida de un modelo de corte transversal con dependencia en los errores y puede ser utilizado como ecuación de anidación en un enfoque más general de selección de modelos. En concreto, a partir de esta ecuación puede obtenerse el Ratio de Verosimilitudes conocido como test de Factores Comunes (LR_{COM}). Como se muestra en Mur y Angulo (2006), este test tiene bue-

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nas propiedades si el modelo está correctamente especificado. Sin embargo, por lo que sabemos, no hay referencias en la literatura sobre el comportamiento de este test bajo condiciones no ideales. En concreto, estudiamos el comportamiento del test en los casos de heterocedasticidad, no normalidad, endogeneidad, matrices de contactos densas y no-linealidad. Nuestros resultados ofrecen una visión positiva del test de Factores Comunes que parece una técnica útil en el instrumental propio de la econometría espacial contemporánea.

Clasificación JEL: C21, C50, R15.

Palabras clave: Contraste de Ratio de Verosimilitudes de Factores Comunes, Heterocedasticitidad, No Normalidad; Endogeneidad, No Linealidad.

1. Introduction

In recent years, there has been an increasing concern about questions related to methodology in Spatial Econometrics. The works of Anselin and Florax (1995), Anselin *et al* (1996) and Anselin and Bera (1998) played a leading role in the revitalisation of the interest in the nineties. These papers underline the difficulties arising from the lack of specificity of the tests based on the Lagrange Multiplier principle and, consequently, the problems of finding the true model when there are various alternatives. In sum, there is a serious risk of obtaining a misspecified model if the user is not sufficiently careful.

In a model selection context, two main strategies can be identified. The first starts with a general model that we try to simplify in a so-called «*General-to-Specific*» approach (Hendry, 1980). This strategy has been supported by an important part of the literature on econometric model selection (Danilov and Magnus, 2004; Hendry and Krolzig, 2005). The second approach, denoted as «*from Specific-to-General*», operates in the opposite direction: starts from a simple model that it is extended depending on the results for certain tests. Comparison of both strategies have been numerous (Campos *et al,* 2005; Lütkepohl, 2007), also in the context of spatial econometrics. Florax *et al* (2003, 2006) compared the two approaches under ideal conditions while Mur and Angulo (2009) introduce different anomalies in the Data Generating Process (DGP). Elhorst (2010) reviews the situation once again.

As indicated in Florax *et al* (2006) or Mur and Angulo (2009) the starting point of the *General-to-Specific* strategy is the Spatial Durbin Model (SDM form now on) or, in other words, an *«autoregressive distributed lag model of the first order»* as defined by Bivand (1984). Lesage and Pace (2009, p. 46) are in favour of the SDM which *«provides a general starting point for discussion of spatial regression model estimation since this model subsumes the spatial error model and the spatial autoregressive model»*. Elhorst (2010) remarks some of the strengths of the SDM: i) «*it produces unbiased coefficient estimates also if the true data-generation process is a spatial lag or a spatial error model*»; ii) *«it does not impose prior restrictions on the magnitude of potential spatial spillover effects»,* which can be global or local and/or different for different explanatory variables*;* and *iii) «it produces correct standard errors or t-values of the coefficient estimates also if the true data-generating process is a spatial error model».* In addition, Elhorst (2010) proposes a test procedure to select the most adequate model which confers an important role to the SDM.

The Spatial Lag Model (SLM) is a particular case of the SDM, when the exogenous interaction effects among the independent variables are not significant. The Spatial Error Model (SEM) is also a particular case of the SDM, once the common factor hypothesis in introduced in the SDM model. Hence, if the null is not rejected the test favours the SEM specification. When the null is not rejected, Florax *et al* (2006) propose to select the Spatial Lag Model (SLM) while Mur and Angulo (2009) and Elhorst (2010) propose to go on testing further hypotheses on the SDM. It is clear that the last equation plays a crucial role in the specification of a spatial model. For this reason it is important to be aware of the weaknesses and strengths of the specification tests applied, like the Likelihood Ratio test of Common Factors (LR_{COM} in what follows), on this equation.

However, the literature on Spatial Econometrics has paid little attention to the Common Factor test. This is a bit surprising. To cite only some of the most recent cases, this test is not included in the comprehensive simulation carried out by Anselin and Florax (1995), nor is it mentioned in the meta-analysis of Florax and de Graaff (2004); the LR_{COM} test does not appears in the manuals of Tiefelsdorf (2000) and Griffith (2003). On the contrary, Lesage and Pace (2009) are very confident about the possibilities of the test. Recently, Mur and Angulo (2006) conducted a Monte Carlo exercise in order to evaluate the behaviour of the test under ideal conditions. In this paper, we go further in the same direction by analysing the performance of the Likelihood Ratio test of Common Factors [1] under non-ideal conditions: heteroscedasticity, non-normality, non-linearity, endogeneity and dense weighting matrices.

The paper is organised as follows. The next section describes the Spatial Durbin model and the Likelihood Ratio test of Common Factors following Mur and Angulo (2009) for the definition of the alternative hypothesis. Section 3 describes a Monte Carlo experiment that provides evidence on the performance of the test for various departures from the case of ideal conditions. The main conclusions are summarised in Section 4.

2. The Spatial Durbin Model and the Likelihood Ratio test of Common Factors

The Durbin model plays a major role in a General-to-specific strategy of model selection. Following a Hendry-like approach, it is a general equation that nests two of

[1] We focus on the Likelihood Ratio version of the test of Common Factors because, in general, it is better-known. Two other alternatives are the Wald and the Lagrange Multiplier versions, as developed by Burridge (1981).

the most popular models in spatial econometrics, the Spatial Lag Model (SLM) and the Spatial Error Model (SEM). Let's analyse this issue more in detail.

The Durbin Model appears in a specific situation in which, using time series, we need to estimate an econometric model with an autoregressive error term, AR(1):

$$\left.\begin{aligned} y_t &= x_t'\beta + u_t \\ u_t &= \rho u_{t-1} + \varepsilon_t \end{aligned}\right\} \tag{1}$$

Durbin (1960) suggested directly estimating the reduced unrestricted form of (1) by least squares:

$$y_t = \rho y_{t-1} + x_t'\beta + x_{t-1}'\eta + \varepsilon_t \tag{2}$$

The adaptation of these results to the spatial case does not involve any special difficulty, as shown by Anselin (1980):

$$\left.\begin{aligned} y &= x\beta + u \\ u &= \rho W u + \varepsilon \end{aligned}\right\} \Rightarrow y = \rho W y + x\beta + Wx\eta + \varepsilon \tag{3}$$

where W is the weighting matrix; y, u and ε are vectors of order ($Rx1$); x is the (Rxk) matrix of observations of the k regressors; β and η are ($kx1$) vectors of parameters and ρ is the parameter of the spatial autoregressive process of the first order, SAR(1), that intervenes in the equation of the errors.

We complete the specification of the model of (3) with the additional assumption of normality in the random terms:

$$\left.\begin{aligned} & y = \rho W y + x\beta + Wx\eta + \varepsilon \\ & \varepsilon \sim N(0, \sigma^2 I) \end{aligned}\right\} \tag{4}$$

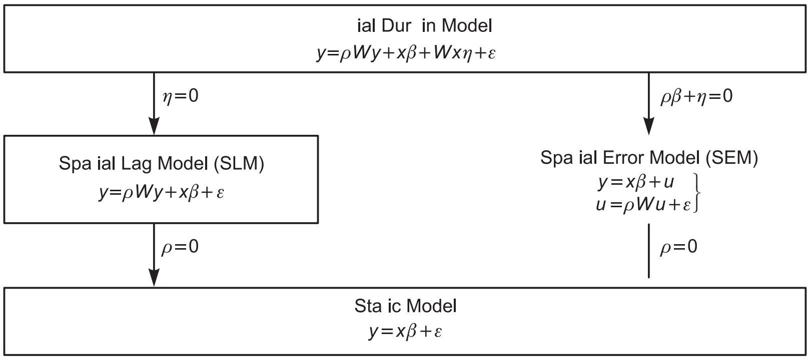
This model can be estimated by maximum-likelihood (ML in what follows). The log-likelihood function is standard:

$$l(y/\varphi_A) = -\frac{R}{2}\ln 2\pi - \frac{R}{2}\ln\sigma^2 - \frac{\left[By - x\beta - Wx\eta\right]'\left[By - x\beta - Wx\eta\right]}{2\sigma^2} + \ln|B| \tag{5}$$

with $\varphi_A = [\beta, \eta, \rho, \sigma^2]'$; B is the matrix $[I\text{-}\rho W]$ and $|B|$ its determinant, the Jacobian term.

Starting form the Durbin model, we can test whether or not some simplified models such as the SLM, SEM or a purely static model without spatial effects are admissible. Figure 1 summarizes the relationship between the four models.

Figure 1. Relationships between different spatial models for cross-sectional data



Starting from the general SDM model, if we cannot reject the null hypothesis that the spatial lag of the x variable is not significant, H_0: $\eta = 0$, the evidence points to an SLM model or to a static model, depending on what happens with the parameter ρ. Hence, the next step consists on the estimation of the SLM model:

$$\left.\begin{aligned} y &= \rho W y + x\beta + \varepsilon \\ \varepsilon &\sim N(0,\sigma^2 I) \end{aligned}\right\} \tag{6}$$

Finally, the null hypothesis that $\rho = 0$ needs to be tested. If this assumption cannot be maintained, the evidence is in favour of the SLM model; otherwise, a simple static model should be the final specification:

$$\left.\begin{aligned} y &= x\beta + \varepsilon \\ \varepsilon &\sim N(0,\sigma^2 I) \end{aligned}\right\} \tag{7}$$

In relation to the SEM model, the Common Factor hypothesis should be tested directly in the SDM equation, which results in k non-linear restrictions: $\eta = -\rho\beta$ on the parameters of the equation. The most popular test in this context is the Likelihood Ratio of Common Factors, LR_{COM}, proposed by Burridge (1981).

Introducing the k non-linear restrictions on the model of (4), we obtain a SEM specification:

$$\left.\begin{aligned} y &= x\beta + u \\ u &= \rho W u + \varepsilon \end{aligned}\right\} \tag{8}$$

whose log-likelihood function is also standard:

$$l(y/\varphi_0) = -\frac{R}{2}\ln 2\pi - \frac{R}{2}\ln\sigma^2 - \left[\frac{(y - x\beta)' B' B (y - x\beta)}{2\sigma^2}\right] + \ln|B| \tag{9}$$

with $\varphi_0 = [\beta,\rho,\sigma^2]'$.

The log Likelihood Ratio compares the maximized values of the log-likelihoods of the models (5) and (9):

$$\left.\begin{array}{l} H_0: \rho\beta + \eta = 0 \\ H_A: \rho\beta + \eta \neq 0 \end{array}\right\} \Rightarrow LR_{COM} = 2\left[l(y/\tilde{\varphi}_A) - l(y/\tilde{\varphi}_0)\right] \sim \chi^2(k) \qquad (10)$$

As in the previous case, if we cannot reject the null hypothesis, the evidence points to a SEM model or to a static model, depending on the significance test of ρ.

Let us finish this section highlighting the most important points, according to our own perspective:

(i) The Spatial Durbin Model occupies a prominent role in the specification process of a spatial model, because it nests other simpler models.

(ii) The connection between the SDM and the SLM model is a single significance test of a maximum-likelihood estimate, whose properties are very well-known.

(iii) The connection between the SDM and the SEM is the Common Factor Test. The Likelihood Ratio version, LR_{COM}, is simple to obtain but its properties are known only under ideal conditions.

3. The LR_{COM} test under non-ideal conditions. A Monte Carlo analysis.

In this section, we evaluate the performance of the LR_{COM} test in different non-ideal situations and for different sample sizes. Section 3.1 describes the characteristics of the experiments and Section 3.2 focuses on the results.

3.1. Design of the Monte Carlo

We use a simple linear model as a starting point:

$$y = x\beta + \varepsilon \qquad (11)$$

where x is an ($Rx2$) matrix whose first column, made of ones, is associated to the intercept whereas the second corresponds to the regressor, x_r; β is a (2x1) vector of parameters, $\beta' = [\beta_0; \beta_1]$, and ε is the ($Rx1$) vector of error terms. From this expression, it is straightforward to obtain a Spatial Error Model, SEM, or a Spatial Lag Model, SLM. In matrix terms:

$$\text{SEM}: \begin{cases} y = x\beta + u \\ u = \rho W u + \varepsilon \\ \varepsilon \sim iid(0;\sigma^2 I) \end{cases} \qquad (12a)$$

$$\text{SLM}:\begin{cases} y=\rho Wy+x\beta+\varepsilon \\ \varepsilon \sim iid(0;\sigma^2 I) \end{cases} \tag{12b}$$

The SEM and the SLM specification of (12a) and (12b) are the two alternative DGPs that we introduce in our simulation (other alternatives are also possible; Elhorst, 2010). The main characteristics of the exercise are the following:

a) Only one regressor has been used in the model. The coefficient associated takes a value of 2, $\beta_1 = 2$, whereas the intercept is equal to 10, $\beta_0 = 10$. Both magnitudes guarantee that, in the absence of spatial effects, the expected R^2 is 0.8.
b) The observations of the *x* variable and of the random terms ε and *u* have been obtained from a univariate normal distribution with zero mean and unit variance. That is, σ^2 is equal to one in all the cases.
c) We have used three different sample sizes, R, with 49, 100 and 225 observations distributed in regular grids of (7×7), (10×10) or (15×15), respectively. The weighting matrix is the row-normalized version of the original rook-type binary matrix.
d) In each case, 11 values of the parameter ρ have been simulated, only on the non-negative range of values, $\{\rho = 0; 0.1; 0.2; 0.3; 0.4; 0.5; 0.6; 0.7; 0.8; 0.9; 0.95\}$.
e) Each combination has been repeated 1000 times.

The two DGPs, SEM or SLM, have been simulated under different conditions, as follows:

i. Ideal conditions. This is the control case that corresponds to expressions (12a) and (12b), in which all the hypotheses are met.
ii. Heteroscedasticity. The error terms are obtained from a normal distribution with non-constant variance: $\varepsilon_r \sim N(0;\ \alpha^2 het_r)$, where het_r reflects the corresponding mechanisms of heteroscedasticy. In this case, we have used two spatial heteroscedaticity patterns, denoted as *h*1 and *h*2, and a non-spatial pattern, *h*3. The skedastic function for the first two cases is: $het_r = d(a,r)$ being $d(–)$ a normalized measure of distance between the centroids of the cells *a* and *r*. In the *h*1 case, *a* is the cell situated in the upper-left corner of the lattice, whereas, in *h*2, this cell is located in the centre of the lattice. The skedastic function in the case *h*3 is $het_r = |x_r|$, *a* non-spatial pattern that depends on the realization of the regressor, x_r, at point *r*.
iii. Non-normal distribution of the error terms. Two distributions are used: a log-normal distribution and a Student-t distribution with 5, 10 or 15 degrees of freedom (*df*, in the following). The first allows us to measure the consequences of the asymmetry of the distribution function and the second provides information about the impact of outliers (a Student-t with few *df* is prone to produce outliers).
iv. We will explore whether the existence of endogeneity in the data, omitted in the equations, affects the performance of the test. In order to do this, we simply introduce a linear relation between the error term and the regressor: iv.1) using a correlation coefficient of 0.2, low; iv.2) 0.59, medium; or, iv.3) 0.99, high.

v. We explore the behaviour of the Likelihood Ratio under several patterns of non-linearity using either: v.1) the sine function, $y = \sin(y^*)$; v.2) the quadratic function, $y = (y^*)^2$; v.3) the inverse function, $y = \frac{1}{y^*}$; v.4) the logarithm function of the absolute value, $y = \log(|y^*|)$; v.5) a discretization of the data of a latent continuous variable, y^*. In all cases, the y^* is obtained directly from expressions (12a) or (12b) of case of i). The discrete transformation of v.5 follows a single rule:

$$y_r = \begin{cases} 0 & \text{if} \quad y_r^* < y_{\{k\}}^* \\ 1 & \text{if} \quad y_r^* \geq y_{\{k\}}^* \end{cases} \tag{13}$$

where $y^*_{\{k\}}$ stands for the k-th quantile of the latent variable $\{y^*_r; r = 1, 2,...; R\}$. We have used two values for the quantile, $k = 0.7$ and 0.5.

vi. As pointed out, among others, by Smith (2009) or Neuman and Mizruchi (2010), the use of dense weighing matrices has severe consequences on maximum likelihood estimation: the estimates are dramatically downward biased and most part of the ML tests loses power. We study this new case in a non-regular lattice support. Each experiment starts by obtaining a random set of spatial coordinates of each sample size (49, 100 or 225, respectively) in a two-dimensional space. Then we use the n nearest-neighbours criterion to build the corresponding weighting matrix. The values of n have been fixed as: $n = [\alpha T]$; $\alpha = 0.05; 0.10; 0.25; 0.50$ where [–] stands for the «integer part of».

3.2. Results of the Monte Carlo experiments

The Monte Carlo experiment provided us with a lot of results. In order to simplify, we focus on the frequency of rejection of the null hypothesis of the LR_{COM} test, at the 5% level of significance. Depending on the DGP used in the simulation, we estimate the size (a SEM model is in the DGP) or the power function of the test (we simulate a SLM model). It is well-known that the LR_{COM} is a good technique to discriminate between SEM and SLM models under ideal conditions. The interest now is to assess the behaviour of the test under non ideal circumstances.

Results are summarized in Figures 2 to 6. Figure 2 shows the performance of the LR_{COM} test under the three patterns of heteroscedasticity ($h1$, $h2$ and $h3$). The two non-normal distributions (the log-normal and the three cases for the Student-t) appear in Figure 3. Figure 4 shows the impact of the density of the weighting matrix on the LR_{COM} test whereas Figure 5 focuses on the case of endogeneity. Finally, in Figure 6 we evaluate the performance of the test for the five non-linear specifications. In all the Figures, «iid» corresponds to the control case (that is, ideal conditions).

Figure 2. Power and empirical size of LR_{COM} test under heteroscedasticity

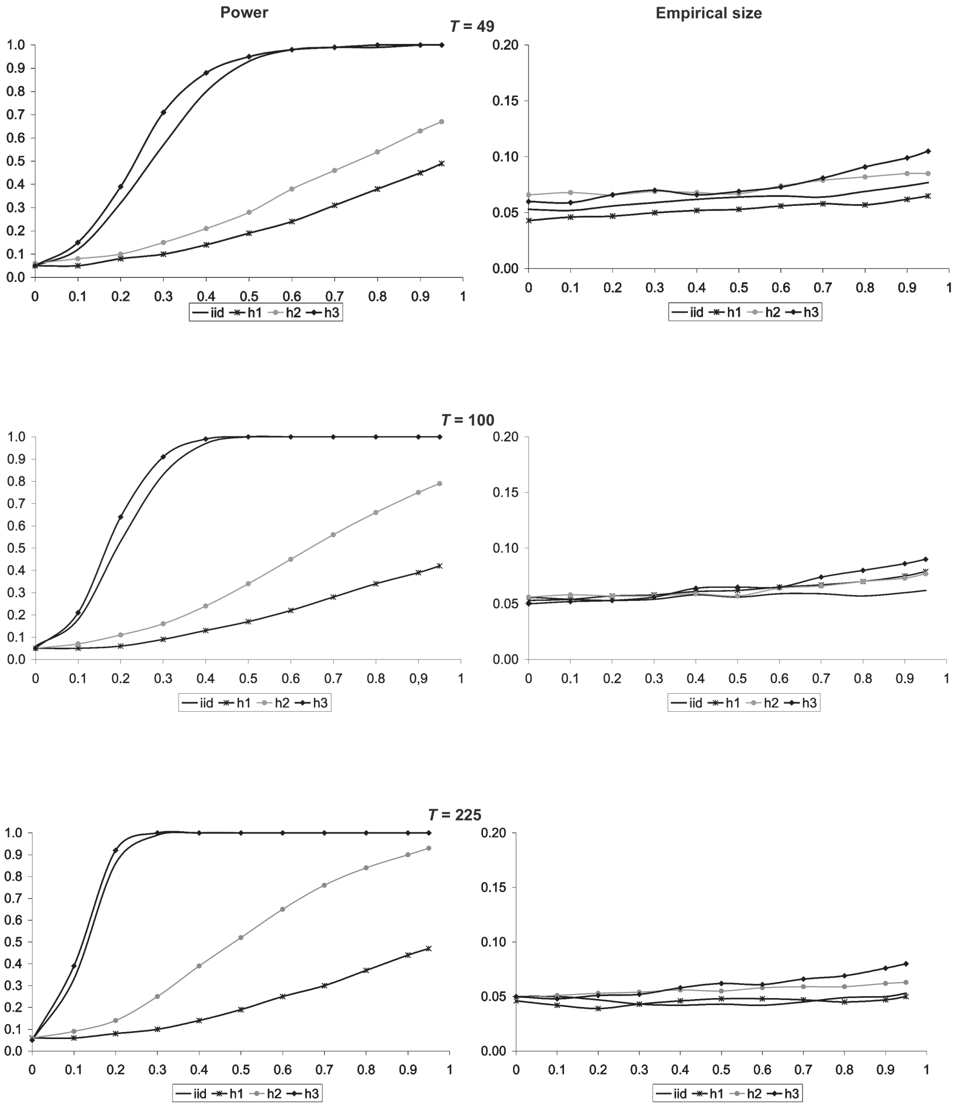


Figure 3. Power and empirical size of LR_{COM} test for non-normal distributions functions

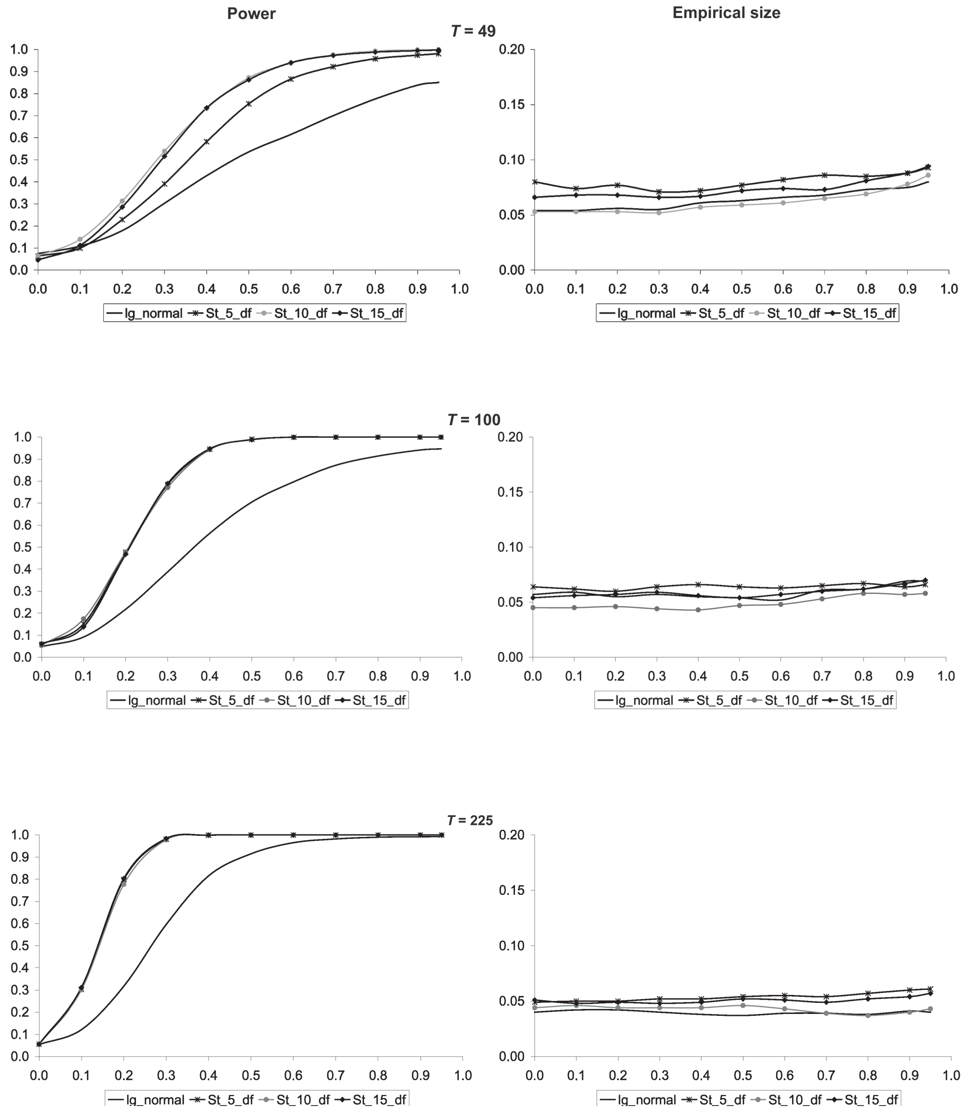


Figure 4. Power and empirical size of LR_{COM} test for dense weighting matrices

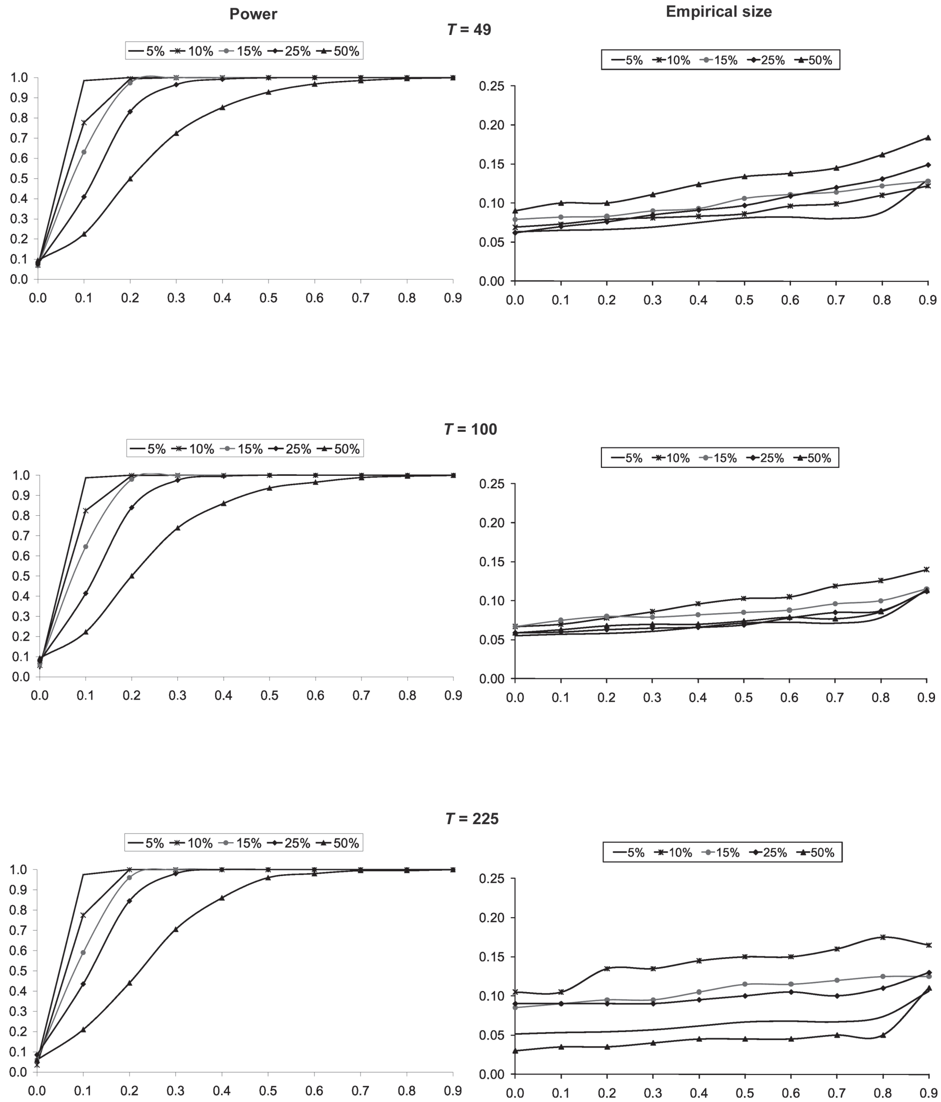


Figure 5. Power and empirical size of LR_{COM} test under different degrees of endogeneity

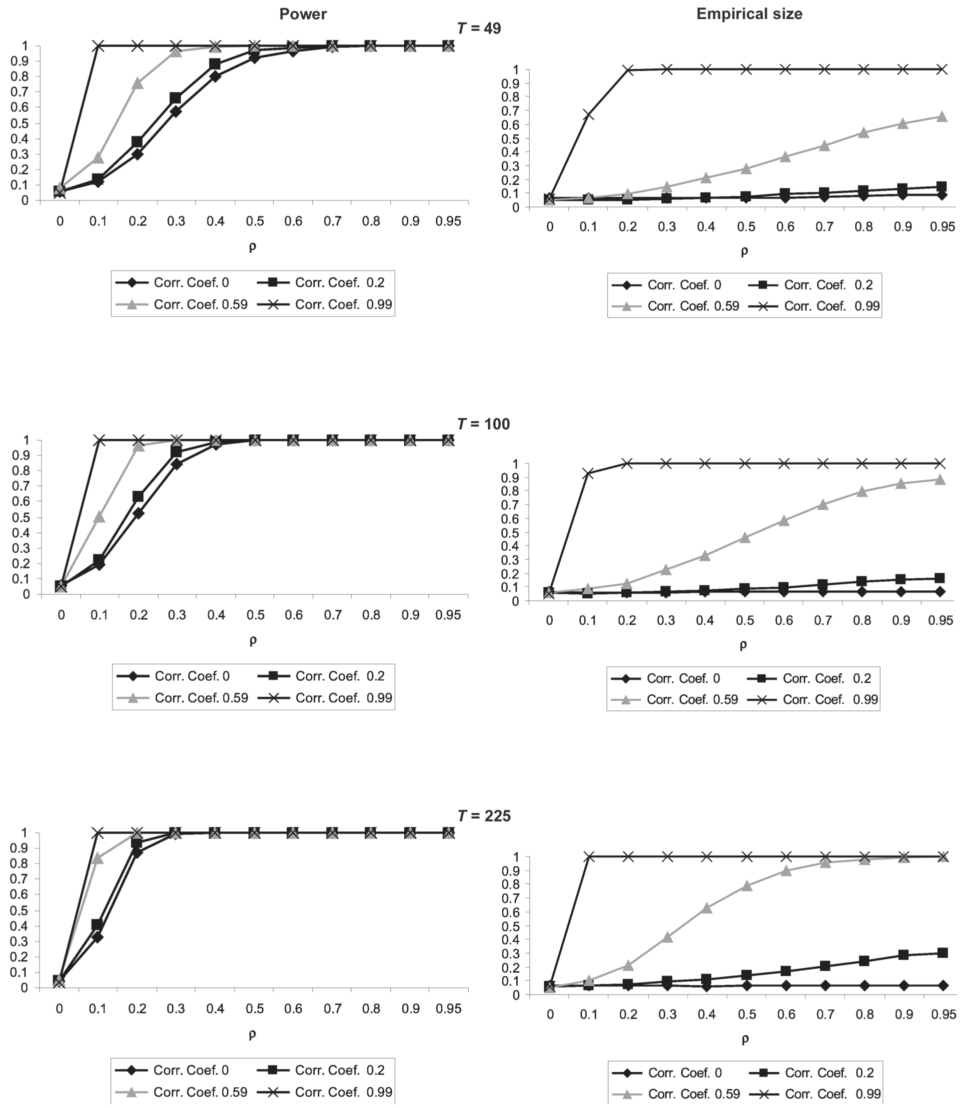


Figure 6. Power and empirical size of LR_{COM} test under different pattern of non-linearity

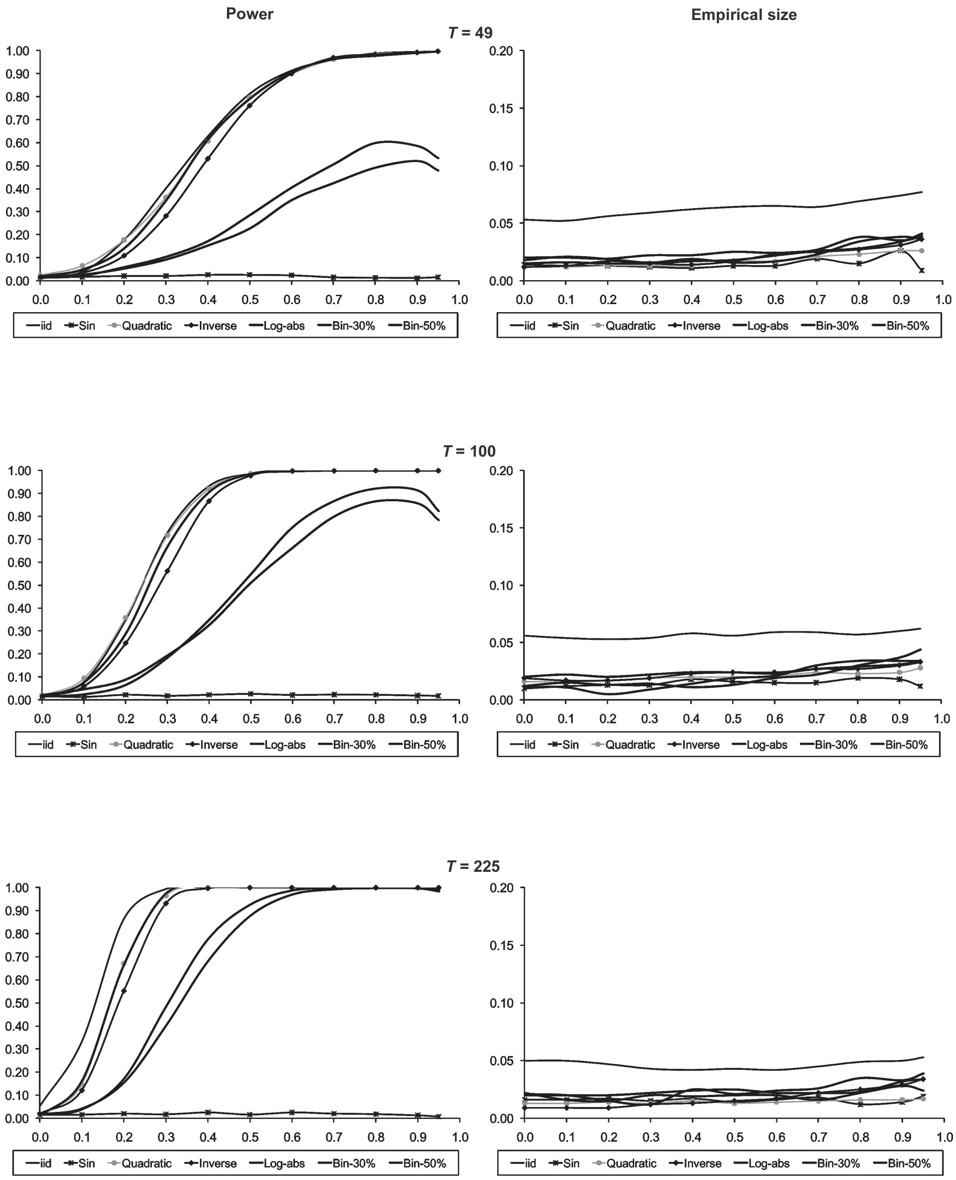


Figure 2 shows that heteroscedasticity affects negatively the performance of the test, especially in what respects to the power function. However, this is true only for the heteroscedasticity spatial patterns: the impact of the non-spatial heteroscedastic pattern (*h*3) is almost negligible, both on the power function and on the empirical size. The other two spatial heteroscedastic patterns (*h*1 and *h*2) suffer severe consequences slashing power and slightly raising the size.

The implications of the non-normality of the data are evident on Figure 4. The impact diminishes as the sample size increases. The asymmetry of the distribution function (log-normal case) seems to have a greater impact that the presence of outliers (Student-t case), especially for small sample sizes ($T = 49$ and 100). The test tends to be slightly oversized in both cases. The situation is more balanced in large sample case where the size is correctly estimated.

The density of the weighting matrix has a clear impact in the behaviour of the LR_{COM} test as it is clear in Figure 4 (the iid case corresponds to «5%», where each cell is connected with to the 5% of its neighbours). The use of dense matrices implies a tendency to slightly overestimate the size of the test, as it appears in the right panel, and severe losses in power especially for a range of intermediate values of the spatial dependence parameter. Denser matrices are a risk factor in spatial models that affects to almost every inference. The Common Factor test does not avoid these problems but the consequences are less severe than in other aspects.

Figure 5 shows that endogeneity has a very damaging effect on the LR_{COM} test, especially in what respect to size (the iid case corresponds to «Corr.Coef.0»). The figures of the right panel clearly indicate a strong tendency to reject, wrongly, the null of the LR_{COM} test for intermediate to high values of the correlation coefficient between the regressor and the error term of the equation. Strong endogeneity means strong over-sizing. This tendency pushes upwards the power function estimated on the left panel (and obtained using the theoretical 5% significant value). Overall, these results indicate that endogeneity is a key issue in relation to the problem of model selection and that, at least for the LR_{COM} test, a bootstrapping approach may be advisable.

Finally, the results for the non-linear processes offer a very heterogeneous picture as it is clear in Figure 6. First of all, looking at the right panels, there is a general tendency to underestimate the size even for very small values of the spatial dependence coefficient. In other words, we are going to select the SEM model more than the necessary. In relation to the power, we can identify three groups of functions: the quasi-linear functions (which includes the quadratic and the logarithm of the absolute value), the binary functions and the strongly non-linear functions (the sine and the inverse functions). The impact for the first group is small and the LR_{COM} tends to work properly. For the case of discretized data, there is a noticeable power loss although the losses tend to diminish as the sample size increases. The left bottom panel indicates that 225 observations are not enough to guarantee a good power for intermediate to small values of the spatial dependence coefficient. In sum, it is clear that the presence of strong nonlinearities in the DGP is a challenge for this test that in some cases (i.e., the sine function) hardly detects SLM processes.

4. Conclusions

The tests of Common Factors were introduced into a spatial context at the beginning of the eighties when the current toolbox was still in its infancy. The Common Factor tests had never occupied a prominent role in this toolbox; only the Likelihood Ratio variant, the $LR_{COM,}$ is popular. Habitually, these tests have been used in an auxiliary form, to corroborate conclusions obtained with other techniques. Nevertheless, we believe that the Common Factors Tests should play a more relevant role as a guide in applied work.

These tests should be used in connection with other techniques in order to explore the adequate direction for the specification process. At least, it should be borne in mind the requirement of Davidson (2000, p. 168): «*The point is that although AR(1) errors may well be the correct specification, they impose a common-factor parameter restriction on the equation that requires to be tested. It would nowadays be regarded as bad practice to impose the AR(1) model without testing the implicit restriction*».

Our position is that, given the peculiarities of the discipline, we must be a little more ambitious. Externalities and dynamic spatial relationships play a strategic role in any spatial model. These elements often have an evasive nature that makes them difficult to detect. For this reason, it is important to have techniques to discriminate between different spatial interaction mechanisms. The Common Factor tests may help in this problem.

The literature has paid attention to its performance under ideal conditions. For this reason, we tried to fill this gap by conducting a Monte Carlo experiment to evaluate its performance under some common non-ideal conditions: heteroscedasticity, non-normality, endogeneity, dense weighting matrices and non-linearity.

Our results have shown evidence on the following points. Regarding the empirical size of the test, results are quite acceptable except when there are endogenous regressors in the equation. As regards to the power, our results are very good in the case of endogeneity, and reasonably good also for the other cases. The worst situation corresponds to a spatial heteroscedastic pattern, to non-symmetric probability distribution functions and to strong departures of the assumption of linearity in the functional form (the sine function it is a pathological case).

In sum, we strongly suggest the use of the Likelihood Ratio test of Common Factors to spatial econometricians as a useful technique in the process of specifying a spatial model.

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Section On theory and methods

Updating weighting matrices by Cross-Entropy

Esteban Fernández Vázquez *

ABSTRACT: The classical approach to estimate spatial models lays on the choice of a spatial weights matrix that reflects the interactions among locations. The rule used to define this matrix is supposed to be the most similar to the «true» spatial relationships, but for the researcher is difficult to elucidate when the choice of this matrix is right and when is wrong. This key step in the process of estimating spatial models is a somewhat arbitrary choice, as Anselin (2002) pointed out, and it can be seen as one of their main methodological problems. This note proposes not imposing the elements of the spatial matrix but estimating them by cross entropy (CE) econometrics. Since the spatial weight matrices are often row-standardized, each one of their rows can be approached as probability distributions. Entropy Econometrics (EE) techniques are a useful tool for recovering unknown probability distributions and its application allows the estimation of the elements of the spatial weights matrix instead of the imposition by researcher. Hence, the spatial lag matrix is not a matter of choice for researcher but of empirical estimation by CE. We compare classical with CE estimators by means of Monte Carlo simulations in several scenarios on the true spatial effect. The results show that Cross Entropy estimates outperform the classical estimates, especially when the specification of the weights matrix is not similar to the true one. This result points to CE as a helpful technique to reduce the degree of arbitrariness imposed in the estimation of spatial models.

JEL Classification: C15, C21.

Keywords: Spatial econometrics, cross entropy econometrics, spatial models specifications, Monte Carlo simulations.

Actualización de matrices de pesos espaciales por Entropía Cruzada

El enfoque clásico para estimar modelos espaciales parte de la elección de una matriz de pesos espaciales que refleje la interacción entre las diferentes zonas. Se asume que la regla para definir esta matriz es que sea lo más parecida a la «verdadera» red de relaciones espaciales, pero para el investigador es difícil dilucidar cuándo la

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elección de esta matriz es correcta. Este paso clave en el proceso de estimación de modelos espaciales es una elección arbitraria, como Anselin (2002) señaló, y puede ser visto como uno de sus principales problemas metodológicos. En esta nota se propone no imponer los elementos de la matriz, sino su estimación basándose en la técnica de Entropía Cruzada (CE). Como las matrices de pesos espaciales son frecuentemente normalizadas por filas, cada una de ellas se puede entender como una distribución de probabilidad. La econometría basada en medidas de entropía es una herramienta útil para la obtención de distribuciones de probabilidad desconocidas, y su aplicación permite la estimación de los elementos de la matriz de pesos espaciales. Así, la matriz ya no depende de una elección impuesta por el investigador, sino de una estimación empírica. Este artículo compara los estimadores clásicos con los basados en medidas de entropía por medio de simulaciones de Monte Carlo en varios escenarios. Los resultados muestran que estas estimaciones superan a las obtenidas por estimadores tradicionales, especialmente cuando la especificación de la matriz no es similar a la real. Este resultado destaca la utilidad de las técnicas CE a la hora de reducir el grado de arbitrariedad impuesta en la estimación de modelos espaciales.

Clasificación JEL: C15, C21.

Palabras clave: Econometría espacial, econometría basada en entropía cruzada, especificación de modelos espaciales, simulaciones de Monte Carlo.

1. Introduction

The literature distinguishes several types of spatial models depending on the assumptions made about the way in which spatial correlation affects the dependent variable. Specifically, Anselin (2003) presents a wide taxonomy of different types of spatial models. Although it can be easily extended to other situations, in this paper we focus on a situation where the externalities spread across space through a spatial lagstructure.

Traditionally, for a set of N locations and T observations in time, the so-calledspatial lag model is written as:

$$y = X\beta + \rho Wy + \epsilon \tag{1}$$

$$y = [I - \rho W]^{-1}[X\beta + \epsilon] \tag{2}$$

where y is the $(NT \times 1)$ vector with the values of the dependent variable, W is the $(N \times N)$ matrix of *a priori* spatial weights which is assumed constant along time, X is a $(NT \times H)$ matrix of exogenous variables, β is a $(H \times 1)$ vector of parameters to estimate and ϵ is a $(NT \times 1)$ stochastic error. In addition, ρ is a spatial interaction parameter that measures how the variable y is spatially influenced. The weighting matrix W represents the spatial structure of the spillovers.

The selection of a specific spatial weights matrix W is a key issue when estimating spatial models, but at the same time there is not a unanimous criterion to choose the most appropriate spatial weights for a given empirical application [1]. Basically, there are two alternative approaches to the problem of the specification of spatial weights. One of the streams promotes fixingthe W matrix exogenously to the model basing on some concept of geographical proximity. For example, a very simple way to characterize their elements w_{ij} is by defining them as binary variables that take value 1 when locations i and j are neighbor and 0 otherwise (depending on the existence or not of a common border, for example). The geographical distance between locations i and j can be used in a more direct way, defining w_{ij} as a distance decay function. Other authors prefer using some economic measure of distance based on interregional trade flows, income differences, etc. [2].

Some other authors, on the contrary, propose the construction of W matrices based on some «empirical» evidence about the variables of the model. They are critical of the «exogenous approach», because the spatial lag operator imposed can be very different from the real spatial structure underlying in the data. For example, Kooijman (1976) or Boots and Dufornaud (1994) define as one criterion the choice of W that maximizes the Moran statistic. Following a similar idea, Mur and Paelinck (2010) base their specification of W on the so-called complete correlation coefficients. Two papers by Getis and Aldstadt base their specification of W on the values of the G_i^* local statistic (Getis and Aldstadt, 2004) and on the use of a multi-directional algorithm (Aldstadt and Getis, 2006). Bhattacharjee and Jensen-Butler (2006) suggest a method to estimate W based on the real structure of the spatial autocovariance, while Conley (1999) proposes the direct estimation of the spatial autocovariances. This data-driven selection of W has been, however, subject to strong criticism from authors supporting the exogenous approach (see, for example, Manski, 1993).

This note explores the use of Generalized Cross Entropy (GCE) econometrics to estimate such models. The GCE approach can be considered an extension of the Generalized Maximum Entropy estimator, which has been applied recently to spatial regression models by Marsh and Mittelhammer (2004) or Fernandez-Vazquez *et al.,* (2009), who estimated a first order spatial lag model using this technique. The present paper will use the GCE technique to define spatial lag operators that can be seen to lie in an intermediate position between the «exogenous» and «empirical» approaches. The basic idea is that we initially fix an exogenous a priori W matrix but, once this is specified, we could modify our initial specification.

The structure of the paper is the following: Section 2 provides an overview of the GCE methodology and shows how it can be applied to the context of spatial lag models. Section 3 evaluates the relative performance of the GCE techniqueusing a sampling experiment under different scenarios of sample size and degrees of divergencebetween the actual spatial network and the weighting matrix W specified in

[1] See Anselin (2002), p. 259.

[2] Some examples of these other approaches can be found in Molho (1995), Fingleton (2001) or López-Bazo, Vayá and Artís (2004).

the estimation. Section 4 shows an empirical application that illustrates how the proposed CE estimation procedure works with a real-world example. Finally, section 5 presents the concluding remarks.

2. Generalized Cross entropy econometrics: an overview

Entropy Econometrics (EE) techniques have interesting properties when dealing with ill-conditioned estimation problems (small samples or data sets affected by large collinearity). In Golan *et al.* (1996) or Kapur and Kesavan (1992) extensive descriptions of the entropy estimation approach can be found. Generally speaking, EE techniques are used to recover unknown probability distributions of random variables that can take M different known values. The estimate $\tilde{p}$ of the unknown probability distribution p must be as similar as possible to an appropriate *a priori* distribution q, constrained by the observed data. Specifically, the Cross-Entropy (CE) procedure estimates $\tilde{p}$ by minimizing the Kullback-Leibler divergence $D(p\,||\,q)$ (Kullback, 1959):

$$\underset{p}{\text{Min}}\ D(p\,||\,q) = \sum_{m=1}^{M} p_m \ln\left(\frac{p_m}{q_m}\right) \tag{3}$$

The divergence $D(p\,||\,q)$ measures the dissimilarity of the distributions p and q. This measure reaches its minimum (zero) when p and q are identical and this minimum is reached when no constrains are imposed. If some information (for example, observations on the variable) is available, each piece of information will lead to a Bayesian update of the *a priori* distribution q.

The underlying idea of the CE methodology can be applied for estimating the parameters of general linear models, which leads us to the so-called Generalized Cross Entropy (GCE). Let us suppose a variable y that depends on H explanatory variables x_h:

$$y = X\beta + \epsilon \tag{4}$$

Where y is a $(NT \times 1)$ vector of observations for y, X is a $(NT \times H)$ matrix of observations for the x_h variables, β is the $(H \times 1)$ vector of unknown parameters $\beta = (\beta_1, ..., \beta_H)$ to be estimated, and ϵ is a $(NT \times 1)$ vector with the random term of the linear model. Each β_h is assumed to be a discrete random variable. We assume that there is some information about its $M \geq 2$ possible realizations. This information is included for the estimation by means of a support vector $b' = (b_1, ..., b_M)$ with corresponding probabilities $p'_h = (p_{h1}, ..., p_{hM})$. The vector bis based on the researcher's a priori belief about the likely values of the parameter. For the sake of convenient exposition, it will be assumed that the M values are the same for every parameter, although this assumption can easily be relaxed. Now, vector β can be written as:

$$\beta = \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_H \end{bmatrix} = BP = \begin{bmatrix} b & 0 & \cdots & 0 \\ 0 & b & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & b \end{bmatrix} \begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_H \end{bmatrix} \tag{5}$$

Where B and P have dimensions $(H \times HM)$ and $(HM \times 1)$ respectively. Now, the value of each parameter β_h is given by the following expression:

$$\beta_h = \boldsymbol{b}'\boldsymbol{p_h} = \sum_{m=1}^{M} b_m\, p_{hm};\ \forall h = 1,\ldots,H \tag{6}$$

For the random term, a similar approach is followed. Oppositely to other estimation techniques, GCE does not require rigid assumptions about a specific probability distribution function of the stochastic component, but it still is necessary to make some assumptions. ϵ isassumed to have mean $E[\epsilon] = 0$ and a finite covariance matrix. Basically, we represent our uncertainty about the realizations of vector ϵ treating each element ϵ_t as a discrete random variable with $J \geq 2$ possible outcomes contained in a convex set $v' = (v_1, ..., v_J)$, which for the sake of simplicity is assumed as common for all the ϵ_t. We also assume that these possible realizations are symmetric around zero $(-v_1, = v_J)$. The traditional way of fixing the upper and lower limits of this set is to apply the three-sigma rule (see Pukelsheim, 1994). Under these conditions, vector ϵ can be defined as:

$$\varepsilon = \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_{NT} \end{bmatrix} = VU = \begin{bmatrix} v & 0 & \cdots & 0 \\ 0 & v & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & v \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_{NT} \end{bmatrix} \tag{7}$$

and the value of the random term for an observation equals:

$$\epsilon_{nt} = \boldsymbol{v}'\boldsymbol{u_{nt}} = \sum_{j=1}^{J} v_j u_{ntj} \tag{8}$$

And, consequently, model (4) can be transformed into:

$$y = XBp + Vu \tag{9}$$

So we need also to estimate the elements of matrix U (denoted by $\tilde{u}_{tj}$) and the estimation problem for the general linear model (4) is transformed into the estimation of $H + NT$ probability distributions. For this estimation, once specified the a priori probability distributions Q and U^0 respectively for P and U, the GCE problem is written in the following terms:

$$\underset{P,U}{\mathrm{Min}}\ D(P,U \,||\, Q,U^0) = \sum_{h=1}^{H}\sum_{m=1}^{M} p_{hm} \ln\left(\frac{p_{hm}}{q_{hm}}\right) + \sum_{n=1}^{N}\sum_{t=1}^{T}\sum_{j=1}^{J} u_{ntj} \ln\left(\frac{u_{ntj}}{u_{ntj}^{0}}\right) \tag{10a}$$

subject to:

$$y_{nt} = \sum_{h=1}^{H}\sum_{m=1}^{M} b_m p_{hm} x_{nt} + \sum_{j=1}^{J} v_j u_{ntj};\ \forall n,t \tag{10b}$$

$$\sum_{m=1}^{M} p_{hm} = 1;\ \forall h \tag{10c}$$

$$\sum_{j=1}^{J} u_{ntj} = 1;\ \forall n,t \tag{10d}$$

The restrictions in (10b) ensure that the posterior probability distributions of the estimates and the errors are compatible with the observations. The equations in (10c) and (10d) are just normalization constraints [3]. In other words, the CE solutions are obtained by minimizing the Kullback-Leibler divergence $D(P \| Q)$ between the unknown p_{hm} and the *a priori* q_{hm}. Similarly, for the estimation of u_{ntj} the divergence $D(U \| U^0)$ is minimized as well. In this case, the *a priori* probabilities are usually fixed as uniform ($u_{ntj}^0 = \frac{1}{J}\ \forall n, t$), which is the natural point of departure to reflect the uncertainty about ϵ.

This GCE procedure can be extended for estimating spatial lagmodels such as (1). Following the same procedure explained above for the β_k parameters, it will be assumed that there are $L \geq 2$ possible realizations for the spatial parameter ρ in a support vector $z' = (z_1, ..., z_L)$, with corresponding probabilities $s' = (s_1, ..., s_L)$. The parameter ρ, consequently, can be estimated by GCE by means of this reparametrization. A similar idea was applied by Marsh and Mittelhamer (2004) for the case of spatial autoregressive models once a matrix of spatial weights W is specified. Fernandez-Vazquez *et al.* (2009) extended this idea and proposed estimating all the ρ_{ij} elements of a matrix of spatial parameters instead of using a predetermined W matrix. This note suggests a solution where only one single spatial parameter ρ is defined, but the elements of a spatial weights matrix W will be updated from the *a priori* values specified.

[3] This GCE estimation procedure can be seen as an extension of the particular Generalized Maximum Entropy (GME) principle, given that the solutions of both approaches are the same when the *a priori* probability distribution contained in Q are all uniform.

The GCE can be naturally applied in this context, given that the elements of matrix W are typically row-standardized and are non-negative. Consequently, each rowof W can be taken as a probability distribution with unknown elements w_{ni} to be recovered:

$$W = \begin{bmatrix} 0 & w_{12} & \cdot & w_{1N} \\ w_{21} & 0 & \cdot & w_{2N} \\ \cdot & \cdot & \cdot & \cdot \\ w_{N1} & w_{N2} & \cdot & 0 \end{bmatrix} \tag{11}$$

This means that equation (1) can be rewritten as:

$$\boldsymbol{y} = \boldsymbol{XBp} + (\boldsymbol{s}'\boldsymbol{z})\boldsymbol{Wy} + \boldsymbol{VU} \tag{12}$$

Now the empirical GCE program estimates H+2NT+1 probability distributions, in the following terms:

$$\begin{aligned} \underset{P,s,W,U}{\text{Min}}\, D(P,s,W,U \,\|\, Q,s^0,W^0,U^0) = \sum_{h=1}^{H}\sum_{m=1}^{M} p_{hm}\ln\left(\frac{p_{hm}}{q_{hm}}\right) + \sum_{l=1}^{L} s_l \ln\left(\frac{s_l}{s_l^0}\right) \\ + \sum_{n=1}^{N}\sum_{i\neq 1}^{N} w_{ni}\ln\left(\frac{w_{ni}}{w_{ni}^0}\right) + \sum_{n=1}^{N}\sum_{t=1}^{T}\sum_{j=1}^{J} u_{ntj}\ln\left(\frac{u_{ntj}}{u_{ntj}^0}\right) \end{aligned} \tag{13a}$$

subject to:

$$y_{nt} = \sum_{h=1}^{H}\sum_{m=1}^{M} b_m p_{hm} x_{hnt} + \left(\sum_{l=1}^{L} s_l z_l\right)\left(\sum_{i\neq n}^{N} w_{ni} y_i\right) + \sum_{j=1}^{J} v_j u_{ntj};\ \forall n,t \tag{13b}$$

$$\sum_{m=1}^{M} p_{hm} = 1;\ \forall h \tag{13c}$$

$$\sum_{j=1}^{J} u_{ntj} = 1;\ \forall h,t \tag{13d}$$

$$\sum_{i\neq n}^{N} w_{ni} = 1;\ \forall n = 1,\ldots,N \tag{13e}$$

$$\sum_{l=1}^{L} s_l = 1 \tag{13f}$$

The GCE program above includes the Kullback divergence associated to the spatial parameter and to the weighting matrix in the objective function (13a). Equations (13c)-(13d) are again normalization constraints. Restriction (13b) forces the recovered probabilities to fit the observations of the dependent variable. This GCE program estimates, together with the parameters of the model, the elements of the matrix of spatial weights. These estimates (namely $\hat{w}_{ni}$) are the closest to the a priori assumptions made about the elements of the W matrix (w^0_{ni}) and that, simultaneously, are compatible with the available information. In other words, we choose as elements of the matrix those $\hat{w}_{ni}$ that, being consistent with the observed data, diverge least with our prior assumption W^0.

Finally, the estimated value of the spatial spillovers will be:

$$\hat{\rho} = \sum_{l=1}^{L} \hat{s}_l z_l \tag{14}$$

3. A numerical experiment

In this section, the performance of the GCE technique will be compared with other competing techniques in a scenario where the spatial structure that generates the data is given by a distance decay matrix. Under this specification, the elements of the W^{exp} matrix are defined as the following function:

$$w_{ni}^{\exp} = \exp(-d_{ni})$$

Where d_{ni} is the distance between the locations n and i, being $w^r_{ii} = 0$. We have simulated the spatial lag model $y = X\beta + \rho W^{exp} y + \in$ with 1,000 replications for two lattices of $N = 15$ and $N = 47$ locations. Specifically, for the case where $N = 15$, we have taken the 15 inland Spanish regions (Autonomous Communities) and when $N = 47$, the set of locations is formed by the 47 inland Spanish provinces. d_{ni} is the distance (km. by road) between the capital cities of regions (provinces) n and i. In our experiment, the error term is generated in each simulation as a $N(0.1)$ distribution. Matrix X is composed by one constant term and one regressor x. The values for the independent variable and for the parameters (kept constant throughout the simulations) are:

$$\beta = \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} = \begin{bmatrix} 0.75 \\ 0.50 \end{bmatrix};\ \rho = 0.25 \tag{15a}$$

$$x_{nt} \sim U(0.10);\ n = 1, \dots, N;\ t = 1, \dots, T \tag{15b}$$

In the experiment, the connectivity between the two sets of locations is given by the spatial pattern contained in the matrix W^{exp}, which is not necessarily equal to the weighting matrix used to estimate the model (W). For example, using the same idea of basing our spatial weights in a distance decay function, we could have specified the elements of our matrix as $w_{ni}^{sqr} = (d_{ni})^{-2}$; which is a specification commonly used in practice as well. We have introduced the possibility of divergence between the real matrix (W^{exp}) and the one specified in the model (W) assuming that $W = (1 - \eta) W^{exp} + \eta W^{sqr}$; η (bounded between 0 and 1) is a scalar that reflects the degree of divergence between the real and the used spatial weighting matrices. If $\eta = 0$ this would indicate that the real and the specified matrix are exactly the same and the higher the value of η, the larger the misspecification of the spatial weighting matrix. In the limit, if $\eta = 1$ we'll be using a matrix of spatial weights completely different of the real one W^{exp}.

In this scenario for the sampling experiment, we compare the GCE approach with other rival procedures. In order to apply the GCE procedure to estimate models like (12), it is necessary to specify some support for the set of parameters and for the errors. For β_0 and β_1 the same support $b = (-1.1.1)$ has been set. Note that the support is not centered on the true value of any of the parameters, which means that we are including not very good prior information for the estimation of the β parameters. The support vector for the spatial parameter ρ was set as $z = (-1.1.1)$. Finally, the support v for the error has been generated as a three-point vector centered about 0 following the common procedure of the 3-sigma rule of variable y in each trial of the experiment (Pulkesheim, 1994; Golan, Judge and Miller, 1996).

The benchmarkfor the comparison will be the estimation by maximum likelihood (ML). One basic difference is that in ML we specify a matrix W and we apply it directly in the estimation. In contrast, using GCE we take W as an *a priori* approximation to W^{exp}, but then we let the data speak for themselves and we could use spatial weights $\hat{w}_{ni}$ (estimates of the elements on W^{exp}) different from our initial assumptions.

Table 1 and 2 summarize the results of the experiment for the two sets of locations assuming that we have observations for $T = 10$ time periods. For each one of the competing estimators we have computed the mean of the estimates of β_0, β_1 and ρ throughout the 1,000 simulations (columns 1, 3 and 5 respectively) and their empirical variance, the mean absolute error of the estimates of β_0 and β_1 (columns 2 and 4) and the mean absolute error (column 6, which quantifies the average absolute differences between the actual ρ and its respective estimate).

Each row of Tables 1 to 4 contains a different value for the scalar η. As expected, the deviations between the actual and the estimated parameters for both methods are relatively low for values of η close to zero. However, the performance of the two competing estimation techniques is remarkably different as η grows. When the differences between the real W^{exp} and the W used in the estimation become larger, the GCE begins to yield comparatively better estimates than ML.

Table 1. Results of the numerical experiment ($N = 47$; $T = 10$; 1,000 replications)

		(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
		Average $\hat{\beta}_0$ *True* $\beta_0 = 0.75$	MAE_{β^0}	*Average* $\hat{\beta}_1$ *True* $\beta_1 = 0.5$	MAE_{β^1}	*Average* $\hat{\rho}$ *True* $\rho = 0.25$	$MAE\rho$
$\eta = 0.00$	ML	0.377 [0.047]	0.393	0.498 [0.001]	0.011	0.341 [0.002]	0.091
	GCE	0.240 [0.014]	0.520	0.502 [0.003]	0.016	0.350 [0.003]	0.105
$\eta = 0.20$	ML	0.132 [0.053]	0.630	0.498 [0.001]	0.011	0.397 [0.002]	0.147
	GCE	0.073 [0.014]	0.687	0.490 [0.003]	0.016	0.350 [0.003]	0.163
$\eta = 0.40$	ML	–0.190 [0.063]	0.954	0.498 [0.001]	0.012	0.469 [0.003]	0.219
	GCE	–0.121 [0.013]	0.887	0.476 [0.003]	0.016	0.474 [0.003]	0.229
$\eta = 0.60$	ML	–0.610 [0.079]	1.371	0.500 [0.001]	0.017	0.564 [0.004]	0.314
	GCE	–0.316 [0.011]	1.090	0.462 [0.003]	0.018	0.541 [0.005]	0.296
$\eta = 0.80$	ML	–1.111 [0.106]	1.857	0.503 [0.001]	0.027	0.675 [0.006]	0.425
	GCE	–0.474 [0.009]	1.256	0.450 [0.003]	0.021	0.596 [0.005]	0.351
$\eta = 1.00$	ML	–1.470 [0.144]	2.214	0.509 [0.001]	0.031	0.748 [0.008]	0.498
	GCE	–0.558 [0.008]	1.337	0.445 [0.003]	0.028	0.624 [0.006]	0.379

Table 2. Results of the numerical experiment
(N = 15; T = 10; 1,000 replications)

		(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
		Average $\hat{\beta}_0$ *True* $\beta_0 = 0.75$	MAE_{β^0}	*Average* $\hat{\beta}_1$ *True* $\beta_1 = 0.5$	MAE_{β^1}	*Average* $\hat{\rho}$ *True* $\rho = 0.25$	$MAE\rho$
$\eta = 0.00$	ML	0.521 [0.176]	0.364	0.487 [0.001]	0.055	0.327 [0.006]	0.091
	GCE	0.216 [0.036]	0.521	0.487 [0.003]	0.016	0.356 [0.004]	0.109
$\eta = 0.20$	ML	0.316 [0.166]	0.371	0.487 [0.004]	0.057	0.376 [0.007]	0.134
	GCE	0.144 [0.036]	0.560	0.488 [0.003]	0.016	0.403 [0.004]	0.154
$\eta = 0.40$	ML	0.060 [0.111]	0.485	0.487 [0.004]	0.074	0.437 [0.010]	0.191
	GCE	0.059 [0.036]	0.601	0.472 [0.003]	0.016	0.449 [0.005]	0.199
$\eta = 0.60$	ML	–0.241 [0.241]	0.576	0.489 [0.004]	0.088	0.507 [0.014]	0.259
	GCE	–0.016 [0.009]	0.644	0.460 [0.004]	0.018	0.488 [0.005]	0.238
$\eta = 0.80$	ML	–0.537 [0.307]	0.684	0.493 [0.005]	0.104	0.573 [0.019]	0.324
	GCE	–0.073 [0.007]	0.668	0.452 [0.004]	0.021	0.514 [0.006]	0.264
$\eta = 1.00$	ML	–0.646 [0.384]	0.801	0.487 [0.004]	0.122	0.589 [0.023]	0.339
	GCE	–0.098 [0.007]	0.725	0.505 [0.003]	0.028	0.520 [0.006]	0.270

Besides, the experiment has been repeated now assuming a cross-section data set (i.e., T = 1) being the results summarized in Tables 3 and 4, which present the same structure as Tables 1 and 2.

Table 3. Results of the numerical experiment
($N = 47$; $T = 1$; 1,000 replications)

		(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
		Average $\hat{\beta}_0$ *True* $\beta_0 = 0.75$	MAE_{β^0}	*Average* $\hat{\beta}_1$ *True* $\beta_1 = 0.5$	MAE_{β^1}	*Average* $\hat{\rho}$ *True* $\rho = 0.25$	$MAE\rho$
$\eta = 0.00$	ML	1.034 [2.536]	1.238	0.485 [0.012]	0.087	0.200 [0.172]	0.327
	GCE	0.102 [0.002]	0.638	0.476 [0.007]	0.071	0.431 [0.014]	0.187
$\eta = 0.20$	ML	0.660 [2.307]	1.233	0.481 [0.011]	0.089	0.299 [0.161]	0.327
	GCE	0.091 [0.002]	0.659	0.469 [0.007]	0.069	0.445 [0.013]	0.199
$\eta = 0.40$	ML	0.293 [2.097]	1.258	0.483 [0.011]	0.088	0.396 [0.150]	0.344
	GCE	0.081 [0.002]	0.663	0.463 [0.006]	0.071	0.458 [0.012]	0.211
$\eta = 0.60$	ML	–0.066 [1.908]	1.355	0.485 [0.012]	0.087	0.492 [0.139]	0.375
	GCE	0.081 [0.002]	0.663	0.460 [0.006]	0.071	0.468 [0.012]	0.221
$\eta = 0.80$	ML	–0.418 [1.741]	1.506	0.488 [0.012]	0.088	0.585 [0.129]	0.422
	GCE	0.070 [0.002]	0.691	0.456 [0.006]	0.073	0.471 [0.012]	0.224
$\eta = 1.00$	ML	–0.763 [1.599]	1.710	0.490 [0.012]	0.088	0.677 [0.120]	0.478
	GCE	0.048 [0.002]	0.702	0.444 [0.006]	0.077	0.496 [0.010]	0.247

In brackets, empirical variance along the simulations.

Table 4. Results of the numerical experiment ($N = 15$, $T = 1$; 1,000 replications)

		(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
		Average $\hat{\beta}_0$ *True* $\beta_0 = 0.75$	MAE_{β^0}	*Average* $\hat{\beta}_1$ *True* $\beta_1 = 0.5$	MAE_{β^1}	*Average* $\hat{\rho}$ *True* $\rho = 0.25$	$MAE\rho$
$\eta = 0.00$	ML	0.721 [1.540]	0.971	0.500 [0.045]	0.169	0.255 [0.074]	0.223
	GCE	0.128 [0.003]	0.622	0.475 [0.011]	0.081	0.324 [0.018]	0.131
$\eta = 0.20$	ML	0.875 [1.602]	0.989	0.499 [0.045]	0.169	0.213 [0.078]	0.230
	GCE	0.134 [0.003]	0.616	0.483 [0.011]	0.081	0.332 [0.019]	0.135
$\eta = 0.40$	ML	1.030 [1.658]	1.026	0.498 [0.045]	0.170	0.171 [0.081]	0.238
	GCE	0.140 [0.003]	0.615	0.491 [0.011]	0.082	0.332 [0.019]	0.137
$\eta = 0.60$	ML	1.185 [1.709]	1.073	0.498 [0.045]	0.170	0.130 [0.084]	0.249
	GCE	0.145 [0.003]	0.616	0.498 [0.011]	0.083	0.333 [0.020]	0.138
$\eta = 0.80$	ML	1.340 [1.754]	1.131	0.497 [0.045]	0.170	0.088 [0.084]	0.266
	GCE	0.151 [0.004]	0.599	0.506 [0.011]	0.085	0.333 [0.020]	0.138
$\eta = 1.00$	ML	1.495 [1.794]	1.194	0.496 [0.045]	0.170	0.047 [0.084]	0.287
	GCE	0.157 [0.005]	0.593	0.513 [0.011]	0.087	0.334 [0.020]	0.138

In brackets, empirical variance along the simulations.

This is because, in the GCE, the specification of W can be seen as an a priori assumption that can be modified by the information contained in the sample. In other words, the data in the sample help to alleviate a wrong assumption about W^{exp}. All in all, the results suggest that with perfect certainty about the actual spatial network W^{exp}, using the GCE technique proposed does not imply gains compared with ML. On the other hand, if we do not have clear evidences for imposing the right structure in the spatial network, using a GCE estimator seems to limit the estimation errors.

4. An empirical application: modeling labor productivity for the Spanish provinces

This section illustrates the performance of the entropy-based adjustment of the W matrix with a simple real world example. The objective will be to estimate a model for the $N = 47$ Spanish inland provinces (we exclude the Canary and Balearic Island off our analysis) where the labor productivity depends on an intercept and the stock of capital per worker and a spatial autoregressive component.

Annual data from 1995 to 2006 for the 47 provinces on gross domestic product and labor have been obtained from the Regional Accounts of Spain compiled by the Spanish Statistical Institute (INE). Data of the stock of private capital have been obtained from the BDMores database elaborated by the Spanish Ministry of Economy for the same time period. All the variables are in logs and, following Holtz-Eakin and Schwartz (1995), they are measured in differences to the initial year in order to capture the long-term relationships between the variables, provided that period t is sufficiently far from the initial period.

Specifically, the model to be estimated is:

$$y = X\beta + \rho Wy + \epsilon \tag{16}$$

Where for each time period t, y is a vector containing labor productivity (gross value added divided by the amount of labor) for each province and X is a matrix with the two exogenous variables of the model, consisting in the stock of labor (L) and the stock of privatephysical capital (K) in each province. Vector β contains two of the unknown parameters of the model; namely the labor (β_L) and capital (β_K) elasticities of a Cobb-Douglas aggregate production function. The model also includes a spatial autoregressive component measured by the parameter ρ which (as well as matrix W) is assumed constant along time.

We have applied the entropy-based adjustment proposed to estimate the model, which implies that an initial specification of matrix W is required. Initially, the elements of this matrix will be based on a distance decay function as $w_{ni}^{sqr} = (d_{ni})^{-2}$, being d_{ni} the distance (km. by road) between the capital cities of two provinces n and i. For applying the CE estimation to equation (16), it is necessary to specify some supports for parameters and for the errors. For all the parameters (β_L, β_K and ρ), we have considered different ranges of plausible values with 3 points. Specifically, the supports specified for have been (–1, 0, 1) that have been later expanded to (–5, 0, 5) and (–10, 0, 10) in order to check the sensitivity of the estimates to changes in the supports [4]. The traditional three-sigma rule is applied for specifying the supporting vectors for the error terms.

[4] Note that supporting vectors centered on zero for the spatial autoregressive parameter implies assuming that sometimes a raise in a neighbor province can generate either an increase in labor productivity ora decrease in other provinces' productivity.

Besides the point estimates, the GCE procedure allows for testing some hypotheses about the model confronting our estimates with the null hypothesis that the parameters are zero. This hypotheses testing can be done with the so-called entropy ratio, which follows a limiting χ^2 distribution. Let KL_R be the Kullback'sdivergence measure of a constrained problem, where the parameter is constrained to be 0 (at the centre of its support). Now let KL_U be the Kullback's divergence measure (objective function of the GCE program) without the restriction that the parameter is equal to zero. The entropy ratio statistic ER for testing the null hypothesis that the parameter is zero is = $2[KL_R - KL_U]$, which under the null hypothesis follows a limiting χ^2 distribution with K degrees of freedom, being K the number of restriction imposed. The results are summarized in Table 5

Table 5. CE estimation of equation (16)

	(1)	*(2)*	*(3)*	*(4)*
	$\hat{\beta}_L$	$\hat{\beta}_K$	$\hat{\rho}$	*% of abs. adjustment in W*
CE estimates				
$b = (-1,0,1)$	0.449**	0.141*	0.652**	8.978
$b = (-5,0,5)$	0.468**	0.118*	0.664**	9.055
$b = (-10,0,10)$	0.468**	0.119*	0.664**	9.057
ML estimation	0.472**	0.128**	0.653**	

* stands for estimates significantly different from 0 at a 10% level and ** stands for estimates significantly different from 0 at a 5% level based on a χ^2 distribution

The first two columns of Table 5 show the estimates for the β_L and β_K parameters and the third one reports the estimates for ρ under the different supporting vectors considered. In order to illustrate the adjustment applied to the initial W matrix based on a squared distance-decay function, the mean percentage of change (in absolute value) between the initial and the posterior matrices are reported in column (4). On average the CE estimation procedure modifies the cells around 9%, which could be considered as a relatively modest adjustment.

Regarding the parameter estimates, the maximum likelihood results are included for comparative purposes. Note that, generally speaking, there is not much variability in the results across the different specifications assumed, all of which get significantly positive estimates of the parameters of the model. The CE estimates are close to those obtained by maximum likelihood, although the later gets a capital elasticity significant at 5% whereas the CE estimation only gets evidence of a positive estimate at 10%. Note also that supporting vectors assumed for the spatial autoregressive parameter were centered on zero, which implies assuming that sometimes a raise in a neighbor province can generate either an increase in labor productivity or a decrease in other provinces' productivity. In this case, under any of the scenarios considered, it seems to be empirical evidences of a positive and significant contagion process among the Spanish regions concerning variations in output.

5. Concluding remarks

The specification of the spatial weighting matrix has been a important issue in the field of spatial econometric analysis that has received considerable attention. The main problem is that there is not a unique approach to define the spatial weights and two alternative streams can be distinguished in the literature. One of the proposals supports using weighting matrices determined exogenously to the model, while other authors prefer to use some empirical evidence to specify them. This paper suggest a sort of intermediate way between these two proposals where the *W* matrix is a priori specified exogenously, but in a second stage the weights are updated by means of the GCE estimator. Focusing in the so-called spatial lagmodels, a numerical experiment compares the performance of the proposed GCE with a traditional ML estimator, and the results suggest that the possibility of updating the prior assumptions made in the *W* matrix facilitates more accurate estimates. Not surprisingly, the comparative performance of GCE gets better when the divergence between the actual and the a priori elements of *W* grows. The results of the numerical experiment are complemented with an application to real data of the method proposed, obtaining empirical evidence of a positive spatial autoregressive process among the aggregate production functions on the Spanish provinces between 1995 and 2006.

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Section On theory and methods

Investigaciones Regionales

A research agenda on general-to-specific spatial model search

Peter Burridge *

ABSTRACT: The paper sets up a nesting spatial regression model incorporating heteroskedastic shocks, and discusses hypothesis testing in both nested and non-nested cases in a quasi-likelihood framework, suggesting directions for future research effort.

JEL Classification: C21.

Keywords: General-to-Specific, Research Agenda, Nesting Spatial Regression Models, Heteroskedasticity.

Una agenda de investigación sobre la búsqueda de modelos espaciales de lo general a lo particular

RESUMEN: El artículo propone un modelo de regresión espacial anidado en el cual se incorporan también *shocks* heteroscedásticos. Sobre este modelo se analizan contrastes de hipótesis tanto en casos anidados como no anidados, utilizando métodos de cuasi-verosimilitud y proponiendo líneas futuras de investigación.

Clasificación JEL: C21.

Palabras clave: De lo general a lo particular, Agenda de investigación, Modelos de regresión espacial anidados, Heteroscedasticidad.

1. Introduction

The paper is motivated by several recent research strands in which spatial econometric models are studied formally from a statistical perspective. Such models are sometimes criticised for a lack of clear economic foundations, yet there are also examples of models in which the features of interest are developed from first principles, such as the study of spillovers by Ertur and Koch (2007), and of trade flows

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by Behrens, Ertur and Koch (2010). Although the economic and social origins of the spatially mediated interactions and structures that enter the formal models are important, the purpose of this paper is to suggest directions in which the more narrowly formal analysis might go. In mainstream (predominantly time-series based) econometrics statistical techniques were developed through the latter half of the last century mostly by elaboration of relatively simple models that failed diagnostic tests - perhaps most notably in response to unfavourable outcomes of the Durbin-Watson test for serial correlation. However, it is now widely accepted that in a contemporary model-building exercise it is inefficient to imitate this historical sequence by starting with a simple model and elaborating it only when diagnostic tests are failed. Rather, a more effective strategy begins with a general model and seeks to reduce this by testing restrictions that lead to simpler models. The latter strategy has come to be associated with the LSE research agenda instigated by Sargan's so-called COMFAC analysis, and carried forward on a wide front in particular by Hendry (for the current state of the art, see Hendry 2011). In the spatial model context, a reconsideration by Mur and Angulo (2009) of the modeling strategies investigated experimentally by Florax, Folmer and Rey (2003) suggests that the so-called general to specific *(Gets)* strategy is superior to the specific-to-general *(Stge)* strategy. This is important, since the prevailing custom of adopting a version of *Stge* will be inefficient in some important cases, in line with the situation prevailing in time series modelling.

Within the model classes over which these searches are conducted, testing between non-nested models may be of interest, either for model selection or for specification checking, and here the improved $J - type$ test of Kelejian and Piras (2011) is a useful advance. Furthermore, there is a general awareness that spatially structured data are likely to be heteroskedastic, and that ignoring this phenomenon may lead at best to inefficient estimation results. Indeed, one of the advantages of the *Gets* strategy identified by Mur and Angulo was that it was much more robust to heteroskedastic, skewed or heavy-tailed disturbances than the competitor *Stge* strategy. Among papers dealing formally with heteroskedasticity, Anselin (1988a) devises a Lagrange Multiplier specification test for a classical linear regression model against a heteroskedastic spatially dependent alternative, and recently a practical algorithm for estimating Anselin's model by maximizing the Normal likelihood has been proposed by Yokoi (2010). IV/GMM-based estimators for Anselin's model with unknown heteroskedasticity have also recently been published by Kelejian and Prucha (2010) and Lin and Lee (2010).

These strands taken together suggest a research agenda:

a) Set up a satisfyingly general spatial model class from which the *Gets* strategy could begin.

b) Investigate identification and estimation algorithms for the general model.

c) Investigate tests of non-nested models for this class.

d) Devise and / or investigate tests for (nested) model reduction where these are unavailable or their properties are not known.

e) Investigate the performance of the *Gets* and *Stge* strategies in this richer setting.

The paper comments on some aspects of a) - d). A significant part of the discussion is speculative. The proposed general model is introduced next, and is seen to nest the SARAR model and the Spatial Durbin Model (SDM), also described as the first order spatial Autoregressive Distributed Lag (ADL) model by Bivand (1984, eq. 4), the Spatial Durbin Error Model, the Spatial Lag Model and the Spatial Error Model, each of which is defined below.

2. A heteroskedastic general nesting model (HGNM)

It would be natural to start a *Gets* - type analysis with a model in which popular simpler ones are nested. In principle, this is achieved by what Elhorst (2010) calls the Manski model, after Manski (1993), also mentioned as a possibility by LeSage and Pace (2009, p. 53), and which could form a starting point for a *Gets* procedure, or a possible endpoint for a *Stge* procedure. This paper prefers to call the model the HGNM because the identification problem discussed by Manski does not arise, in general, for this model, contrary to the impression given by some authors because of its formal similarity to Manski's model. The nesting model is elaborated slightly here by the inclusion of heteroskedastic shocks and by relaxing the restriction that weight matrices are equal [1]:

$$\begin{aligned}
\mathbf{Y} &= \lambda_0 \mathbf{W}_0 \mathbf{Y} + 1\delta_0 + \mathbf{X}_0 \beta_0 + \mathbf{Q}_0 \mathbf{X}_0 \gamma_0 + \mathbf{U}_0 \\
\mathbf{U}_0 &= \rho_0 \mathbf{M}_0 \mathbf{U}_0 + \varepsilon_0 \\
& \varepsilon_0 \sim N(0, \Omega_0) \\
\omega_{0,ii} &= h_0(\alpha_0' \mathbf{Z}_{0,i}) > 0, \quad \omega_{0,ij} = 0, \quad i \neq j.
\end{aligned} \tag{1}$$

The constant regressor, $\mathbf{1} = [1, 1, 1,..., 1]'$ is separately treated in the notation to allow for weight matrices that are row-normalised, such that, for example, $\mathbf{Q}_0\, 1 = 1$. In a very simple case, the variance of the i^{th} shock might be proportional to some measure of the «size» of region *i*. An alternative Bayesian approach to heteroskedasticity that does not depend on a prespecified *h*() function is described by LeSage and Pace (2009, Section 5.6.1). As is often remarked, a more local spatial averaging of shocks could be achieved by the use of a moving average specification, such as $\mathbf{U}_0 = \varepsilon_0 + \rho_0 \mathbf{M}_0 \varepsilon_0$ but this possibility is not taken up here.

As soon as the model (1) is contemplated, an obvious restriction that might need to be tested is that the weight matrices are the same: $\mathbf{W} = \mathbf{Q} = \mathbf{M}$; indeed, only if $\mathbf{W} = \mathbf{Q}$ does the possible existence of the common factor mentioned below arise. Also, there may be competing models within the same class, just as in the $J-test$ set-up adopted by Kelejian (2008) and Kelejian and Piras (2011).

[1] Anselin (1988b) attributes to Hordijk (1979) the introduction of a SARAR model with weights that are different for the spatial lag and spatial error.

Before settling on (1) as the general model, however, we should consider whether or not a yet more general starting point is required. In the time series context, it is now usual to regard models with serially correlated disturbances as restricted forms of more general models with richer dynamics. Following Hendry and Mizon (1978) who implemented the COMFAC analysis being developed by Sargan in the mid 1970's that was eventually published in Sargan (1980), we might consider (1) as itself a restricted form of the model,

$$\mathbf{Y} = \lambda_1 \mathbf{W}_1 \mathbf{Y} + \lambda_2 \mathbf{W}_2 \mathbf{Y} + 1\delta + \mathbf{X}\beta_0 + \mathbf{W}_3 \mathbf{X}\beta_1 + \mathbf{W}_4 \mathbf{X}\beta_2 + \varepsilon. \tag{2}$$

This possibility has been discussed by Blommestein (1983), and again recently by Mur and Angulo (2006). If we take (2) seriously, then a first model simplification step would seem to be to test the hypothesis,

$$\mathcal{H}_w : \mathbf{W}_2 = \mathbf{W}_1^2, \mathbf{W}_4 = \mathbf{W}_3^2, \mathbf{W}_3 = \mathbf{W}_1; \tag{3}$$

however, the essential difference between the time series and spatial cross-section cases then becomes apparent: while in time series the term, $\mathbf{W}_2\mathbf{Y}$ just represents a two-period lag of $\mathbf{Y}$ which results from applying the lag operator twice, in the spatial setting there is in general no obvious equivalent construction [2] . Thus if the analysis were to start from (2) the specification of the four weight matrices would be problematic from the outset if it were desired to test for the possible simplification. Of course, a more feasible alternative starting point would be to impose $\mathcal{H}_w$ and test the implied common factor restriction that would then reduce (2), with $\mathcal{H}_w$ maintained, to (1).

In time series models, there is an obvious value in representations in which the unobserved shocks may be treated as innovations, that is, as independent of the previous history of the quantities under study, including previous innovations. How far it is appropriate to seek models in which shocks are independent over space has been, I think, much debated. The key may be in the conditioning information brought into the analysis at the outset. For example, as long argued in the literature, and described by LeSage and Pace (2009, pp. 27-28, 67-68) when spatially-patterned explanatory variables are omitted from the model's mean function, they will enter the disturbance term, thus producing a spatially autocorrelated disturbance that could be eliminated by their inclusion in the mean. On the other hand, rather stronger grounds may be found for introducing spatially lagged dependent variables to the right-hand-side, such as when data are observed at a lower frequency (in time) than that at which agents take decisions that can be influenced by those of their neighbours, or in the group interaction models now gaining in popularity (see Lee, Liu and Lin (2010) for a recent example). Although a residual doubt over model specification is unavoidable, to make progress, we have to suppose that the investigator gets something right,

[2] Exceptions are the «two weight matrix» model of Lacombe (2004) discussed by Le Sage and Pace (2009, p. 52), and the model explored by Brandsma and Ketellapper (1979) in which $\mathbf{Y} = \mathbf{X}\beta + \mathbf{U}$ with $(\mathbf{I} - \rho_1 \mathbf{W}_1 - \rho_2 \mathbf{W}_2)\mathbf{U} = \varepsilon$, and a likelihood ratio test of the hypothesis that $\rho_1 = \rho_2 = 0$ is implemented.

and so for this rather pragmatic reason, and because it has not received much attention, this paper treats (1) as the initial general model, supposing it to have passed such diagnostic checks as are available. If, in fact, a test of the hypothesis, $\rho_0 = 0$, failed to reject, our confidence that no major systematic spatially patterned explanatory factor had been omitted would of course increase.

2.1. Nested Models

2.1.1. The SARAR model

Elhorst (2010) designates the model containing a spatially lagged dependent variable and a spatially autoregressive disturbance, the Kelejian-Prucha model - see Elhorst (2010, p. 13). LeSage and Pace (2009 p. 32) on the other hand designate this the SAC model; since Kelejian (2008) calls the model the SARAR model, that name seems a reasonable compromise, the repeated AR a reminder of its essential feature.

In Yokoi (2010) the MLE for the heteroskedastic SARAR model described by Anselin (1988a,b) is studied. The model is:

$$\mathbf{Y} = \lambda_0 \mathbf{W}_0 \mathbf{Y} + 1\delta_0 + \mathbf{X}_0 \beta_0 + \mathbf{U}_0 \tag{4}$$

$$\begin{aligned} U_0 &= \rho_0 \mathbf{M}_0 \mathbf{U}_0 + \varepsilon_0 \\ &\quad \varepsilon_0 - N(0, \Omega_0) \end{aligned} \tag{5}$$

$$\omega_{0,ii} = h_0(\alpha_0' \mathbf{Z}_{0,i}) > 0, \quad \omega_{0,ij} = 0, \quad i \neq j. \tag{6}$$

As can be seen, it arises from the HGNM by the exclusion of the spatially lagged exogenous variables, $\mathbf{Q}_0\, \mathbf{X}_0\, \gamma_0$. However, with a little care over the treatment of any accidental collinearity between $\mathbf{X}$, $\mathbf{WX}$ and $\mathbf{QX}$, it is easy to see that the definition of $\mathbf{X}_0\, \beta_0$ in (4) can be expanded to include $\mathbf{Q}_0\, \mathbf{X}_0\, \gamma_0$ from (1). This is useful because it means that estimator properties derived for the SARAR model may, with a little care, apply readily to the more general model. The extra care involved is obvious in the case of IV based estimators that rely on use of instruments such as $\mathbf{W}_0\, \mathbf{X}_0$, and so on, to take care of the correlation between the disturbances and the spatially lagged dependent variable: any spatially lagged exogenous variables that are already present on the right-hand side are not available as additional instruments.

2.1.2. The Spatial Durbin Model

Consider the so-called Spatial Durbin model (SDM), obtained from the HGNM when $\rho_0 = 0$. This model has been widely promoted as a possible starting point because it nests two popular simpler models; LeSage and Pace (2009, pp. 67-68) also argue that the model produces estimates with a degree of robustness to omitted variables not shared for example by the nested models. The SDM is

$$\begin{aligned} \mathbf{Y} &= \lambda_0 \mathbf{W}_0 \mathbf{Y} + 1\delta_0 + \mathbf{X}_0\beta_0 + \mathbf{W}_0\mathbf{X}_0\gamma_0 + \varepsilon_0 \\ & \varepsilon_0 \_ N(0, \Omega_0). \end{aligned} \tag{7}$$

The Spatial Error Model. To see how the SDM may be simplified under certain restrictions, suppose, for convenience, that the rows of $\mathbf{W}_0$ sum to 1 so that $\mathbf{W}_0\ 1 = 1$ and observe that (7) may be written equivalently, by taking out a factor of $(I - \lambda_0\ \mathbf{W}_0)$ on the right-hand side, as

$$(\mathbf{I} - \lambda_0 \mathbf{W}_0)\mathbf{Y} = (\mathbf{I} - \lambda_0 \mathbf{W}_0)1\delta_0 / (1 - \lambda_0) + (\mathbf{I} - \lambda_0 \mathbf{W}_0)\mathbf{X}_0\beta_0 + \mathbf{W}_0\mathbf{X}_0(\lambda_0\beta_0 + \gamma_0) + \varepsilon_0$$

where the remainder, $\mathbf{W}_0\ \mathbf{X}_0\ (\lambda_0\ \beta_0\ +\ \lambda_0)$ is now of interest. If the parameters satisfy the so-called common-factor restriction,

$$\lambda_0 = \lambda_0\beta_0 \tag{8}$$

the remainder vanishes, and the matrix, $(\mathrm{I} - \lambda_0\ \mathbf{W}_0)$, is seen to be a common factor in the model. If this matrix is invertible, as usually assumed, the model simplifies to the spatial error model[3].

$$\mathbf{Y} = 1\delta_0 / (1 - \lambda_0) + \mathbf{X}_0\beta_0 + \mathbf{U}_0 \tag{9}$$

$$= 1\delta_0^* + \mathbf{X}_0\beta_0 + \mathbf{U}_0 \text{ say, with} \tag{10}$$

$$(\mathbf{I} - \lambda_0 \mathbf{W}_0)\mathbf{U}_0 = \varepsilon_0.$$

The Spatial Lag Model. More obviously perhaps, when $\lambda_0 = 0$ the SDM reduces to the spatial lag model, studied in a Normal likelihood framework by Ord (1975). The SLM is:

$$\mathbf{Y} = \lambda_0 \mathbf{W}_0 \mathbf{Y} + 1\delta_0 + \mathbf{X}_0\beta_0 + \varepsilon_0 \tag{11}$$

and is the generic model for spatially interacting responses to changes in conditioning variables and shocks.

2.1.3. The Spatial Durbin Error model

Elhorst (2010) comments that the model that results from (1) when $\lambda = 0$, called the SDEM by LeSage and Pace (2009, p. 42) does not seem to have been used much.

[3] See also Burridge (1981), Bivand (1984), Anselin (1988b), Folmer Florax and Rey (2003), Elhorst (2001, 2010), LeSage and Pace (2009), and Mur and Angulo (2009) for more discussion.

I don't know why it should have been overlooked, however, though nesting it in the more general model being discussed here may lead to its more frequent use.

2.1.4. Preference for the SDM

Of course, neither the restriction that $\mathbf{Q} = \mathbf{W}$, nor the common-factor restriction (8), nor the zero restrictions for λ_0 ρ_0 or γ_0 leading to the simpler models may be plausible; besides the nesting of (9) and (11) the SDM has other merits, delivering unbiased coefficient estimates, according to LeSage and Pace (2009, pp. 56-158) when the other models may fail to do so, a point echoed by Elhorst (2010, pp. 14-15).

3. The General-to-Specific Strategy in Outline

With a single fixed weight matrix, treated as given, the first few steps, which expand the strategy investigated by Mur and Angulo (2009), could be as follows

1. Estimate (1) with $\mathbf{M} = \mathbf{W} = \mathbf{Q}$ (it is assumed that any available diagnostic tests have been passed, see Section 4.1 below for more on this point).
2. Test for simplification to homoskedasticity $\mathcal{H}_\alpha : \alpha_2 = \alpha_3 = ... = \alpha_m = 0$.
3. Test for simplification to SDM/ADL $\mathcal{H}_\rho : \rho = 0$.
4. If $\mathcal{H}_\rho$ is not rejected test for simplification to SLM $\mathcal{H}_\gamma : \gamma = 0$; if $\mathcal{H}_\rho$ is rejected test for simplification to SARAR $\mathcal{H}_\gamma : \gamma = 0$.
5. If $\mathcal{H}_\rho$ is not rejected at Step 3 but $\mathcal{H}_\gamma$ is rejected at Step 4, test for common factor and reduction to SEM; if $\mathcal{H}_\rho$ is rejected at Step 3, and $\mathcal{H}_\gamma$ is rejected at Step 4, test $\mathcal{H}_\lambda : \lambda = 0$ for simplification to the SDEM.

With different, but fixed, weight matrices, the first step could be to seek a simplification via a non-nested test, as described below.

4. Test procedures

4.1. Diagnostics for the HGNM?

A critical ingredient in the *Gets* strategy is the assumption that the general nesting model is itself an adequate description of the data generating process, the DGP. In the time series context, in which the detection and accommodation of serial correlation was the key problem, the leading requirement was for a test for serial correlation in the disturbances of a dynamic model that could be applied after, say, an ARMA(p,q) model had been fitted to the data. As is well known, the Durbin-Watson test could not be used in such a model as the sampling distribution of the statistic is shifted when lagged values of the dependent variable are present resulting in a bias towards acceptance of the null hypothesis. The critical advance here was the development of a

Lagrange multiplier test for serial correlation in dynamic models by Breusch (1978) and Godfrey (1978). In the spatial case the main diagnostic required will play a similar role, and is thus a test for neglected spatial correlation in the disturbance, ε_0 of (1). Such a test has yet to be developed, apparently.

4.2. A general non-nested test procedure $\bar{\beta}_0$

Consider the problem of testing a model of the form (1) against a non-nested alternative, of the same form, Model$_1$, say. Broadly speaking, the *J*-test approach implemented for the SARAR model by Kelejian (2008), as modified by Kelejian and Piras (2011), would entail the construction of a prediction of $(\mathbf{I} - \rho_0 \mathbf{M}_0)Y$ from Model$_1$ which would be added as an explanatory variable to an equation predicting $(\mathbf{I} - \rho_0 \mathbf{M}_0)\mathbf{Y}$ using Model$_0$. Suppose the models satisfy relevant sets of sufficient conditions for identification, and that Gaussian quasi-maximum likelihood[4] estimates of the parameters of the two models are available, and write these as $\tilde{\delta}_0$, $\bar{\beta}_0$, ..., $\tilde{\delta}_1$, $\bar{\beta}_1$, ..., and so on. Imitating the Kelejian and Piras approach but implementing QMLE for all but the final test regression leads to the following. Initially, ignoring the heteroskedasticity, using Model$_1$ construct the predictor,

$$\bar{\mathbf{Y}}^1 = \tilde{\lambda}_1 \mathbf{W}_1 \mathbf{Y} + 1\tilde{\delta}_1 + \mathbf{X}_1 \bar{\beta}_1 + \mathbf{Q}_1 \mathbf{X}_1 \bar{\gamma}_1.$$

From Model$_0$ estimate $\tilde{\lambda}_0$, $\tilde{\delta}_0$, $\bar{\beta}_0$, $\bar{\gamma}_0$, $\tilde{\rho}_0$. Using $\tilde{\rho}_0$ construct the «whitened» dependent variable,

$$\mathbf{Y}^*(\tilde{\rho}_0) = (\mathbf{I} - \tilde{\rho}_0 \mathbf{M}_0)\mathbf{Y} \tag{12}$$

together with the transformed RHS variables,

$$\mathbf{Z}_0^*(\tilde{\rho}_0) = (\mathbf{I} - \tilde{\rho}_0 \mathbf{M}_0)\, [\mathbf{X}_0,\ \mathbf{Q}_0 \mathbf{X}_0,\ \mathbf{W}_0, \mathbf{Y}] \tag{13}$$

and the transformed predictor,

$$\bar{\mathbf{Y}}^1(\tilde{\rho}_0) = (\mathbf{I} - \tilde{\rho}_0 \mathbf{M}_0)\ \bar{\mathbf{Y}}^1. \tag{14}$$

The idea behind the test is now to add $\bar{\mathbf{Y}}^1(\tilde{\rho}_0)$ to the right-hand side of the equation,

$$\mathbf{Y}^*(\tilde{\rho}_0) = \mathbf{Z}_0^*(\tilde{\rho}_0)\hat{\phi}_0^* + \bar{\mathbf{Y}}^1(\tilde{\rho}_0)\hat{\psi}_{01}^* + \mathbf{e}_0^*, \text{ say,} \tag{15}$$

[4] Kelejian and Piras do not employ quasi-maximum likelihood estimators, but they are preferred here for use in modestly-sized samples because they satisfy the determinantal conditions on λ and ρ.

and test the hypothesis that $\psi_{01}^{*} = 0$. To extend the procedure to the heteroskedastic case it would seem natural to premultiply (15) by $\tilde{\Omega}_0^{-1/2}$ which is the estimate of the diagonal variance matrix of the disturbance that corresponds to the residual, $\mathbf{e}_0^{*}$ under the null hypothesis. The specification of the test based on (15) differs from the Kelejian and Piras test for the SARAR model in two respects. Evidently, the model has been expanded by the introduction of the spatially lagged exogenous regressors, $\mathbf{Q}_i\ \mathbf{X}_i$ (i = 0, 1); however, their presence introduces nothing of great significance since the various conditions imposed by Kelejian and Piras should require only a very minor expansion to accommodate this change - conditions on the matrix, $\mathbf{X}$ must now be applied to the matrix, $[\mathbf{X}, \mathbf{QX}]$ and in their approach instruments would need to be chosen with care to avoid rank deficiency. Secondly, except for the final equation which is estimated using instrumental variables, the parameters are estimated by Gaussian QML to guarantee that they satisfy the determinantal conditions, $|(\mathbf{I} - \rho\mathbf{M}_0)| > 0$, $|(\mathbf{I} - \lambda\mathbf{W}_0)| > 0$ and similarly for Model_1 . To the best of the author's knowledge, a J-type test adapted to accommodate heteroskedasticity has not yet been implemented, and so its development along the lines above seems warranted. The tasks involved include establishing the asymptotic sampling distribution of such a statistic, checking its small sample performance and devising any correction that may be necessary to control significance levels.

4.3. Information Criteria and the Likelihood

In a time series modelling exercise it is usual to examine a so-called «information criterion» such as AIC, or BIC, to select model order. For example, when fitting an AR(p) model to a single time series, such as

$$y_t = \sum_{j=1}^{j=p_0} \phi_j y_{t-j} + \varepsilon_t \qquad (16)$$

under the maintained assumption that ε_t is while noise, the order of the autoregressive operator could be chosen to minimise the BIC, $\ln \hat{\sigma}_p^2 + p \ln n/n$, in which $\hat{\sigma}_p^2$ is the quasi maximum likelihood estimate of the innovation variance from the model with $j = p$, and is proportional to the negative of the log conditional likelihood. That the choice, $\tilde{p}_n$ say, which minimises this criterion, is consistent in the sense that $\lim_{n\to\infty} \Pr[\tilde{p}_n = p_0] = 1$ has been demonstrated under very general conditions, reviewed and extended in a recent contribution by Burridge and Hristova (2008). However, although the parallel with time series modelling is appealing, and model selection via an information criterion was suggested as a simpler alternative to use of a $J - type$ test 25 years ago by Haining (1986), there does not appear to have been a systematic investigation of its properties in the spatial case; it should be noted that a treatment of consistency would require explicit conditions relating to the evolution of the weights matrices as sample size increased, moment conditions on regressors, and the like, similar in nature to those introduced by Lee (2004), but also that a fundamental problem remains to be addressed. The difficulty arises from the fact that the competing models are not nested; because of this, the fact that Model A delivers a higher value of its maximised likelihood than Model B does of *its* likelihood is not sufficient for Model A to be preferred, and introduction of a «penalty» for additional parameters, as in the BIC, has no bearing on this fundamental problem. Nevertheless, as suggested by a referee, a comparison between such model selection and use of the $J-$ *test* in finite samples could be interesting. Closely related is the Bayesian approach described by Le Sage and Pace (2009, Section 6.3) and applied by Pijnenburg and Kholodilin (2011) who consider 43 different weight matrices in their study of entrepreneurial spillovers, choosing the one that delivers the highest posterior model probability. In this framework, there are three components to the model posterior probability, a prior over the various weight matrices, $\pi(W)$, a prior over the parameters for each W, $\pi(\theta|W)$, and the likelihood of the data given W and θ, $p(D|\theta, W)$. In effect, if $\pi(W)$ is chosen to be uninformative, choosing the model with the highest posterior probability amounts to choosing the model for which the smoothed ([i.e. integrated over $\pi(\theta|W)$] likelihood is highest. The problem of comparing likelihoods from different|probability models remains, therefore, within the Bayesian formalism.

4.4. Tests of nested models

With the rather general starting point, (1), natural hypotheses to test are parametric restrictions that simplify the model. These could be of various kinds, of which several are described below.

4.4.1. Tests on weight matrices

Hypotheses that might be tested include, as an example, $H_{01} : \mathbf{Q} = \mathbf{W} = \mathbf{W}_0$ say, with $\mathbf{M} = \mathbf{M}_0$ maintained vs $H_{11} : \mathbf{Q} = \mathbf{Q}_1$ and $\mathbf{W} = \mathbf{W}_0$ with $\mathbf{M} = \mathbf{M}_0$ maintained. The point here is to seek model simplification, since the common factor reduction only arises as a possibility if $\mathbf{Q} = \mathbf{W}$. At the current state of development of the field (in which results for structures within which $\mathbf{W}$ and so on may be *estimated* from the sample, are not yet available) such hypotheses should probably be approached via methods developed for testing non-nested models. Thus H_{01} would correspond to Model_0 and H_{11} to Model_1 and a test could be based on (15).

4.4.2. A test for heteroskedasticity

To test parametric restrictions that simplify the model, the usual likelihood ratio machinery could be used, or LM-type tests be developed for cases in which the restricted model was significantly simpler to estimate than the unrestricted one. A case in point could be, given a parametric model (or a linear approximation to such a model) for the covariance matrix, Ω, a test of the homoskedastic null hypothesis, $h(\alpha'\mathbf{z}_i) = h([\alpha_1, 0, ..., 0]'\mathbf{z}_i) = \sigma^2$ = a constant, say. To see the form such a test could take[5], consider the first-order condition, (27)

$$\frac{\partial l}{\partial \alpha_p} = -\frac{1}{2} Tr\{\Omega^{-1}\mathbf{H}_p\} + \frac{1}{2}\varepsilon'\Omega^{-2}\mathbf{H}_p\varepsilon$$

where $\mathbf{H}_p = diag\{\partial\omega_{ii}/\partial\alpha_p\}$, and the corresponding block of the information matrix, which has typical element (76)

$$-E\left\{\frac{\partial^2 l}{\partial\alpha_p\partial\alpha_q}\right\} = \frac{1}{2}Tr\{\Omega^{-2}\mathbf{H}_p\mathbf{H}_q\}.$$

Stacking the first derivatives for $\alpha_2, ..., \alpha_m$ into the vector, $\mathbf{d}$, and writing $\mathbf{I}_{\alpha\alpha}$ for the corresponding part of the information matrix, the usual form for the LM statistic (in the block diagonal case) would be

$$LM = \bar{\mathbf{d}}'\bar{\mathbf{I}}_{\alpha\alpha}^{-1}\bar{\mathbf{d}}$$

in which both $\mathbf{d}$ and $\mathbf{I}_{\alpha\alpha}$ are evaluated at the null hypothesis. Now, observe, as in Breusch and Pagan (1979) and Anselin (1988), that

$$\mathbf{H}_p(i, i) = \partial\omega_{ii}/\partial\alpha_p = \frac{\partial}{\partial\alpha_p}\{h(\alpha'\mathbf{z}_i)\} = h\cdot(\alpha'\mathbf{z}_i)z_{ip}$$

where $h\cdot(s_i) = \partial h/\partial s_i$ with $s_i = \alpha'\mathbf{z}_i$. Under the homoskedastic null, the covariance matrix estimator reduces to $\bar{\Omega} = \hat{\sigma}^2\mathbf{I}$ and $h\cdot(\alpha'\mathbf{z}_i) = h\cdot(\alpha_1)$, so that, evaluated at the constrained estimator,

$$\frac{\partial l}{\partial\alpha_p}\Big|_{null} = -\frac{1}{2}\sum_{i=1}^{i=n}\tilde{\sigma}^{-2}h\cdot(\alpha_1)z_{ip} + \frac{1}{2}\sum_{i=1}^{i=n}\tilde{\sigma}^{-4}h\cdot(\alpha_1)z_{ip}\tilde{\varepsilon}_i^2.$$

Writing $g_i = \dfrac{\tilde{\varepsilon}_i^2}{\tilde{\sigma}^2}$ this can be simplified to

$$\frac{\partial l}{\partial\alpha_p}\Big|_{null} = \frac{1}{2}\tilde{\sigma}^{-2}h\cdot(\alpha_1)\sum_{i=1}^{i=n}z_{ip}(g_1 - 1). \tag{17}$$

[5] Ignoring the off-diagonal blocks involving ρ and λ.

Similarly,

$$-E\left\{\frac{\partial^2 l}{\partial\alpha_p\partial\alpha_q}\right\}|_{null} = \frac{1}{2}\tilde{\sigma}^{-4}\sum_{i=1}^{i=n}[h\cdot(\alpha_1)]^2 z_{ip}z_{ip}. \tag{18}$$

Putting these objects together the test statistic,

$$LM = \bar{\mathbf{d}}'\bar{\mathbf{I}}_{\alpha\alpha}^{-1}\bar{\mathbf{d}} = \frac{1}{2}\mathbf{f}'\mathbf{Z}(\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{Z}'\mathbf{f} \tag{19}$$

is obtained, where $\mathbf{Z} = [\mathbf{z}_1, ..., \mathbf{z}_n]'$ and $\mathbf{f} = \mathbf{g} - \mathbf{1}$. As in Breusch and Pagan (1979, p. 1290) it is found that (19) is one half the explained sum of squares from regression of g_i on $\mathbf{z}_i$. Notice that the test for heteroskedasticity in the presence of spatially lagged dependent variables devised by Anselin (1988a) maintains $(\lambda, \rho) = (0, 0)$ which is quite restrictive. Whether or not information about (ρ, λ) can be exploited to improve the test at (19) is a question that should be investigated.

Kelejian and Robinson (1998) present a test they designate, KR-SPHET, that has the absence of both spatial correlation and heteroskedasticity as its null hypothesis, mentioning in a remark (Remark 5, p. 395) a possible modification that could be used to test for heteroskedasticity with spatial correlation maintained. Their test is similar in spirit to the Breusch-Pagan test in that it employs a regression of squares and cross-products of residuals on regressors supposed related to the heteroskedasticity under the alternative.

4.4.3. A better approach to tests on the weights matrices?

While the non-nested testing procedure could be used to test hypotheses about the weights, a more natural and flexible approach would be to have a parametric model for the weights matrices derived from economic theory, and to construct tests in a nesting model. Suppose $\mathbf{W}$ has elements $w_{ij} = f(d_{ij}, \tau_w)$, $\mathbf{M}$ has elements $m_{ij} = f(d_{ij}, \tau_m)$ and $\mathbf{Q}$ has elements $q_{ij} = f(d_{ij}, \tau_q)$ in which the d_{ij} are observed (distances or adjacency measures, or other indices of interactivity) and the τ are parameters to be estimated. In this framework, likelihood ratio tests of restrictions on the τ parameters can easily be formulated. To begin the development of such tests, a simpler homoskedastic nesting model could be studied. Consider the following model, in which $\varepsilon = \eta\cdot\sigma$ with $\eta \sim \mathbf{N}(\mathbf{0}, \mathbf{I})$. The log-likelihood can be written

$$l(\mathbf{Y}, \mathbf{X}, \mathbf{W}, \mathbf{Q}, \mathbf{M}, \delta, \beta, \gamma, \lambda, \rho, \sigma^2) = -\frac{n}{2}\ln 2\pi - \frac{n}{2}\ln\sigma^2 + \ln|\mathbf{I} - \lambda\mathbf{W}| + \ln|\mathbf{I} - \rho\mathbf{M}| - \frac{1}{2}\eta'\eta$$

where as above, the sum of squares term is

$$\eta'\eta = \varepsilon'\varepsilon / \sigma^2$$
$$\varepsilon = (\mathbf{I} - \rho\mathbf{M})([\mathbf{I} - \lambda\mathbf{W}]\mathbf{Y} - 1\delta - \mathbf{X}\beta - \mathbf{QX}\gamma)$$
$$= (\mathbf{I} - \rho\mathbf{M})\mathbf{U}.$$

The matrices **M**, **W** and **Q** are defined by

$$m_{ij} = f(d_{ij}, \tau_m)$$
$$w_{ij} = f(d_{ij}, \tau_w)$$
$$q_{ij} = f(d_{ij}, \tau_q)$$

For compactness, as before, write $\mathbf{B} = (\mathbf{I} - \rho\mathbf{M})$ and $\mathbf{A} = (\mathbf{I} - \lambda\mathbf{W})$, with **A** being non-singular for (λ, τ_w) in a neighbourhood of $(\lambda_0, \tau_{w,0})$ and similarly **B** being non-singular for (ρ, τ_m) in a neighbourhood of $(\rho_0, \tau_{m,0})$. Evidently, provided the model is identified, LR tests could be constructed numerically. Whether convenient alternative tests can be devised is another open question. A precedent for estimating the weights does exist, in the work of Bodson and Peeters (1975, p.467), though no systematic treatment appears to be available in the literature.

4.5. Approximate sampling distributions and the bootstrap

In the model class under discussion here, neither least squares regression estimates nor likelihood ratio statistics will have exactly known sampling distributions except possibly in very special cases. There are at least two responses to this. First, it is possible to search for meaningful conditions under which the sampling distributions of estimators and test statistics converge to known standard distributions as the sample size increases. If such conditions turn out to be difficult to obtain, or at odds with the way in which empirical models are usually specified, then due caution needs to be exercised. However, even if the conditions under which the relevant convergence in distribution can be established are empirically reasonable, there remains the problem of controlling significance levels in finite samples. This motivates the second response, namely the use of resampling to obtain approximate sampling distributions. The properties of bootstrap-based approximations to sampling distributions have yet to be investigated in the context of this model.

5. Final comments

The formal statistical analysis of regression models that embody spatial interactions is enjoying a resurgence of interest, and some of the important properties of estimators and test statistics have been established with the help of equipment developed over the past decade and a half in numerous papers by Kelejian and Prucha, and Lee, their collaborators, and others. These authors' work provides a rigorous account of the large sample behaviour of various tests and estimators in which, as the sample size grows, so the elements of the spatial weight matrix, **W**, evolve in a specific way, and in which the regressors obey some quite natural restrictions. These are real advances. However, in spite of all this progress, we are still unable to provide satisfactory answers to some seemingly obvious questions about the structure of the models themselves. These questions are the subject of the present paper, and of other recent contributions that focus on model selection. In writing rather speculatively about a model that nests many of those currently in favour for handling data derived from a single crosssection, my purpose has been to suggest avenues that merit further exploration and formal study.

6. Appendix: The likelihood for the general nesting model

For convenience, write $\varepsilon = \Omega^{1/2}\eta$ where $\eta \sim \mathbf{N}(\mathbf{0}, \mathbf{I})$. The heteroskedastic nesting model with Normal shocks has log-likelihood that can be written

$$l(\mathbf{Y}, \mathbf{X}, \mathbf{W}, \mathbf{Q}, \mathbf{M}, \delta, \beta, \gamma, \lambda, \rho, \Omega) = -\frac{n}{2}\ln 2\pi - \frac{1}{2}\ln|\Omega| + \ln|\mathbf{I} - \lambda\mathbf{W}| + \ln|\mathbf{I} - \rho\mathbf{M}| - \frac{1}{2}\eta'\eta \tag{21}$$

where the sum of squares term is

$$\begin{aligned} \eta'\eta &= \varepsilon'\Omega^{-1}\varepsilon \\ \varepsilon &= (\mathbf{I} - \rho\mathbf{M})([\mathbf{I} - \lambda\mathbf{W}]\mathbf{Y} - 1\delta_0 - \mathbf{X}\beta - \mathbf{QX}\gamma) \\ &= (\mathbf{I} - \rho\mathbf{M})\mathbf{U}. \end{aligned}$$

For compactness, write $\mathbf{B} = (\mathbf{I} - \rho\mathbf{M})$ and $\mathbf{A} = (\mathbf{I} - \lambda\mathbf{W})$, both matrices being non-singular by assumption. The first partial derivatives of the log-likelihood are (cf. Anselin (1988a) where the roles of λ and ρ are reversed, and our **W**, **M** are his $\mathbf{W}_1$, $\mathbf{W}_2$ but the lagged exogenous variables, **QX** do not appear in his model):

$$\frac{\partial l}{\partial \delta} = \mathbf{1}'\mathbf{B}'\Omega^{-1}\varepsilon \tag{22}$$

$$\frac{\partial l}{\partial \beta} = \mathbf{X}'\mathbf{B}'\Omega^{-1}\varepsilon \tag{23}$$

$$\frac{\partial l}{\partial \gamma} = \mathbf{X}'\mathbf{Q}'\mathbf{B}'\Omega^{-1}\varepsilon \tag{24}$$

$$\frac{\partial l}{\partial \lambda} = -Tr\{\mathbf{W}\mathbf{A}^{-1}\mathbf{W}\} + \varepsilon'\Omega^{-1}\mathbf{B}\mathbf{W}\mathbf{Y} \tag{25}$$

$$\frac{\partial l}{\partial \rho} = -Tr\{\mathbf{B}^{-1}\mathbf{M}\} + \varepsilon'\Omega^{-1}\mathbf{M}\mathbf{B}^{-1}\varepsilon \tag{26}$$

$$\frac{\partial l}{\partial \alpha_p} = -\frac{1}{2}Tr\{\Omega^{-1}\mathbf{H}_p\} + \frac{1}{2}\varepsilon'\Omega^{-2}\mathbf{H}_p\varepsilon \tag{27}$$

where $\mathbf{H}_p = diag\{\partial\omega_{ii}/\partial\alpha_p\}$. The second partial derivatives are

$$\frac{\partial^2 l}{\partial \delta^2} = -\mathbf{1}'\mathbf{B}'\Omega^{-1}\mathbf{B}\mathbf{1} \tag{28}$$

$$\frac{\partial^2 l}{\partial \beta \partial \beta'} = -\mathbf{X}'\mathbf{B}'\Omega^{-1}\mathbf{B}\mathbf{X} \tag{29}$$

$$\frac{\partial^2 l}{\partial \gamma \partial \gamma'} = -\mathbf{X}'\mathbf{Q}'\mathbf{B}'\Omega^{-1}\mathbf{B}\mathbf{Q}\mathbf{X} \tag{30}$$

$$\frac{\partial^2 l}{\partial \lambda^2} = -Tr\{[\mathbf{A}^{-1}\mathbf{W}]^2\} \tag{31}$$

$$-\mathbf{Y}'\mathbf{W}'\mathbf{B}'\Omega^{-1}\mathbf{B}\mathbf{W}\mathbf{Y} \tag{32}$$

$$\frac{\partial^2 l}{\partial \rho^2} = -Tr\{[\mathbf{B}^{-1}\mathbf{M}]^2\} - \mathbf{U}'\mathbf{M}'\Omega^{-1}\mathbf{M}\mathbf{U} \tag{33}$$

$$\frac{\partial^2 l}{\partial \alpha_p^2} = \frac{1}{2}\{Tr[\Omega^{-2}\mathbf{H}_p^2 - \Omega^{-1}\mathbf{H}_{pp}] + \varepsilon'\Omega^{-2}\mathbf{H}_{pp}\varepsilon\} \tag{34}$$

$$-\varepsilon'\Omega^{-3}\mathbf{H}_p^2\varepsilon \tag{35}$$

with cross-partials

$$\frac{\partial^2 l}{\partial \delta \partial \beta'} = -\mathbf{1}'\mathbf{B}'\Omega^{-1}\mathbf{B}\mathbf{X} \tag{36}$$

$$\frac{\partial^2 l}{\partial \delta \partial \gamma'} = -\mathbf{1}'\mathbf{B}'\Omega^{-1}\mathbf{B}\mathbf{Q}\mathbf{X} \tag{37}$$

$$\frac{\partial^2 l}{\partial \delta \partial \lambda} = -\mathbf{1}'\mathbf{B}'\Omega^{-1}\mathbf{B}\mathbf{W}\mathbf{X} \tag{38}$$

$$\frac{\partial^2 l}{\partial\delta\partial\rho} = -\mathbf{1}'(M'\Omega^{-1}\mathbf{B} + \mathbf{B}'\Omega^{-1}\mathbf{M})\mathbf{U} \tag{39}$$

$$\frac{\partial^2 l}{\partial\delta\partial\alpha_p} = -\mathbf{1}'\mathbf{B}'\Omega^{-2}\mathbf{H}_p\varepsilon \tag{40}$$

$$\frac{\partial^2 l}{\partial\delta\partial\gamma'} = -\mathbf{X}'\mathbf{B}'\Omega^{-1}\mathbf{BQX} \tag{41}$$

$$\frac{\partial^2 l}{\partial\beta\partial\lambda} = -\mathbf{X}'\mathbf{B}'\Omega^{-1}\mathbf{BWY} \tag{42}$$

$$\frac{\partial^2 l}{\partial\beta\partial\rho} = -\mathbf{X}'(\mathbf{M}'\Omega^{-1}\mathbf{B} + \mathbf{B}'\Omega^{-1}\mathbf{M})\mathbf{U} \tag{43}$$

$$\frac{\partial^2 l}{\partial\beta\partial\alpha_p} = -\mathbf{X}'\mathbf{B}'\Omega^{-2}\mathbf{H}_p\varepsilon \tag{44}$$

$$\frac{\partial^2 l}{\partial\gamma\partial\lambda} = -\mathbf{X}'\mathbf{Q}'\mathbf{B}'\Omega^{-1}\mathbf{BWY} \tag{45}$$

$$\frac{\partial^2 l}{\partial\gamma\partial\rho} = -\mathbf{X}'\mathbf{Q}'(\mathbf{B}'\Omega^{-1}\mathbf{M} + \mathbf{M}'\Omega^{-1}\mathbf{B})\mathbf{U} \tag{46}$$

$$\frac{\partial^2 l}{\partial\gamma\partial\alpha_p} = -\mathbf{X}'\mathbf{Q}'\mathbf{B}'\Omega^{-2}\mathbf{H}_p\varepsilon \tag{47}$$

$$\frac{\partial^2 l}{\partial\gamma\partial\rho} = -\mathbf{X}'\mathbf{W}'(\mathbf{B}'\Omega^{-1}\mathbf{M} + \mathbf{M}'\Omega^{-1}\mathbf{B})\mathbf{U} \tag{48}$$

$$\frac{\partial^2 l}{\partial\lambda\partial\alpha_p} = -\varepsilon'\Omega^{-2}\mathbf{H}_p\mathbf{BWY} \tag{49}$$

$$\frac{\partial^2 l}{\partial\rho\partial\alpha_p} = -\varepsilon'\Omega^{-2}\mathbf{H}_p\mathbf{MU} \tag{50}$$

$$\frac{\partial^2 l}{\partial\alpha_\rho\partial\alpha_p} = -\frac{1}{2}\{Tr[\Omega^{-1}\mathbf{H}_{pq} - \Omega^{-2}\mathbf{H}_p\mathbf{H}_q] - \varepsilon'\Omega^{-2}\mathbf{H}_{pq}\varepsilon\} \tag{51}$$

$$-\varepsilon'\Omega^{-3}\mathbf{H}_p\mathbf{H}_q\varepsilon \tag{52}$$

The corresponding elements of the information matrix are thus:

$$-E\left\{\frac{\partial^2 l}{\partial\lambda^2}\right\} = -\mathbf{1}'\mathbf{B}'\Omega^{-1}\mathbf{B1} \tag{53}$$

$$-E\left\{\frac{\partial^2 l}{\partial\beta\partial\beta'}\right\} = \mathbf{X}'\mathbf{B}'\Omega^{-1}\mathbf{B}\mathbf{X} \tag{54}$$

$$-E\left\{\frac{\partial^2 l}{\partial\gamma\partial\gamma'}\right\} = -\mathbf{X}'\mathbf{Q}'\mathbf{B}'\Omega^{-1}\mathbf{B}\mathbf{Q}\mathbf{X} \tag{55}$$

$$-E\left\{\frac{\partial^2 l}{\partial\lambda^2}\right\} = Tr\{[\mathbf{A}^{-1}\mathbf{W}]^2 + \Omega(\mathbf{A}'\mathbf{B}')^{-1}\mathbf{W}'\mathbf{B}'\Omega^{-1}\mathbf{B}\mathbf{W}(\mathbf{B}\mathbf{A})^{-1} \tag{56}$$

$$+(1\delta + \mathbf{X}\beta + \mathbf{Q}\mathbf{X}\gamma)'(\mathbf{A}')^{-1}\mathbf{W}'\mathbf{B}'\Omega^{-1}\mathbf{B}\mathbf{W}\mathbf{A}^{-1} \tag{57}$$

$$(1\delta + \mathbf{X}\beta + \mathbf{Q}\mathbf{X}\gamma)\} \tag{58}$$

$$-E\left\{\frac{\partial^2 l}{\partial\rho^2}\right\} = Tr\{[\mathbf{B}^{-1}\mathbf{M}]^2 + \Omega(\mathbf{B}')^{-1}\mathbf{M}'\Omega^{-1}\mathbf{M}\mathbf{B}^{-1}\} \tag{59}$$

$$-E\left\{\frac{\partial^2 l}{\partial\alpha_p^2}\right\} = \frac{1}{2}Tr\{\Omega^{-2}\mathbf{H}_p^2\} \tag{60}$$

$$-E\left\{\frac{\partial^2 l}{\partial\delta\partial\beta'}\right\} = -\mathbf{1}'\mathbf{B}'\Omega^{-1}\mathbf{B}\mathbf{X} \tag{61}$$

$$-E\left\{\frac{\partial^2 l}{\partial\delta\partial\gamma'}\right\} = -\mathbf{1}'\mathbf{B}'\Omega^{-1}\mathbf{B}\mathbf{Q}\mathbf{X} \tag{62}$$

$$-E\left\{\frac{\partial^2 l}{\partial\delta\partial\lambda}\right\} = -\mathbf{1}'\mathbf{B}'\Omega^{-1}\mathbf{B}\mathbf{W}\mathbf{A}^{-1}(\mathbf{1}\delta + \mathbf{X}\beta + \mathbf{Q}\mathbf{X}\gamma) \tag{63}$$

$$-E\left\{\frac{\partial^2 l}{\partial\delta\partial\rho}\right\} = 0 \tag{64}$$

$$-E\left\{\frac{\partial^2 l}{\partial\delta\partial\alpha_\rho}\right\} = 0 \tag{65}$$

$$-E\left\{\frac{\partial^2 l}{\partial\beta\partial\gamma'}\right\} = -\mathbf{X}'\mathbf{B}'\Omega^{-1}\mathbf{B}\mathbf{Q}\mathbf{X} \tag{66}$$

$$-E\left\{\frac{\partial^2 l}{\partial\beta\partial\lambda}\right\} = \mathbf{X}'\mathbf{B}'\Omega^{-1}\mathbf{B}\mathbf{W}\mathbf{A}^{-1}(\mathbf{1}\delta + \mathbf{X}\beta + \mathbf{Q}\mathbf{X}\gamma) \tag{67}$$

$$-E\left\{\frac{\partial^2 l}{\partial\beta\partial\rho}\right\} = 0 \tag{68}$$

$$-E\left\{\frac{\partial^2 l}{\partial\beta\partial\alpha_p}\right\} = 0 \tag{69}$$

$$-E\left\{\frac{\partial^2 l}{\partial\lambda\partial\gamma'}\right\} = -(\mathbf{1}\delta + \mathbf{X}\beta + \mathbf{QX}\gamma)'(\mathbf{A}')^{-1}\mathbf{W}'\mathbf{B}'\Omega^{-1}\mathbf{B}\,\mathbf{QX} \tag{70}$$

$$-E\left\{\frac{\partial^2 l}{\partial\rho\partial\gamma'}\right\} = -0' \tag{71}$$

$$-E\left\{\frac{\partial^2 l}{\partial\lambda\partial\alpha_\rho}\right\} = 0 \tag{72}$$

$$-E\left\{\frac{\partial^2 l}{\partial\rho\partial\lambda}\right\} = Tr\{\Omega(\mathbf{B}')^{-1}(\mathbf{B}'\Omega^{-1}\mathbf{M} + \mathbf{M}'\Omega^{-1}\mathbf{B})\mathbf{WA}^{-1}\mathbf{B}^{-1}\} \tag{73}$$

$$-E\left\{\frac{\partial^2 l}{\partial\lambda\partial\alpha_p}\right\} = Tr\{\Omega^{-1}\mathbf{H}_p\mathbf{BWA}^{-1}\mathbf{B}^{-1}\} \tag{74}$$

$$-E\left\{\frac{\partial^2 l}{\partial\rho\partial\alpha_p}\right\} = Tr\{\Omega^{-1}\mathbf{H}_p\mathbf{MB}^{-1}\} \tag{75}$$

$$-E\left\{\frac{\partial^2 l}{\partial\alpha_\rho\partial\alpha_q}\right\} = \frac{1}{2}Tr\{\Omega^{-2}\mathbf{H}_p\mathbf{H}_q\} \tag{76}$$

The information matrix is of the form

$$I(\theta) = \begin{array}{c@{\;}c} Dim & \begin{array}{cccccc} 1 & k & k & 1 & 1 & m \end{array} \\ \begin{array}{c} 1\\ k\\ k\\ 1\\ 1\\ m \end{array} & \begin{pmatrix} I_{\delta\delta} & \mathbf{I}_{\delta\beta'} & \mathbf{I}_{\delta\gamma'} & I_{\delta\lambda} & 0 & \mathbf{0}' \\ \mathbf{I}_{\beta\delta} & \mathbf{I}_{\beta\beta'} & \mathbf{I}_{\beta\gamma'} & \mathbf{I}_{\beta\lambda} & \mathbf{0} & \mathbf{0}' \\ \mathbf{I}_{\gamma\delta} & \mathbf{I}_{\gamma\beta'} & \mathbf{I}_{\gamma\gamma'} & \mathbf{I}_{\gamma\lambda} & \mathbf{0} & \mathbf{0}' \\ I_{\lambda\delta} & \mathbf{I}_{\lambda\beta'} & \mathbf{I}_{\lambda\gamma'} & I_{\lambda\lambda} & I_{\lambda\rho} & \mathbf{I}_{\lambda\alpha'} \\ 0 & \mathbf{0}' & \mathbf{0}' & I_{\rho\lambda} & I_{\rho\rho} & \mathbf{I}_{\rho\alpha'} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{I}_{\alpha\lambda} & \mathbf{I}_{\alpha\rho} & \mathbf{I}_{\alpha\alpha'} \end{pmatrix} \end{array} \tag{77}$$

$$= \begin{array}{c@{\;}c} & \begin{array}{cc} 2k+1 & m+2 \end{array} \\ \begin{array}{c} 2k+1 \\ m+2 \end{array} & \begin{pmatrix} \mathbf{I}_{11} & \mathbf{I}_{12} \\ \mathbf{I}_{21} & \mathbf{I}_{22} \end{pmatrix} \end{array}, \text{ say.} \tag{78}$$

in which the dimensions of the blocks appear in the margins. As can be seen, this matrix is *not* block-diagonal between the mean and variance-covariance parameters of the model; this is because the spatial lag parameter, λ, enters both mean and covariance structure in this formulation.

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Empirical contributions

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Section Empirical contributions

Investigaciones Regionales

Within and Between Panel Cointegration in the German Regional Output-Trade-FDI Nexus

Timo Mitze *

ABSTRACT: For spatial data with a sufficiently long time dimension, the concept of «global» cointegration has been recently introduced to the econometrics research agenda. Global cointegration arises when non-stationary time series are cointegrated both within and between spatial units. In this paper, we analyze the role of globally cointegrated variable relationships using German regional data (NUTS1 level) for GDP, trade, and FDI activity during the period 1976-2005. Applying various homogeneous and heterogeneous panel data estimators to a Spatial Panel Error Correction Model (SpECM) for regional output growth allows us to analyze the short- and long-run impacts of internationalization activities. For the long-run cointegration equation, the empirical results support the hypothesis of export- and FDI-led growth. We also show that for export and outward FDI activity positive cross-regional effects are at work. Likewise, in the short-run SpECM specification, direct and indirect spatial externalities are found to be present.

JEL Classification: C21, C23, F43.

Keywords: Global cointegration, Spatial Durbin model, Growth, Trade, FDI

Cointegración de panel entre e intra-grupos: las relaciones entre producción, comercio e inversión extranjera directa para las regiones alemanas

RESUMEN: El concepto de cointegración global ha sido recientemente introducido en la agenda de la investigación econométrica para datos espaciales con una dimensión de tiempo suficientemente larga. La cointegración global surge cuando series temporales no estacionarias están cointegradas, tanto dentro como entre las unidades espaciales. En este trabajo se analiza el papel de las relaciones cointegradas globales a partir de datos regionales de Alemania (a nivel de NUTS1) para

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el PIB, el comercio y la Inversión Extranjera Directa (IED) durante el periodo 1976-2005. La aplicación de varios estimadores de datos de panel homogéneos y heterogéneos a un modelo de corrección de error espacial de panel (SpECM) al crecimiento de la producción regional, nos permite analizar los efectos a corto y largo plazo de la internacionalización de las actividades. Para la ecuación de cointegración de largo plazo, los resultados empíricos apoyan la hipótesis de que las exportaciones y la IED son los motores del crecimiento. También se observan externalidades interregionales positivas para la exportación y la IED. Asimismo, en la especificación del SpECM en el corto plazo, se detecta la presencia de externalidades espaciales directas e indirectas.

Clasificación JEL: C21, C23, F43.

Palabras clave: Cointegración global, modelo espacial Durbin, Crecimiento, comercio, inversión extranjera directa.

1. Introduction

The relationship between economic growth and internationalization activity is an active field of economic research at the firm, regional and national levels. Two of the central transmission channels through which trade and international investment activity (the latter typically in the form of Foreign Direct Investment, henceforth FDI) may affect economic growth and development are the existence of technological diffusion via spillovers and the exploitation of market-size effects. While the latter mechanism is closely related to the classical work on «export-led-growth» in the field of trade theory and regional economics (see, e.g., Hirschman, 1958), the importance of technological diffusion and spillover effects has been particularly emphasized in the new growth theory (see, e.g., Barro & Sala-i-Martin, 2004, for an overview).

In seminal papers, Romer & Rivera-Batiz (1991) as well as Rivera-Batiz & Xie (1993) already hinted at the importance of knowledge spillovers in generating permanent growth effects from trade opening, while Feenstra (1990) demonstrated that, without technological diffusion, an economy will experience a decline of its growth rate after liberalizing trade. Summarizing the findings of the theoretical literature dealing with the spatial distribution of growth related to trade openness, Tondl (2001) argues that perfect integration with trade liberalization and technology diffusion may spur growth and eventually lead to income convergence among the group of participating regions/countries in an endogenous growth world. However, for the medium run, imperfect integration may lead to growth divergence or convergence among different «clubs». In this sense, it may be important to account for potentially different short- and long-run effects of trade on growth in a more complex empirical modelling framework.

The likely uneven evolution of economic growth due to internationalization activity across time and space is also prominently discussed within the field of new economic geography (NEG). Long-run spatial divergence may be the result of a concentration of economic activity in certain agglomerations. In almost all NEG models, free trade and capital movement play a key role. Whether agglomeration or dispersion forces dominate depends crucially on the underlying core-periphery pattern as well as the impact of trade liberalization on the reduction of the transaction costs and the size of agglomeration effects such as market size and economies of scale. Especially for FDI, the latter size factors are identified as key determinants across space rather than differences in saving rates as typically specified in the standard Solow model of growth. The latter neoclassical transmission channel is assumed to solely operate via capital accumulation, which takes place across space, when the capital-to-labour ratio is low and marginal products from capital investment are high. While the Solow model predicts (conditional) convergence, for models driven by market potential and increasing economies of scale, Martin & Ottaviano (1996) as well as Baldwin et al. (1998) show that along the lines of the new economic geography and growth models there might be a long-term equilibrium, which exhibits an asymmetric (divergent) location pattern.

As the discussion above shows, the interplay between economic growth and internationalization activity is a complex issue both across time and space. It is rather difficult to derive clear-cut results, given the plurality of different approaches. In this paper, we thus tackle this issue at the empirical level by analyzing the growth-trade-FDI nexus for West German federal states (NUTS1 Level) for the period 1976-2005. Our methodological approach rests on the analysis of merging the long- and short-run perspective by means of cointegration analysis, which aims to identify co-movements of the variables within and between cross-sections. The notion of a global panel cointegration approach has been recently introduced by Beenstock & Felsenstein (2010). This framework allows us to specify spatial panel error correction models (SpECM) which are able to identify short- and long-run co-movements of the variables in focus and avoid any bias stemming from spurious regressions.

From a statistical point of view, a proper handling of variables that may contain unit roots in the time dimension is of vital importance [1]. The merit of the global cointegration approach is that it aims at analyzing the consequences of spatial effects for the time series behavior of variables. That is, consider the case of two regions of which one region is heavily engaged in international trade or FDI and directly benefits from this activity in terms of output growth, e.g. through the exploitation of market potentials and technological diffusion. The second region instead is not actively engaged in trade activity but benefits from the first region's openness via forward and backward linkages, which in turn raise output for the second region, too. Thus, rather than having a stable long-run co-movement between its own level of internationalization activity and output evolution, the inclusion of a spatially lagged trade variable is needed to ensure cointegration of the second region's output level with trade and FDI activity. Moreover, apart from the importance of spatial lags in finding stable cointegration relationships for output, trade, and FDI in a time-series perspective, the

[1] Note that this analysis does not address the handling of variables containing spatial unit roots in the definition of Fingleton (1999).

method may also help to control for any cross-sectional dependence in the long- and short-run specification of the SpECM.

The remainder of the paper is organized as follows. In the next section, we give a brief overview of recent empirical contributions regarding the relationship of economic growth, trade, and international capital movement. So far, the empirical literature has focused on the time-series perspective, aiming at identifying cointegration relationships and analyzing the direction of causality among the variables involved. Opening up the field of research to an explicit account of space may add further insights. Section 3 then briefly discusses the database used and presents some stylized facts at the German regional level. Section 4 presents the econometric specification used and, in Section 5 we report the main estimation results for our chosen SpECM modelling framework. Section 6 concludes the analysis.

2. Theory and Empirics of Output-Trade-FDI Linkages

As already sketched above, there are various approaches in order to motivate the link between output determination and internationalization activity at the regional level. To elaborate different testable hypothesis, in the conduct of this analysis we start from export-base driven theoretical models (see, e.g., McCann, 2001, for an overview) [2]. According to the export base approach, regional output determination is mainly driven by its internationalization activity given that the regional private and public consumption level is limited to a certain amount. In contrast, foreign demand for regional products does not face these capacity constraints. Regional agents have then to decide about how to serve foreign demands, either by means of export or FDI activity. As argued above, next to this direct link between internationalization activity and regional output, the latter may also be determined by indirect spatial spillovers given that intranational input-output relationships exist. A stylized output function can then be written as

$$Y_t = f(FDI_t, TR_t, FDI^*_t, TR^*_t, \Omega), \tag{1}$$

where Y_t denotes the aggregate production of the economy at time t as a function of internationalization activity in terms of FDI and Trade (TR), where «*» indicate variables measuring spatial spillovers. Details on how to construct such spatial lag variables are given in Section 4. Ω is a vector of further domestic determinants of the region's output level. We use this augmented export base framework as a starting point for our empirical model specification with theoretically motivated variable selection. At the empirical level, many studies have already hinted at the strong correlation among these variables either in a pairwise or more general testing approach.

[2] An alternative starting point would be the specification of an aggregate production function framework, which is particularly useful to highlight the link between internationalization activity and technology growth (see, e.g., Edwards, 1998).

In a recent survey dealing with the FDI-growth relationship, the OECD (2002) finds for 11 out of 14 studies that FDI contributes positively to income growth and factor productivity. A further meta-analysis of the latter literature is also presented by Ozturk (2007). The author likewise concludes that most studies find a positive effect of FDI on growth.

Investigating the simultaneous interference of trade and FDI on growth and vice versa, Ekanayake et al. (2003), Dritsaki et al. (2004), Wang et al. (2004), Makki & Somwaru (2004) as well as Hansen & Rand (2006) among others use cointegration analysis to identify the long- and short-run effects among the variables and, by means of Granger causality tests, get general evidence for a bi-directional causal relationship between internationalization activity and economic growth. Using data for North and South American countries between 1960 and 2001 (including Brazil, Canada, Chile, Mexico, and USA), Ekanayake et al. (2003), for instance, report evidence in favor of trade-led growth, while results for (inward) FDI-led growth are mixed. For a panel of 79 countries, Wang et al. (2004) report that FDI has a positive impact on growth in high- and middle-income countries, but not in low-income countries. Looking closer at a subsample of developing countries, Hansen & Rand (2006) find that FDI has an impact on GDP via knowledge transfers and the adoption of new technology.

Only very few studies give an explicit account of spatially related variables in the analysis of the trade-FDI-growth nexus. One exception is Ozyurt (2008), who estimates a long-run model for labour productivity of Chinese provinces driven by trade and FDI as well as their respective spatial lags [3]. The author finds that FDI and trade volumes have a positive direct effect on labour productivity. The results for the sample period 1979-2006 show that the geographical environment has a subsequent influence on labour productivity in a certain region. Besides the spatial lag of the endogenous variable as a «catch-all» proxy for spatial effects, FDI spillovers turn out to be of specific interregional nature. These findings give a first indication that spillovers from internationalization activity are not restricted to a direct effect, but may also influence the economic development of neighboring regions.

The above sketched literature gives rise to a set of testable hypotheses, which can be summarized as follows:

— *Hypothesis 1:* Trade and FDI activities are directly related through market size and intraregional technological spillover effects to the economy's output performance both in the long- and short-run («Trade-led» and «FDI-led» growth).

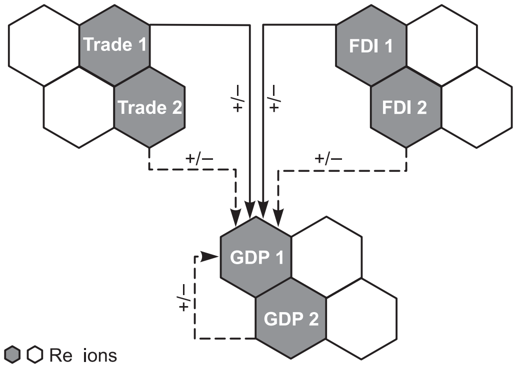
— *Hypothesis 2:* Trade and FDI activities are indirectly related to the economy's output performance through forward and backward linkages as a source of interregional spillover effects both in the long- and short-run.

— *Hypothesis 3:* Besides trade and FDI spillovers, there are also direct short-run linkages between the economic growth performances of neighboring regions, which may stem from domestic rather than international sources.

[3] Additionally, there is a growing literature with respect to third-country effects of FDI activity. See, e.g., Baltagi et al. (2007).

The different direct and indirect transmission channels from internationalization activity for the stylized case of two regions are illustrated in Figure 1. Solid arrows in the figure indicate a direct relationship between regional output and the region's internationalization activity, while dashed arrows mark indirect spatial spillover effects. The reader has to note that the reduction of the system to a single equation approach, with causality being assumed to run from trade and FDI to growth, abstracts from the likely role of feedback effects and bidirectional causality.

Figure 1. Sources of internationalization effects on regional output



3. Data and Stylized Facts

For the empirical analysis, we use regional panel data for the 10 West German federal states between 1976 and 2005. Our data comprise GDP levels, export and import volumes, as well as inward and outward stocks of FDI. All data are used in real terms. For the analysis, all variables are transformed into logarithms [4]. We use a spatial weighting scheme that contains binary information on whether two states share a common border or not (queen contiguity). The spatial weighting matrix is used in its row-standardized form. The sources and summary statistics of the data are given in Table 2. Additionally, Figure 2 plots the time evolution of the variables for each West German federal state. As the figure shows, all variables increase over time. The evolution of real GDP shows the smoothest time trend, while the values for trade and FDI activities show a more volatile pattern. The figure also displays that both inward as outward FDI stocks start from a rather low level in the 1970s but increase rapidly over time. Except for the small states *Bremen* and *Saarland*, which show to have a strong trade performance, the gap between trade and FDI activity gradually decreases

[4] It would be desirable to have a higher degree of regional disaggregation rather than $N=10$ with $T=30$. However, no such data on trade and FDI activity is available. The panel structure of the data is nevertheless still comparable to Beenstock & Felsenstein (2010) with $N=9$ and $T=18$, so that it should be feasible to apply their proposed method to our regional data.

Table 1. Data sources and summary statistics of the variables

Variable	*Description*	*Source*	*Obs.*	*in logarithms*			
				Mean	*Std. Dev.*	*Min*	*Max*
y	Real GDP (in Euro)	VGR der Länder (VGRdL, 2009)	300	10.95	1.17	8.19	13.12
ex	Real Exports (in Euro)	Destatis (2009)	300	9.66	1.12	7.19	11.9
im	Real Imports (in Euro)	Destatis (2009)	300	9.76	1.01	7.37	11.93
fdi in	Real Stock of inward FDI (in Euro)	Deutsche Bundesbank (2009)	300	8.16	1.57	5.3	11.57
fdi out	Real Stock of outward FDI (in Euro)	Deutsche Bundesbank (2009)	300	8.32	2.03	3	12.36

Table 2. Panel unit root tests

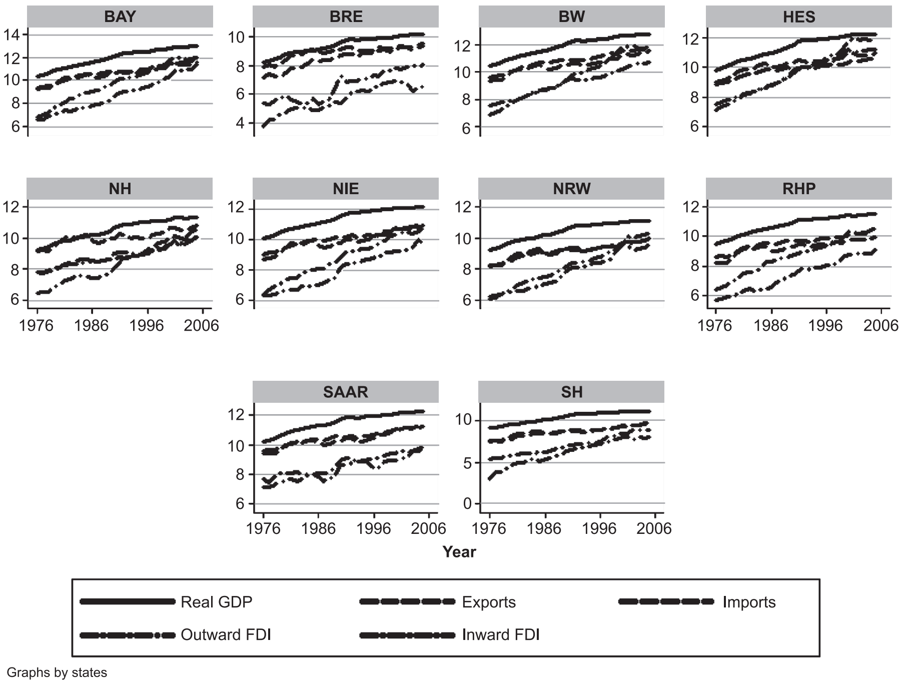
	IPS test for N =*10,* T =*30*		*CADF test for* N =*10,* T =*30*	
Variable	*W[t-bar] (P-Value)*	*Av. Lags*	*Z[t-bar] (P-Value)*	*Av. Lags*
y	0.07 (0.53)	1.50	0.53 (0.70)	2
ex	–1.37* (0.09)	1.10	–1.16 (0.12)	1
im	2.69 (0.99)	0.50	–0.59 (0.28)	1
fdi in	0.56 (0.71)	1.20	–2.21** (0.02)	1
fdi out	–0.91 (0.18)	0.70	1.45 (0.93)	1
Δ y	–9.27***(0.00)	1.10	–4.51***(0.00)	1
Δ ex	–13.52*** (0.00)	0.70	–7.08*** (0.00)	1
Δ im	–9.85*** (0.00)	0.70	–6.83*** (0.00)	1
Δ fdi in	–13.58*** (0.00)	0.70	–5.34*** (0.00)	1
Δ fdi out	–9.81*** (0.00)	0.90	–3.88*** (0.00)	1

Note: ***, **, * denote significance at the 1, 5 and 10% level. For IPS, the optimal lag length is chosen according to the AIC. H_0 for both panel unit root test states that all series contain a unit root.

over time. In the following, we will more carefully account for the co-evolution of GDP and internationalization activity by means of cointegration analysis.

As we have seen from Figure 1 all variables grow over time, indicating that the variables are likely to be non-stationary. To analyze this more in depth, we therefore compute standard panel unit root tests proposed by Im et al. (2003) as well as Pesaran (2007). The latter test has the advantage that it is more robust to cross-sectional correlation brought in by spatial dependence (see, e.g., Baltagi et al., 2007), while the Im et al. (2003) test is found to be oversized, when the spatial autocorrelation coefficient of the residual is large (around 0.8). The results of both panel unit root

Figure 2. GDP, trade and FDI by German states (in logs)



Source: See Table 1.
Note: BW = Baden Württemberg, BAY = Bavaria, BRE = Bremen, HH = Hamburg, HES = Hessen, NIE = Lower Saxony, NRW = North Rhine-Westphalia, RHP = Rhineland-Palatine, SAAR = Saarland, SH = Schleswig-Holstein.

tests are reported in Table 2. As the results show, both test statistics give evidence that all variables are integrated of order $I(1)$ and are stationary after taking first differences.

4. Econometric Specification

The estimation of $I(1)$ –variables has a long tradition in time-series modelling and has recently been adapted to panel data econometrics (see, e.g., Hamilton, 1994, Baltagi, 2008). In this section, we expand the scope of the analysis from a within-panel perspective to a simultaneous account of between-panel linkages, leading to a more global concept of cointegration (see Beenstock & Felsenstein, 2010). To show this, we start from a spatial panel data model with the following general long-run form:

$$Y_{it} = \alpha_i + \beta X_{it} + \theta Y_{it}^{*} + \delta X_{it}^{*} + u_{it} \quad (2)$$

where Y_{it} is the dependent variable of the model for $i = 1, 2, \ldots, N$ spatial cross-sections, $t = 1, 2, \ldots, T$ is the time dimension of the model. X_{it} is a vector of exogenous control variables; α_i denote cross-sectional fixed effects, and u_{it} is the model's residual term. Both Y and X are assumed to be time-integrated of order $Y \sim I(d)$ and $X \sim I(d)$ with $d \leq 1$. If X and Y are co-integrated, the error term u should be stationary as $u \sim I(0)$. Asterisked variables refer to spatial lags defined as

$$Y_{it}^{*} = \sum_{j \neq i}^{N} w_{ij} Y_{jt}, \tag{3}$$

$$X_{it}^{*} = \sum_{j \neq i}^{N} w_{ij} X_{jt}, \tag{4}$$

where w_{ij} are typically row-standardized spatial weights with $\sum_j w_{ij} = 1$. As Beenstock & Felsenstein (2010) point out, in an aspatial specification u_{it} may be potentially affected by cross-sectional dependence. However, the presence of spatial lags should capture these effects and account for any bias stemming from omitted variables. Further, since the spatial lags Y_{it}^{*} and X^{*}_{it} are linear combinations of the underlying data, they have the same order of integration as Y_{it}^{*} and X^{*}_{it}, respectively. For the non-stationary case, the presence of spatial lags thus enlarges the cointegration space to find long-run specifications with a stationary residual term u_{it}.

As pointed out in the seminal work of Engle & Granger (1987), cointegration and error correction are mirror images of each other. We may thus move from the specification of the long-run equation in eq.(2) to a dynamic specification in first differences, which nevertheless preserves the information of the long-run equation. The resulting (Vector) error correction model [(V)ECM] describes the dynamic process through which cointegrated variables are driven in the adjustment process to their long-run equilibrium. In the following we build on the concept proposed by Beenstock & Felsenstein (2010) and specify a spatial ECM (SpECM) as dynamic process, in which spatially cointegrated variables co-move over time. We allow for deviations from a stable long-run equilibrium relationship in the short-run. However, the «error correction» mechanism ensures the stability of the system in the long-run.

Therefore, the SpECM concept encompasses three important types of cointegration: (i) If cointegration only applies within spatial units but not between them, we refer to «local» cointegration. The latter is the standard concept of cointegration with respect to (panel) time series analysis. (ii) «Spatial» cointegration refers to the case in which non-stationary variables are cointegrated between spatial units but not within them. As Beenstock & Felsenstein (2010) point out, in this case, the long-term trends in spatial units are mutually determined and do not depend upon developments within spatial units. (iii) Finally, if nonstationary spatial panel data are both cointegrated within and between cross-sections, we refer to «global» cointegration.

The resulting SpECM associated with eq.(2) in its first-order form can be written:

$$\Delta Y_{it} = \gamma_{0i} + \gamma_1 \Delta Y_{it-1} + \gamma_2 \Delta X_{it-1} + \gamma_3 \Delta Y^*_{it-1} + \gamma_4 \Delta X^*_{it-1} + \gamma_5 u_{it-1} + \gamma_6 u^*_{it-1} + e_{it} \qquad (5)$$

where e_{it} is the short-run residual which is assumed to be temporally uncorrelated, but might be spatially correlated such that $Cov(e_{it}\, e_{jt}) = \sigma_{ij}$ is nonzero. The terms u_{it-1} and u^*_{it-1} are the (spatially weighted) residuals from the long-term relationships of the system. The latter are stationary for the case of a cointegration system. The coefficients for u and u^* can be interpreted as error correction coefficients, which drive the system to its long-run equilibrium state. Global error correction arises if γ_5 and γ_6 are non-zero. For the nested case of local cointegration, we typically assume that $\gamma_5 < 0$ in order to restore the long-run equilibrium.

It is straightforward to see that if the coefficients for u and u^* are zero, the long-run information used for estimation drops out and the system in eq.(5) reduces to a single equation in a spatial VAR (SpVAR) formulation. Note, that in the short run, X may affect Y differently from how it affects Y in the long run. Hence, γ_2 in eq.(5) may be different from δ in eq.(2). It is also important to note that the coefficient for the time lag of the dependent variable (γ_1) is typically expected to have the same sign as the coefficient for u^* (γ_6), since the dynamics of Y will be affected by u^* among neighbors. For the case of γ_5, $\gamma_6 \neq 0$ the resulting SpECM specification exhibits «global error correction». As Beenstock & Felsenstein (2010) point out, the SpECM in eq.(5) should only contain contemporaneous terms for ΔX and ΔX^* if credible instrument variables could be specified for them or if these variables are assumed to be exogenous. The latter implies for our empirical case, that error correction runs from X to Y but not the other way around.

5. Empirical Results

5.1. Within Panel Cointegration and ECM

In this section, we first start with the analysis of a aspatial model for output and internationalization activity as typically done in the empirical literature. We then test whether the inclusion of spatial lags improves our empirical model – both from a statistical as well economic perspective. As it has been shown in Table 2, all five variables are integrated time series. In order to use both the information in levels as well in first differences, the variables should be co-integrated to avoid the risk of getting spurious estimation results. Several methods have been derived to test for panel cointegration (see, e.g., Wagner & Hlouskova, 2009, for a recent survey and performance test of alternative approaches). These can be classified as single-equation and system tests, with the most prominent operationalizations in time-series analysis being the Engle-Granger (1987) and Johansen (1991) VECM approaches, respectively. For this analysis, we apply the Kao (1999) and Pedroni (1999) panel ρ tests as residual based approaches in the spirit of the Engle-Granger and additionally a Fisher (1932) type test, where the latter combines the probability values for single cross-section estimates of the Johansen (1991) system approach [5]. If we get evidence for a stable cointegration relationship among the variables, we are then able to move on and specify different regression models which are capable of estimating non-stationary panel data models including information in levels and first differences.

Since we have rather limited time-series observations, this makes it hard to estimate individual models for each German region. A natural starting point would thus be to pool the time-series and cross-section data for purposes of estimation. However, this is only feasible if the data is actually «poolable» (see, e.g., Baltagi, 2008). Among the common estimation alternatives in this setting with small N and increasing T are the pooled mean group (PMG) and the dynamic fixed effects (DFE) model. While the PMG estimator allows for cross-section specific heterogeneity in the coefficients of the short run parameters of the model (see Pesaran et al., 1999), the DFE model assumes homogeneity of short and long-run parameters in the estimation approach. Given a consistent benchmark (such as the standard mean group estimator, see Pesaran & Smith, 1995), we are also able to test for the appropriateness of the pooling approach by means of standard Hausman (1978) tests. Table 3 first presents the results of the cointegration tests among output, trade and FDI, Table 4 then gives a detailed overview of the regression output for the PMG and DFE estimator using the sample period 1976 to 2005.

Table 3. Panel cointegration tests for regional output, trade and FDI in the aspatial model

	Coint.	*P-Val.*
Kao (1999) ADF	–4.23***	(0.00)
Pedroni (1999) ρ	2.01*	(0.06)
χ-*max* of Johansen (1991)	115.2***	(0.00)

Note: ***, **, * denote significance at the 1, 5 and 10% level. H_0 for panel cointegration tests is the no-cointegration case. For the Johansen maximum eigenvalue test MacKinnon-Haug-Michelis (1999) p-values are reported. The test is applied to the null hypothesis of rank ($r \leq 0$) against the alternative of ($r+1$).

[5] The Fisher-type test can be defined as $-2 \sum_{i=1}^{N} \log(\phi_i) \rightarrow \chi^2 2N$, where ϕ_i is the p-value from an individual Johansen cointegration test for cross-section i. Here, we apply the Fisher test to the maximum eigenvalue (χ-*max*) of the Johansen (1991) approach, which tests the null hypothesis of r cointegration relationships against the alternative of (r + 1) relationships. At this point we restrict the Johansen approach to test the null hypothesis of *rank* ≤ 0. If the null hypothesis is rejected, for the underlying single cointegration vector we then assume that it has the form of a stylized output equation driven by trade and FDI as, e.g., outlined for the case of the augmented export base model outlined above.

Table 4. Aspatial model estimates for the growth-trade-FDI Nexus

Dep. Var.: Δ y	*PMG*	*DFE*
	Long run estimates	
ex_{it}	1.02***	0.78***
	(0.337)	(0.299)
im_{it}	-0.42*	-0.47
	(0.224)	(0.323)
$fdi\ out_{it}$	-0.21	-0.15
	(0.157)	(0.235)
$fdi\ in_{it}$	0.16	0.16
	(0.118)	(0.169)
	Short run estimates	
u_{it-1}	-0.06***	-0.05***
	(0.009)	(0.014)
$\Delta\ y_{it-1}$	0.29***	0.33***
	(0.048)	(0.048)
$\Delta\ ex_{it}$	-0.08**	-0.01
	(0.038)	(0.033)
$\Delta\ im_{it}$	0.10***	0.07***
	(0.016)	(0.022)
$\Delta\ fdi\ out_{it}$	0.07***	0.06***
	(0.019)	(0.013)
$\Delta\ fdi\ in_{it}$	0.06***	0.06***
	(0.012)	(0.013)
Hausman Test $\chi^2(4)$	15.29***	0.01
p-value	(0.00)	(0.00)
STMI residuals	5.96***	7.45***
p-value	(0.00)	(0.00)
p^b-value	(0.00)	(0.00)

Note: ***, **, * denote significance at the 1, 5 and 10% level. Standard errors in brackets. The Hausman test checks for the validity of the PMG and DFE specifications against the MG estimation results. *STMI* is the spatio-temporal extension of the Moran's *I* statistic, which tests for H_0 of spatial independence among observations. Since we are dealing with a small number of cross-sections, we use standard as well as bootstrapped *p*-values of the test. The latter are marked by a «*b*».

If we first look at the panel cointegration tests in Table 3, we see that the Kao (1999) and Fisher-type Johansen (1991) tests clearly rejects the null hypothesis of no cointegration for the five variables employed. However, the result of the Pedroni panel ρ test is less clear cut. Here, we only get empirical support for a stable cointegration relationship at the 10% significance level. Regarding the estimated coefficients, the results in Table 4 show that we find a positive long-run effect of export activity on growth, both for the PMG and the DFE models. This is consistent with the export-led growth theory of regional economics. However, for imports, we find a negative impact on GDP, which is, however, only statistically significant at the 10% level.

The models do not find any long-run causation from FDI activity (both inward and outward) to GDP. Looking at the short-run coefficients, we see that the coefficient of the error correction term is statistically significant and of expected sign, although the speed of adjustment to the long-run equilibrium is rather slow (around 5-6% per year). Though we do not find a statistical long-run impact of import and FDI activity on economic growth, there is a multidimensional positive short-run correlation from import and both FDI variables to output growth. The sole exception is export flows, for which we do not find any short-run effect in the DFE model and a reversed coefficient sign in the PMG model.

If we finally check for the statistical appropriateness of the respective estimators, we see from the results of the Hausman *m*-statistic that only for the DFE model we cannot reject the null hypothesis of consistency and efficiency of the DFE relative to the benchmark mean group (MG) estimator [6]. On the contrary, the PMG is found to be inconsistent. Thus, we conclude that the DFE is the preferred (aspatial) model specification in the context of the German growth-trade-FDI nexus.

So far we did not account for the spatial dimension of the data. As Beenstock & Felsenstein (2010) point out, this may lead to a severe bias of the estimation results both in terms of the cointegration space of the variables as well as incomplete handling of spatial dependence in the model. To check for the appropriateness of our aspatial cointegration relationship from Table 4, we calculate a spatio-temporal extension to the Moran's *I* statistic (thereafter labeled *STMI*) for the estimated models' residuals, which has recently been proposed by Lopez et al. (2011). Since we are dealing with a small number of cross-sections, we compute both asymptotic as well as bootstrapped test statistics to get an indication of the degree of misspecification in the model. Lin et al. (2009) have shown that bootstrap based Moran's *I* values are an effective alternative to the asymptotic test in small-sample settings. Details about the computation of the *STMI* and bootstrapped inference are given in the Appendix. As the results show, the *STMI* strongly rejects the null hypothesis of spatial independence among the observed regions for both the asymptotic as well bootstrapped-based test statistic using a distance matrix based on common borders among German states. In sum, these results may be seen as a first strong indication that the absence of explicit spatial terms in the regression may induce the problem of spurious regression.

5.2. Global Cointegration and SpECM

We now move on to an explicit account of the spatial dimension both in the long- and short-run specification of the model. First, we estimate the long-run equation for the relationship of GDP, trade, and FDI. The results for the augmented panel

[6] We do not report regression results of the MG estimator here. They can be obtained from the author upon request. The MG estimator assumes individual regression coefficients in the short- and long-run and simply averages the coefficients over the individuals. Pesaran & Smith (1995) have shown that this results in a consistent benchmark estimator.

cointegration tests and different estimation strategies are shown in Table 5 and Table 6, respectively. We start from a simple fixed effects specification. However, due to the inclusion of spatial lags, OLS estimation may lead to inconsistent estimates of the regression parameters (see, e.g., Fischer et al., 2009). Since eq.(2) takes the form of a general spatial Durbin model, it may be appropriately estimated by maximum likelihood (ML), which has recently been proposed for panel data settings in Beer & Riedl (2009). The estimator of Beer & Riedl (2009) makes use of a fixed-effects (generalized Helmert) transformation proposed by Lee & Yu (2010) and maximizes the log-likelihood function with imposed functional form for the individual variances to keep the number of parameters to be estimated small (for details, see Beer & Riedl, 2009). The authors show by means of a Monte Carlo simulation experiment that the SDM-ML estimator has satisfactory small-sample properties. Besides the SDM-ML model, which includes spatial lags of the endogenous and exogenous variables, we also estimate a spatial Durbin error model (SDEM), which includes spatial lags of the exogenous variables and a spatially lagged error term as well as estimate the SDM by GMM.

Table 5. Panel cointegration tests for regional output, trade and FDI in spatially augmented model

	Coint.	*P-Val.*
Kao (1999) ADF	–3.70***	(0.00)
Pedroni (1999) ρ	2.74***	(0.00)
χ-*max* of Johansen (1991)	741.0***	(0.00)

Note: ***, **, * denote significance at the 1, 5 and 10% level. H_0 for panel cointegration tests is the no-cointegration case. For the Johansen maximum eigenvalue test MacKinnon-Haug-Michelis (1999) p-values are reported. The test is applied to the null hypothesis of rank ($r \leq 0$) against the alternative of ($r + 1$).

Again, we first look at the obtained test results from the panel cointegration tests including spatial lags of the exogenous variables. The results in Table 5 give strong empirical evidence that the variables cointegrated. Compared to the aspatial specification the result of the Pedroni (1999) test is improved (statistically significant at the 1% level), indicating that the inclusion of spatial lags of exogenous variables is necessary to ensure a stable cointegration relationship for a regional economic model as already pointed out by Felsenstein & Beenstock (2010).

Regarding the estimated coefficients, again we observe a positive effect from exports on GPD in the spatially augmented long-run relationship. The estimated elasticity is somewhat smaller compared to the aspatial estimators from above. Next to the direct export effect for the DFE, we also observe an indirect effect from the spatial lag of the export variable (ex^*). That is, an increased export activity in neighboring regions also spills over and leads to an increased GDP level in the home region. The effect, however, becomes insignificant if we move from a simple FEM regression to a ML based estimator for the general spatial Durbin model (SDM) and spatial Durbin error model (SDEM) as well as the GMM approach in Table 6 [7]. All specifications show a significant direct effect of outward FDI on regional output. The latter can be associated with the FDI-led growth hypothesis. Additionally, the SDM-ML model also finds a significant positive coefficient for interregional spillovers from outward FDI stocks on the output level. The direct impact of import flows turns out to be insignificant. However, we get a significant negative coefficient for the indirect spillover effect (both for the FEM and SDM-ML), indicating that higher importing activity in neighboring regions are correlated with GDP levels in the own region. For inward FDI, we hardly find any direct or indirect spatial effect on GDP.

While the partial derivatives of direct and indirect effects for each exogenous variable can be immediately assessed for the FEM and SDEM-ML results in Ta-

Table 6. Spatially augmented long-run estimates of GDP, trade and FDI

Dep. Var.: y	*Spatial FEM*	*SDM-ML*	*SDEM-ML*	*SDM-GMM*
ex_{it}	0.27***	0.49***	0.41***	0.55**
	(0.098)	(0.089)	(0.076)	(0.232)
im_{it}	0.08	–0.03	0.06	0.40
	(0.086)	(0.106)	(0.072)	(0.247)
$fdi\ out_{it}$	0.28***	0.28***	0.19***	0.36**
	(0.040)	(0.057)	(0.029)	(0.158)
$fdi\ in_{it}$	0.04	–0.01	0.06**	–0.41
	(0.037)	(0.049)	(0.028)	(0.258)
ex^*_{it}	0.19*	0.07	0.05	–0.02
	(0.101)	(0.049)	(0.078)	(0.320)
im^*_{it}	–0.20**	–0.10**	0.03	0.33
	(0.103)	(0.042)	(0.082)	(0.285)
$fdi\ out^*_{it}$	0.04	0.18***	0.04	–0.04
	(0.049)	(0.032)	(0.036)	(0.084)
$fdi\ in^*_{it}$	–0.01	–0.05*	–0.02	–0.01
	(0.048)	(0.029)	(0.034)	(0.147)
y^*_{it}		–0.23***		–0.06
		(0.021)		(0.582)
$error^*_{it}$			0.19***	
			(0.012)	

Note: ***, **, * denote significance at the 1, 5 and 10% level. Standard errors in brackets. The SDM-GMM uses up to two lags for the exogenous variables and their spatial lags, as well as the twice lagged value of the spatial lag of the endogenous variable.

[7] We specify the GMM approach in extension to the ML estimators, since the model may be a good candidate for estimation of the time and spatial dynamic processes in the second step short-run specification.

ble 6 [8], LeSage & Pace (2009) have recently shown that for model specifications including a spatial lag of the endogenous variable, impact interpretation is more complex. Table 7 therefore additionally computes summary measures for the SDM-ML based on a decomposition of the average total effect from an observation into the direct and indirect effect. The table shows that there is a significant total effect of export flows on the regional GDP level, which can be almost entirely attributed to its direct effect. Imports and inward FDI are not found to have either a significant direct or indirect effect, while for the case of outward FDI, we find both a positive direct as well as indirect effect. The latter results contrast findings from the SDEM-ML, indicating a significant effect running from inward FDI to growth. As LeSage & Pace (2009) point out, we cannot directly judge about the validity of one of the two models, since the SDEM does not nest the SDM and vice versa. However, one potential disadvantage of the SDEM compared to the SDM is that it could result in severe underestimation of higher-order (global) indirect impacts (see LeSage & Pace, 2009, for details). We may thus argue that SDM-ML is the most reliable specification for the long-run estimation of the output-Trade-FDI system.

Table 7. Direct, indirect and total effect of variables in SDM-ML

	direct	*indirect*	*total*
ex_{it}	0.52***	–0.07	0.46***
im_{it}	0.03	–0.14	–0.11
$fdi\ out_{it}$	0.21***	0.17***	0.37***
$fdi\ in_{it}$	0.03	–0.08	–0.05

Note: ***, **, * denote significance at the 1, 5 and 10%-level using simulated parameters as described in LeSage & Pace (2009).

We then move on and use the obtained long-run cointegration relationship in a SpECM framework for regional GDP growth. The estimation results of the SpECM are shown in Table 8. For estimation of the SpECM, we apply the standard DFE model, the SDM-ML from Beer & Riedl (2009), as well as the spatial dynamic GMM specification. The latter estimator explicitly accounts for the endogeneity of the time lag of the dependent variable by valid instrumental variables. Although the time dimension of our data is reasonably long, the bias of the fixed effects estimator may still be in order.[9] The spatial dynamic GMM estimator using an augmented instrument set in addition to the aspatial version proposed by Arellano & Bond (1991) as well as Blundell & Bond (1998) has recently performed well in Monte Carlo simulations (see Kukenova & Monteiro, 2009) as well as in empirical applications (e.g., Bouayad-Agha & Vedrine, 2010). Valid moment conditions for instrumenting the spatial lag of the endogenous variable besides the time lag are given in the Ap-

[8] This also holds for the SDM-GMM since the spatial lag coefficient of the dependent variable is insignificant.

[9] Using Monte Carlo simulations, Judson & Owen (1999), for instance, report a bias of about 20% of the true parameter value for the FEM, even when the time dimension is $T = 30$.

Table 8. Spatially augmented short-run estimates of GDP, trade and FDI}

Dep. Var.: Δ y	*DFE*	*SDM-ML*	*SDM-GMM*
u_{it-1}	–0.16***	–0.05*	–0.21***
	(0.025)	(0.033)	(0.034)
u^*_{it-1}	0.14***	–0.01	0.20***
	(0.025)	(0.012)	(0.036)
Δy_{it-1}	0.49***	0.36***	0.47***
	(0.040)	(0.099)	(0.049)
Δex_{it}	0.04	0.06	0.03
	(0.032)	(0.051)	(0.044)
Δim_{it}	0.10***	0.06	0.14***
	(0.024)	(0.047)	(0.011)
$\Delta fdi\ out_{it}$	0.09***	0.07***	0.08***
	(0.016)	(0.025)	(0.019)
$\Delta fdi\ in_{it}$	0.06***	0.06***	0.06***
	(0.012)	(0.020)	(0.011)
Δex^*_{it}	0.05**	0.01	0.02*
	(0.021)	(0.026)	(0.010)
Δim^*_{it}	–0.04*	–0.01	–0.04**
	(0.019)	(0.183)	(0.013)
$\Delta fdi\ out^*_{it}$	0.01	0.02	–0.02
	(0.009)	(0.014)	(0.018)
$\Delta fdi\ in^*_{it}$	0.01	0.06***	0.01
	(0.011)	(0.011)	(0.010)
Δy^*_{it}		0.22***	0.11**
		(0.036)	(0.044)
STMI residuals	–2.85***	–1.08	–1.41
p-value	(0.00)	(0.14)	(0.08)
p^b-value	(0.00)	(0.84)	(0.12)

Note: ***, **, * denote significance at the 1, 5 and 10% level. Standard errors in brackets. SMTI is the spatio-temporal extension of the Moran's I statistic, which tests for Ho of spatial independence among observations. Since we are dealing with a small number of cross-sections, we use standard as well as bootstrapped *p*-values of the tests. The latter are marked by a «b».

pendix. The inclusion of time and spatial lags in the SpECM results in a «time-space-simultaneous» specification (see, e.g., Anselin et al., 2007).

With respect to the included variables, all model specifications report qualitatively similar results. For the standard EC-term we get a highly significant regression parameter in the DFE- and GMM-based specification, which is of expected sign. Besides the results from the panel cointegration tests from Table 6, this is a further indication that GDP and the variables for internationalization activity co-move over time in a long-run cointegration relationship, where short-term deviations balance out in the long-run. For the size of the EC-term, the spatial dynamic GMM model comes closest to values typically found in the empirical literature, with about one-fifth of short-run deviations being corrected after one year (see, e.g., Ekanayake et al., 2003). Also, the coefficient for the spatialized EC-term (u^*) is significantly different from zero in the DFE and GMM specification.

Looking at the short-run correlation between growth, trade, and FDI in Table 8, we see that both direct and indirect (spatial) forces are present. As for the direct effects, the results do not differ substantially from the aspatial SpECM specification in Table 4. We do not find any significant short-run effect from export activity on growth. However, all other variables are positively correlated with the latter. Looking more carefully at the spatial transformations of these variables, we see that a higher export activity has a positive spillover effect on the output growth of neighboring regions while imports have a negative indirect effect (in line with the long-run findings). We also check for the significance of spatial lags in the endogenous variable and the error term. Here we find that there are indeed spatial spillovers from an increased growth performance in neighboring regions, a result which mirrors related findings for German regional growth analysis (see, e.g., Niebuhr, 2000, as well as Eckey et al., 2007). This result is also supported by the significant and positive coefficient for the spatial lag of the error correction variable (u^*). We do not find any sign for significant spatial autocorrelation left in the residuals of the SDM-ML and SDM-GMM using the (bootstrapped) *STMI* test.

6. Conclusion

The aim of this paper was to analyze the role of within and between panel cointegration for the German regional output-trade-FDI nexus. While investigating the co-movements among non-stationary variables is by now a common standard in panel time-series analysis, less attention has been paid to the importance of spatial lags in the long-run formulation of a regression model. Applying the novel concept of global cointegration, as recently proposed by Beenstock & Felsenstein (2010), enables us to estimate spatially-augmented error correction models (SpECM) for West German data between 1976 and 2005. Our results show that both direct as well as indirect spatial linkages among the variables matter when tracking their long-run co-movement.

First, the regression results for the long-run equation give empirical support for a direct cointegration relationship among economic output and internationalization activity. In particular, export flows show a significant and positive long-run impact on GPD, supporting the export-led growth hypothesis from regional and international economics. Moreover, we also get evidence that outward FDI drives output in the long-run. Second, besides these direct effects, the latter variable is also found to exhibit significant positive spatial spillovers. In general, augmenting the model by spatial lags of the trade and FDI variables significantly increases the model performance both regarding the applied panel cointegration tests as well as tests for spatial dependence in the regression residuals. Our results can thus be interpreted in similar veins as Beenstock & Felsenstein (2010), who find that the inclusion of spatial lags of exogenous variables may have important implications for the stability of a cointegration relationship among variables for a regional economic system. As empirical identification strategy in the spatially augmented model we employ both ML- as well as GMM-based estimators.

Regarding the short-run determinants of economic growth, for most variables in the specified spatial error correction model (SpECM) we observe positive direct effects. Regarding the spatial lags, we find that a rise in the export flows in neighboring regions significantly increases the region's own growth rate, while imports show negative feedback effects. Finally, we also find positive growth relationship among German regions if we augment the model by the spatial lag of the endogenous variables. This result mirrors earlier evidence for Germany, reporting positive spatial autocorrelation in regional growth rates. Our specified SpECM (both using ML as well as GMM with appropriate instruments for the time and spatial lag of the endogenous variable) passes residual based spatial dependence tests. For the latter, we use a spatio-temporal extension of the Moran's *I* statistic, for which we calculate both asymptotic as well as bootstrapped standard errors.

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Appendix

A.1. Bootstrapping the Spatio-Temporal Extension of Moran's *I*

Recently, different attempts have been made to improve statistical inference based on the Moran's *I* statistic to detect spatial dependence in the data. First, Lin et al. (2009 & 2010) have shown that the power of Moran's *I* statistic can be enhanced in small sample settings if bootstrapped test statistics are calculated instead of their asymptotic counterparts. Second, Lopez et al. (2011) have extended Moran's *I* to the case of spatio-temporal data. The authors label the extended version as the «*STMI* test». In the following, we will combine both proposals for the application in spatial panel data settings with a small number of cross-sections. We thus first sketch the *STMI* test and then build a «wild» bootstrap version of the test in the spirit of Lin et al. (2009).

The *STMI* test proposed by Lopez et al. (2011) is a straightforward extension of the cross-section test. In the latter setting, Moran's *I* can be defined as

$$I = \frac{N}{S} \frac{\sum_{r \neq s} (y_r - \overline{y}) w_{rs} (y_s - \overline{y})}{\sum_{r=1}^{R} (y_r - \overline{y})} \tag{6}$$

where $\bar{y}$ is the sample mean for a variable y, w_{rs} is the (r,s) element of a spatial weighting matrix W, N is the total number of cross-sections and S is a measure of overall connectivity for the geographical system. The null hypothesis of Moran's I is the absence of correlation between the spatial series y_r with $r = 1, \ldots, N$ and its spatial lag $\sum_{s=1}^{N} w_{rs} y_s$. Building upon I and a measure for its standard deviation, Moran's I statistic is shown to be asymptotically normal with (see Lopez et al. (2011) as well as Kelejian & Prucha, 2001, for details)

$$\frac{I}{\sqrt{Var(I)}} \sim N(0,1). \tag{7}$$

As Lopez et al. (2011) point out, it is not strictly necessary to restrict the application of Moran's I to just one time period. Starting from a model with T consecutive cross-sections with N observations in each of them, stacked in an (NT x 1) vector, the authors show that the spatio-temporal version of Moran's I can be computed as

$$STMI = \frac{NT}{S} \frac{\sum_{(t,s)\neq(r,k)} (y_{ts} - \overline{y}) w^{*}_{(t-1)T+s,(r-1)T+k} (y_{rk} - \overline{y})}{\sum_{ts} (y_{ts} - \overline{y})^2}, \tag{8}$$

where y_{ts} is a spatio-temporal process with $t \in Z$ and $s \in S$, where Z and S are sets of time and spatial coordinates with cardinality $|Z|=T$ and $|S| = R$, respectively. Each element w^* is taken from the following weighting matrix:

$$W^{*}_{NT} = \begin{bmatrix} W_N & 0 & 0 & \dots & 0 & 0 \\ I_N & W_N & 0 & \dots & 0 & 0 \\ 0 & I_N & W_N & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & W_N & 0 \\ 0 & 0 & 0 & \dots & I_N & W_N \end{bmatrix} \tag{9}$$

where the cross-section based spatial weighting matrix of order N x N appears along the main diagonal and the diagonal below the main diagonal contains the temporal weighting matrix I_N. The latter is defined as the identity matrix of order N (for further details, see Lopez et al., 2011). In a Monte Carlo simulation, Lopez et al. (2011) show that the *STMI* test is robust to different types of distribution functions and has satisfactory finite sample properties.

Building upon the findings in Lin et al. (2009), we additionally develop a «wild» bootstrap based test version for the *STMI*, which is implemented through the following steps:

Step 1: Estimate the residuals $\hat{e}_{it}$ as $\hat{e}_{it} = y - V\hat{\delta}$ for the spatial or aspatial estimator with regressors V and coefficients $\hat{\delta}$ (either short- or long-run specification) in focus and obtain a value for the *STMI*. Save the obtained *STMI*.

Step 2: Re-scale and re-center the regression residuals $\tilde{e}_{it}$ according to

$$\tilde{e}_{it} = \frac{\hat{e}_{it}}{(1 - h_{it})^{1/2}}, \tag{10}$$

where h_{it} is the model's projection matrix so that a division by $(1 - h_{it})^{1/2}$ ensures that the transformed residuals have the same variance (for details, see MacKinnon, 2002).

Step 3: Choose the number of bootstrap samples B and proceed as follows for any j sample with $j = 1, \ldots, B$:

Step 3.1: According to the wild bootstrap procedure, multiply $\tilde{e}_{it}$ with $\tilde{v}_{it}$, where the latter is defined as a two-point distribution (the so-called Rademacher distribution) with

$$\tilde{v}_{it} = \begin{cases} 1 & \text{with probability } 1/2 \\ -1 & \text{with probability } 1/2 \end{cases} \tag{11}$$

Step 3.2: For each of the $i = 1, \ldots, N$ cross-sections, draw randomly (with replacement) T observations with probability $1/T$ from $\tilde{e}_{it} \times \tilde{v}_{it}$ to obtain $\tilde{e}^*_{it}$.

Step 3.3: Generate a bootstrap sample for variable y (and its spatial lag) as

$$y^*_{it} = V^*\hat{\delta} + \tilde{e}^*_{it} \tag{12}$$

where $V^* = (Wy^*_{it}, y^*_{it-1}\}, X)$ and, for a time-dynamic specification, initialization as $y^*_{i0} = y_{i0}$. Thus, for a regression equation with a lagged endogenous variable, we condition on the initial values of y_{i0}, the exogenous variables X, and the spatial weighting matrix W[10].

Step 3.4: Obtain the residuals from the regression including y^* and V^*, calculate the bootstrap based $STMI^*$.

The full set of resulting bootstrap test statistics are $STMI^*_1$, $STMI^*_2$, …, $STMI^*_B$. From the empirical distribution, we can then calculate p-values out of the nonparametric bootstrap exercise in order to perform hypothesis testing. There are various ways to do so. Lin et al. (2009), for instance, express equal-tail p-values for $STMI^*$ as

$$P^*(STMI^*) = 2\min\left(\frac{1}{B}\sum_{j=1}^{B} C(STMI^*_j \le STMI), \frac{1}{B}\sum_{j=1}^{B} C(STMI^*_j > STMI)\right), \tag{13}$$

where $C(.)$ denotes the indicator function, which is equal to 1 if its argument is true and zero otherwise. Then, given a nominal level of significance α, we compare $P^*(STMI^*_j)$ with α. Following Lin et al. (2009), one can reject the null hypothesis of no spatial dependence if $P^*(STMI^*_j) < \alpha$.

[10] See, e.g., Everaert & Pozzi (2007) for the treatment of initial values to bootstrap dynamic panel data processes. In the following, by default, we generate y^* based on the long-run cointegration specification, where we do not face the problem of time dynamics in the bootstrapping exercise. However, we additionally need to account for the generated error term and its spatial lag as explanatory regressors in the short-run equation.

A.2. Moment Conditions for the Spatial Dynamic GMM Model

The use of GMM-based inference in dynamic panel data models is a common practice in applied research. Most specifications rest on instruments sets as proposed by Blundell & Bond (1998). Their so-called system GMM (SYS-GMM) approach combines moment conditions for the joint estimation of a regression equation in first differences and levels. The latter part helps to increase the efficiency of the GMM methods compared to earlier specifications solely in first differences (e.g., Arellano & Bond, 1991). Subsequently, extensions of the SYS-GMM approach have been proposed, which make use of valid moment conditions for the instrumentation of the spatial lag coefficient of the endogenous variable (see, e.g., Kukenova & Monteiro, 2009, Bouayad-Agha & Vedrine, 2010). Kukenova & Monteiro (2009) have also shown, by means of Monte Carlo simulations, that the spatial dynamic SYS-GMM model exhibits satisfactory finite sample properties.

For the purpose of this analysis, we focus on appropriate moment conditions for the time-space simultaneous model including a time and spatial lag of the endogenous variable. Instruments can be built based on transformations of the endogenous variable as well as the set of exogenous regressors. Assuming strict exogeneity of current and lagged values for any exogenous variable $x_{i,t}$, then the full set of potential moment conditions for the spatial lag of $y_{i,t}$ is given by

First differenced equation:

$$E\left(\sum_{i\neq j} w_{ij} \times y_{i,t-s} \quad \Delta u_{i,t}\right) = 0 \quad t = 3,\ldots,T \quad s = 2,\ldots t-1, \tag{14}$$

$$E\left(\sum_{i\neq j} w_{ij} \times x_{i,t+/-s} \quad \Delta u_{i,t}\right) = 0 \quad t = 3,\ldots,T \quad \forall \text{s}. \tag{15}$$

Level equation:

$$E\left(\sum_{i\neq j} w_{ij} \times \Delta y_{i,t-1} \quad u_{i,t}\right) = 0 \quad t = 3,\ldots,T, \tag{16}$$

$$E\left(\sum_{i\neq j} w_{ij} \times \Delta x_{i,t} \quad u_{i,t}\right) = 0 \quad t = 2,\ldots,T. \tag{17}$$

One has to note that the consistency of the SYS-GMM estimator relies on the validity of these moment conditions. Moreover, in empirical application we have to carefully account for the «many» and/or «weak instrument» problem typically associated with GMM estimation, since the instrument count grows as the sample size *T* rises. We thus put special attention to this problem and use restriction rules specifying the maximum number of instruments employed as proposed by Bowsher (2002) and Roodman (2009).

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Section Empirical contributions

How important is access to employment offices in Spain? An urban and non-urban perspective

Patricia Suárez Cano*, Matías Mayor Fernández*, Begoña Cueto Iglesias*

ABSTRACT: The aim of this paper is to analyze the effect of the accessibility to employment offices on local unemployment rates according to the distribution of three different types of municipalities: large urban, small urban and non-urban. We built a new accessibility measure taking into account the number of employment offices together with the distance and size of their catchment area. We propose an empirical model with spatial regimes that allows including simultaneously spatial heterogeneity and spatial autocorrelation.

The results suggest that the accessibility to employment offices is especially important in non-urban areas where employment opportunities are limited. Employment services are important because bridge the gap between unemployed workers and employers where job opportunities are unclear.

JEL Classification: J68, C21, R12.

Keywords: Accessibility, employment services, spatial autocorrelation, spatial heterogeneity, spatial regimes.

¿Importa el acceso a las oficinas de empleo en España? Un análisis por tipo de municipio: urbano *vs* no urbano

RESUMEN: El objetivo de este trabajo es analizar el efecto de la accesibilidad a las oficinas de empleo sobre la tasa absoluta de paro teniendo en cuenta la relación de cada municipio con el fenómeno urbano, es decir, si pertenecen a grandes áreas urbanas, a pequeñas áreas urbanas o a áreas no urbanas. Se ha construido un índice de accesibilidad teniendo en cuenta el número de oficinas de empleo, la distancia desde cada municipio al municipio en el que se encuentra la oficina de empleo de referencia y el tamaño del mercado de trabajo de cada oficina de empleo. Se ha estimado un modelo que distingue estos tres tipos de regímenes espaciales incluyendo de forma simultánea la existencia de autocorrelación y heterogeneidad espacial.

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Los resultados sugieren que la accesibilidad a las oficinas de empleo es especialmente importante en las áreas no urbanas donde las oportunidades de empleo son más limitadas y confusas.

Clasificación JEL: J68, C21, R12.

Palabras clave: Accesibilidad, servicios de empleo, autocorrelación espacial, heterogeneidad espacial, regímenes espaciales.

1. Introduction

Regional labor market disparities in Spain are rather large and persistent; hence they must be addressed in active labor market policies (ALMPs). The decentralization of ALMPs has greatly changed the legislation governing the institutional structure of the labor market over the last decade. At present, local employment offices under regional public employment services are responsible for the implementation of active programs. Therefore labor market policies have become a central concern in Spain and politicians have started to recognize the need for further evaluation to assess their current state. The resources in terms of the number of employment offices are not uniform across autonomous communities and, consequently, some are doing better than others.

With respect to the Public Employment Service (PES), in theory it provides jobseekers easy access to employers and labor markets at local, regional, national and European level. Placement services are located in space, hence analyses of the accessibility to employment offices require spatially explicit tools. Also, any improvements in accessibility would translate into better PES performance, so we need to discuss whether the accessibility to employment offices is really equitable regardless of place of residence. Also, recent planning, evaluation and policy analysis have devoted more attention to accessibility measures.

This paper focuses on the spatial distributions of unemployed workers and public employment offices in Spain. Clearly, the distribution of public employment offices in the territory may lead to differences in accessibility for the unemployed and, in turn, have effect on the PES performance.

Studies on the efficiency of PES offices at local level have been done in Germany (Hagen, 2003), Switzerland (Sheldon, 2003) and Sweden (Althin and Behrenz, 2004). However, these studies have not analyzed whether the spatial distribution of employment offices ensures equal access to such offices. In Spain there are no studies of employment offices at local level and, as in other countries (Fertig *et al.,* 2006), we do not know how public funding is distributed among the offices.

The aim of this paper is twofold. First we present a new approach for tackling differences in access which combines the methodology of spatial methods with new accessibility measures that take into account the size of an employment office catchment area. Second we explore whether the spatial heterogeneity shown in several studies, viz. that labor market problems in large cities greatly differ from those in non-urban areas, may have a substantive interpretation in the sense that different spatial regimes apply for different types of municipalities.

The outline of the paper is as follows: Section II describes the data used in the paper and examines basic features of the unemployed and employment offices in relation to the different types of municipalities existing in Spain. It also introduces the accessibility measures proposed. In Section III we estimate an unemployment rate equation which includes the accessibility to employment offices as explanatory variable. Section V concludes with some policy recommendations.

2. Data and methodology

2.1. Data

Unemployment data in the following pages have been taken from the Official Unemployment Statistics, which are published monthly by the SPEE. Data refering to the local employment offices and their catchment areas have been taken from the regional employment authorities websites and the SPEE website. It is essential to establish clusters of unemployed people at local level, since active job-seeking policies and the modernization of PESs should be more intense in such municipalities.

Figure 1 shows the spatial distribution of employment offices in Spain. Clearly, its most striking feature is the large number of municipalities lacking employment offices –7,524 out of 8,109.

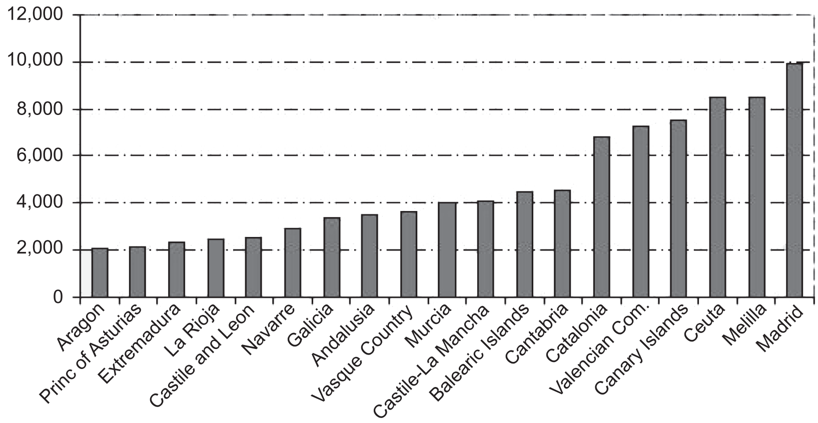
Figure 1. Employment office location (2009)

Source: own elaboration.

The many municipalities with zero employment offices are predominantly concentrated in Castile and Leon, whereas the nonzero ones are in the south and the south-east, Madrid and Barcelona. Notwithstanding that, the data shows employment offices in every municipality with over 4,000 jobless, except Paterna and Mislata (Valencia metropolitan area), San Vicent del Raspeig (Alicante metropolitan area), Mijas (Malaga) and Los Realejos (Tenerife).

Graph 1 shows the existence of steep differences between the Spanish autonomous communities in the number of unemployed workers per employment office. The number of employment offices seems to be far below the number of jobless they have to attend to, especially in Madrid, the Canary Islands, the Valencian Community and Catalonia, so differences in accessibility may be expected.

Graph 1. Average number of unemployed workers per placement office. NUTS-II (2009)



Source: own elaboration.

2.2. Measuring accessibility

Several authors from different perspectives have analyzed the concept of accessibility within the framework of urban and regional economies. For instance, Krugman (1991) and Fujita *et al.* (1999) study the importance of accessibility in economic development from a regional perspective. Most existing studies on accessibility belong to the field of transportation economy. Gutierrez (2001) and Holl (2007) analyze accessibility improvements in Spain. From a theoretical perspective, Geurs and Van Wee (2004) review is remarkable for its analysis of the usefulness of accessibility measures in the evaluation of changes in transportation infrastructures and its use by researchers and policy makers alike. With respect to labor markets, accessibility measures are given consideration in few works. For instance, Van Wee *et al.* (2001) develop a concept of accessibility to analyze whether jobs are accessible for employees. Détang-Dessendre and Gaigné (2009) study the impact of the place of residence on unemployment duration. They rely on an accessibility measure to convey workers' competition for jobs and subsequently tackle labor market tightness. Joassart-Marcelli and Giordano (2006) use a geographic information system to look into the location of One-Stop Centers in Southern California and their level of accessibility. Consequently, their research is closely related to ours. As far as we know, in Spain there is no research on the spatial distribution of employment offices and their levels of accessibility.

It is currently intended that active employment policies become an asset in the fight against unemployment so that assurance of equal access to employment offices is essential. We may begin by stating that, even though employment offices are administrative units that were created long ago, their spatial distribution is by no means random. However, regardless of the fact that it does follow a pattern, such distribution may cause either equity or inequity of access to the offices. Accessibility conditions should be the same regardless of the autonomous community of residence —whose government, in turn, is responsible for the administration of the employment offices. In other words, every unemployed worker should be equally treated, no matter where they may live. Talen and Anselin (1998) analyze the accessibility measures from a methodological point of view and take into account the spatial dimensions of equity.

The simplest measure to analyze job-seeker accessibility to employment offices consists in counting the existing employment offices within a given area. Suárez (2011) developed a range of accessibility measures to employment offices, so this work relies on one of these accessibility measures, considered like the best option. This measure takes into account the number of employment offices together with the distance and size of their catchment areas. Consequently, the proposed accessibility measure is more empirically adequate, since some employment offices attend to approx. 20,000 jobless —e.g. Fuenlabrada (Madrid)—, whilst others attend to just 1,000 jobless —e.g. Caudete (Albacete)—. The accessibility to employment services is determined by this fact and that cannot be overlooked. We would like to have had access to the number of job counselors and/or counseling sessions per unemployed worker, but access to this information is not provided at local level.

This measure is based on the number of employment offices per unemployed worker within a catchment area, adjusted for the distance between the municipality *i* and its corresponding employment office

$$A_i = \left[\frac{EO_j}{\sum\limits_{i \in j} u_i} (e^{-\lambda d_{ij}}) \right] \rightarrow A_i = \left[w_j (e^{-\lambda d_{ij}}) \right] \quad (1)$$

where A_{i} is the municipality accessibility, w_j is the number of employment offices (EO_j) per employment office catchment area ($\sum\limits_{i=j} u_i$), measured as the number of unemployed workers in the municipalities i within a single catchment area. Finally, d_{ij} is the distance between a municipality i and its corresponding employment office, and λ is a parameter of the distance-decay function. This parameter determines the degree of interaction between the place of residence of the jobless and the employment office they have to go to, the accessibility quality decreasing as distance to the office increase. Even though several values were used for this parameter in Suárez (2011), the performance of a sensitivity analysis led us to set $\lambda = 0.10$.

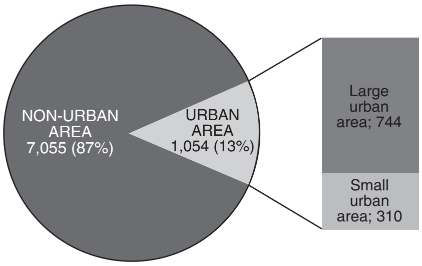
The study of the internal accessibility or 'self-potential' of employment offices presents further problems, since there are no data on the exact distance to the office when job-seekers are assigned an office within their municipality of residence. Even though this problem has been studied by some authors (Bröcker, 1989; Frost and Spence, 1995), it remains unsolved in the literature. One option consists on the estimation of the internal distance using the formula proposed by Zwakhals *et al.* (1998) which is based on the surface of the municipalities considered [1].

Since these municipalities are very similar (73% of the municipalities lacking employment offices are located in urban areas), another alternative is to assign the same distance value to such municipalities. Gutiérrez-i-Puigarnau *et al.* (2011) applies a similar solution to that of ours in the assignment of daily commuting distances for workers who commute to workplace locations within their municipality of residence. In our study, the first option rendered the results unreliable, so we imputed a value of 1 km for these municipalities (7.2% out of total), once the distribution of d_{ij} had been considered.

2.3. Municipalities classification

Before discussing in detail the classification of municipalities, we must examine the classification properties themselves. Graph 2 shows the classification of Spanish municipalities developed by the Department of Public Works [2], which has established

Graph 2. Type of municipality



[1] $d_i = \left(2\sqrt{surface_i}/3\right)$.

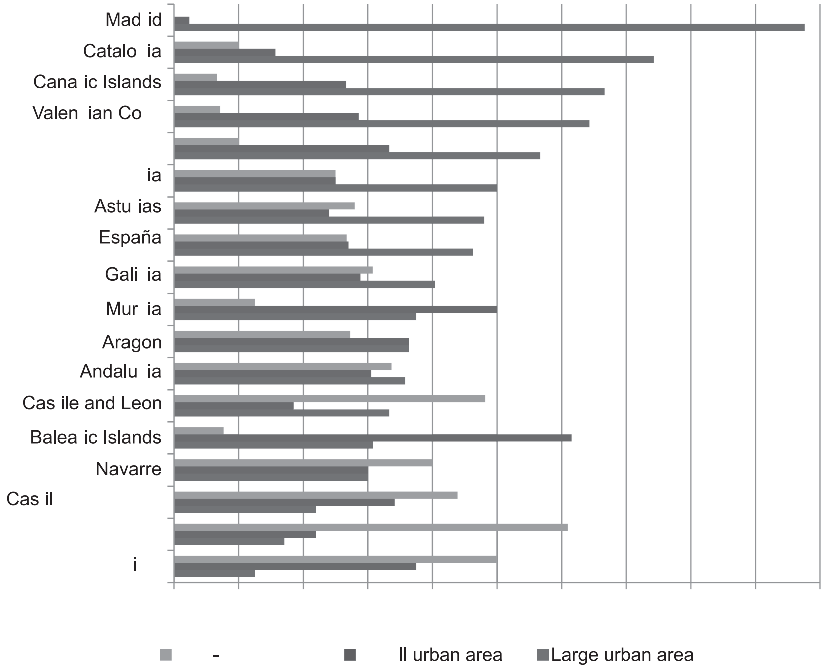
[2] This classification is currently under review following the Population Name Index 2009.

three different types of areas, viz. large urban, small urban and non-urban, according to their degree of urbanization. This classification has been built using data from the Population and Housing Census 2001, which have in turn been supplemented by more up to date information from the Population Name Index 2006. Both have been used as sources because they provide larger amounts of data at local level.

Generally it has been established that every large urban area must include one municipality with a population of at least 50,000 inhabitants. Any other municipality within the same area should have a minimum of 1,000 inhabitants. In total there are 83 large urban areas in Spain (744 municipalities, 9.2% out of total), of which 19 comprise just one municipality and the remaining 64 comprise more than one. 310 municipalities (3.8% out of total) belong to small urban areas. On the whole, urban areas add up to 1,054 municipalities (13% out of total). They also account for about 80% of the total population and 20% of the surface area of the country. Non-urban areas comprise 7,055 municipalities (87% out of total).

The main purpose of the classification is to identify differences between employment offices at regional level, so Graph 3 shows the classification of employment offices by type of municipality. In effect, 73% of the employment offices are located in urban areas. However, the distribution of employment offices differs across autonomous communities. Thus, Madrid, Catalonia and the Valencian Community have

Graph 3. Classification of employment offices by type of municipality



Source: own elaboration.

98%, 74% and 64% of their employment offices located in municipalities within large urban areas, respectively. Other autonomous communities such as Extremadura, Castile-La Mancha and Castile and Leon have about 50% of their employment offices in municipalities which do not belong to either large or small urban areas. It may naturally be expected that this fact has effect on job-seeker access to employment offices. We should bear in mind that employment offices, like ALMPs, have been transferred to the autonomous communities so that regional PES are responsible for the administration of both employment offices and a broad range of active labor market policies.

The three maps in Figure 2 show the classification of municipalities according to their degree of urbanization, as previously mentioned. Then the three maps in Figure 3 show the distribution at local level of the accessibility variable for large urban areas, small urban areas and non-urban areas, respectively. The conclusions we get from these maps are in accordance with what was expected. Thus, whereas the differences between non-urban areas are quite significant, those between urban areas are less so. Notwithstanding that, we may further remark that some large urban areas (e.g., central Asturias; Badajoz, Caceres and Merida; Vigo-Pontevedra) show high degrees of accessibility. Also, the quite significant differences between non-urban areas bear out the importance of the distribution of employment offices and the definition of their catchment areas. Since generally employment offices located in municipalities within non-urban areas are the least crowded, accessibility is higher in such municipalities and, consequently, it may be expected that access to employment offices reduces local unemployment rates, especially in municipalities with limited employment opportunities (i.e., training and job placement). In non-urban municipalities, the benefits from having access to an employment office may be greater.

2.4. Spatial autocorrelation

Within the field of labor market studies, several contributions have taken into account the spatial dimension of regional labor markets and pointed out the high degree of interdependence of local labor markets (Molho, 1995; Lopéz-Bazo *et al.,* 2002; Overman and Puga, 2002). Furthermore, Patacchini and Zenou (2007) analyze the reasons for the spatial dependence in local unemployment rates. This spatial autocorrelation is mainly due to the fact that the unemployed may seek and find work in different areas, so spatial interactions result from the mobility of the unemployed. When the data is collected at the administrative level, spatial autocorrelation is likely to be a relevant issue. This paper adds consideration of spatial dependences in local unemployment rates to the diverse influences exerted by public employment services across different levels of accessibility.

A spatial analytical perspective is also recommended by Tsou *et al.* (2005) to evaluate suitability of urban public facilities in assessing whether or not, or to what degree, the distribution of urban public facilities is equitable.

Notwithstanding that, not only is the spatial pattern of the offices relevant, but more complex aspects must also be taken into account, such as those relating to the

Figure 2. Types of municipalities. From left to right: large urban areas, small urban areas and non-urban areas

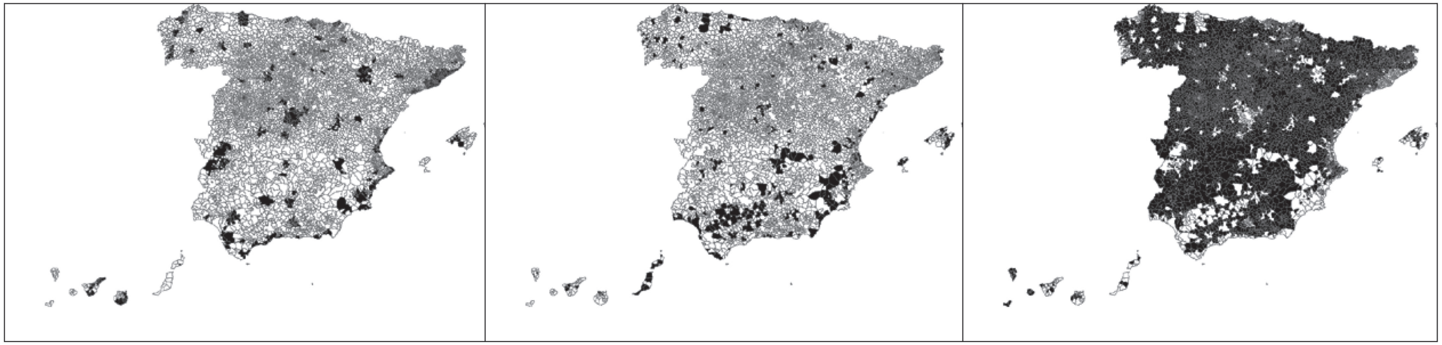
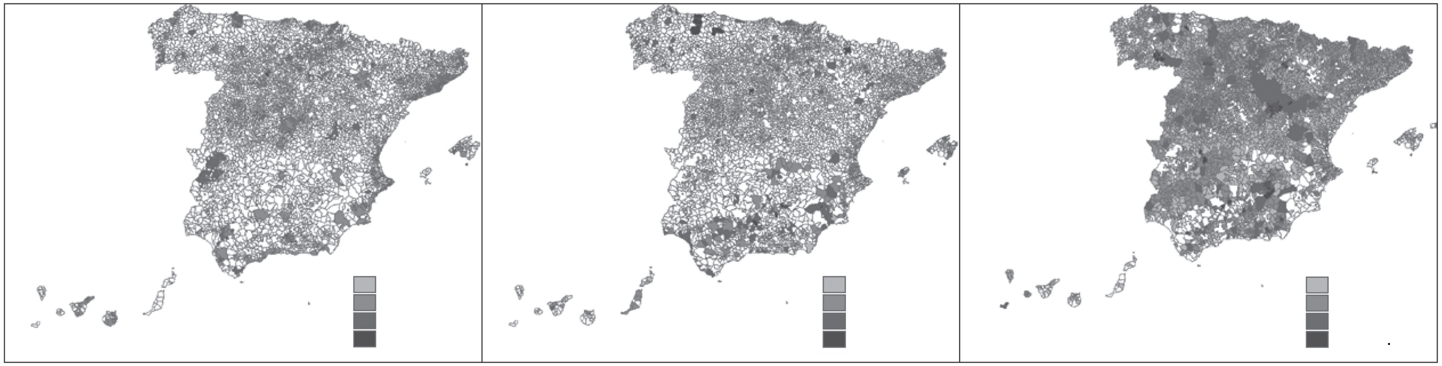


Figure 3. Accessibility to employment offices by type of municipality. From left to right: large urban areas, small urban areas and non-urban areas



Source: own elaboration.

accessibility indices calculated. Ideally, accessibility to employment offices should be kept at an adequate level even in high local unemployment rate contexts —in other words, there should be no municipalities with low accessibility levels.

This section examines global spatial autocorrelation in local unemployment rates, employment offices and accessibility measure. Firstly, we analyze the existence of spatial autocorrelations using Moran's I and the randomization approximation (Cliff and Ord, 1981). Table 1 displays Moran's I for local unemployment rates and the accessibility measure defined previously. Since the statistics are significant, all the variables show positive spatial autocorrelation, which suggests the existence of spillovers across municipalities. That is, the spatial structure of these variables is clear so that none is scattered randomly or independently in space.

Table 1. Measure of global spatial autocorrelation (Moran's I)

Variables		I	Z
Unemployed people		0.147	24.334
Local unemployment rate		0.574	85.300
Employment offices*		0.119	18.214
A_i	($\lambda = 0.1$)	0.625	92.272
	($\lambda = 0.25$)	0.624	91.711

Note: All statistics are significant at the 1% level. The expected value for Moran's I is –1.234e-04.
* We also applied Moran's I to the square root transformed employment offices variable due to the large number of municipalities without employment offices (I = 0.137; Z = 20.230***). The conclusion is the same when BB joint-count statistics and Empirical Bayes test are computed (EB, Assunção y Reis, 1999); the p-value is 0.001 y 0.016 respectively.

These results suggest that it is necessary to test the need for including explicitly the spatial relationships between unemployment rates in an empirical model avoiding a misspecification problem and improving its performance.

3. How important is access to employment offices?

3.1. Theoretical framework

Finally, we will consider in this section whether the accessibility to employment offices has any effect on local unemployment rates. Recent studies on spatial job search have shown that distance to jobs may reduce the likelihood of leaving unemployment (e.g. Détang-Dessendre and Gaigné, 2009). Ihlanfeldt (1997) asserts that labor market information acquisition is considered a type of investment behavior. At present, theory suggests that the unemployed will go to placement offices in search of information or job-broking services when benefits are greater than costs. The unemployed may refuse to go to a placement office because traveling expenses are too costly and, in some cases, they have to queue at the office.

From a political perspective, insofar as the relation between unemployment rates and accessibility to employment offices remains negative, investments in accessibility bettering will be regarded as meaningful. Joassart-Marcelli and Giordano (2006) point out that One-Stops are well positioned to serve the unemployed and that access to them does help to reduce local unemployment rates. In our study, it should be taken into account that the accessibility variable covers the idea that, whenever a job-seeker finds work, the unemployment rate in their municipality of residence is reduced, accessibility levels (w_j) grow in municipalities within the same regional labor office and, consequently, the performance of the employment services improves. When we refer to employment services, we mean not only job-seeking mediation but also career counseling, which allows the identification and development of each individual's talent (2008 SPEE Annual Report).

Regional unemployment differentials have been analyzed theoretically and empirically. Elhorst (2003) has reviewed the papers on regional and labor economics published since 1985. He asserts that «Whichever model is used, [...] they all result in the same reduced form equation of the regional unemployment rate». In this equation, labor supply, labor demand and wage-setting factors are usually used as explanatory variables, but in this case, as we work with a high level of disaggregation, the available information is limited. Consequently, the model in this paper includes as explanatory variables the rates of foreign population and males and females of working-age, the educational attainment of the population, industries' employment shares and two dummy variables, one for municipalities within high-high (HH) clusters of unemployed and the other for municipalities within low-low (LL) ones [3]. The local accessibility level to placement offices is also included. All the variable related information is in Table 2. The basic specification is:

$$\log\left(u_i\right) = \eta \log\left(A_i\right) + \beta X_i + e_i \qquad (2)$$

where u_i is the unemployment rate of each municipality, A_i is the accessibility measure and the X matrix collects the explanatory variables described above. Since there are no data on the economically active population at municipal level, local unemployment rates have been calculated by dividing the number of unemployed workers registered at PES offices by the number of people of working age (i.e., population aged 16-64) on the 2009 municipal register. Alonso-Villar and Río (2008) and Alonso-Villar *et al.* (2009) also rely on this definition to obtain unemployment rates at municipal level.

When spatial data are analyzed two different types of spatial effects appear: spatial dependence and spatial heterogeneity. Spatial dependence and spatial heterogeneity are really difficult to disentangle between them. In this idea, Florax *et al.* (2002) asserted that: «spatial heterogeneity and spatial dependence usually concur as meaningful interpretations of a spatial process because the uniqueness or heterogeneity of

[3] These clusters are identified by means of local indicator of spatial association (LISA, Anselin,1995) in Suárez (2011).

Table 2. Summary statistics

Variable	*Mean*	*SD*	*Definition*	*Data source*
Local unemployment rate	0.087	0.043	Unemployed population / Total population of working age (16-64)	SPEE and Municipal Register
ILLI	0.024	0.028	% Illiteracy	Population Census
PRI*	0.324	0.149	% Primary education	Population Census
SEC	0.396	0.138	% Secondary education or vocational training	Population Census
UNI	0.079	0.048	% Higher education	Population Census
HH	–	–	HH cluster	Own elaboration
LL	–	–	LL cluster	Own elaboration
A_i with $\lambda = 0.10$	0.155	0.204	Accessibility measure	Own elaboration
FLF	0.571	0.103	Female population 16-64 / Total female population	Municipal Register
MLF	0.644	0.074	Male population 16-64 / Total male population	Municipal Register
FOR	0.088	0.093	Foreign population (16-64) / Total population of working age (16-64)	Municipal Register
WI	0.191	0.119	Share of employment in industry	Population Census
WB	0.115	0.078	Share of employment in construction	Population Census
WS*	0.628	0.221	Share of employment in services	Population Census

* The percentage of population with incomplete primary education and the share of employment in agriculture have been omitted so as to avoid multicollinearity.

an attribute observed for a subset of the data can coincide with spatial proximity and hence autocorrelation for that attribute among the same observations».

We focused in discrete spatial heterogeneity where spatial instability of the parameters is linked to the characteristics of each spatial unit (municipalities in this case). In the discrete case, the spatial observations can be grouped in such a way that the variation pertains to different spatial subsamples, where each group can be treated as homogeneous [4]. This can be easily modeled by means of spatial regimes. In this method, prior information is needed to define these spatial subsets, and in this study we distinguish three types of municipalities based on the urban/non-urban classification described above. We explore whether this spatial heterogeneity can be given a substantive interpretation in the sense that different spatial regimes apply for the different types of municipalities.

[4] This type of models is commonly applied to test the convergence hypothesis (e.g. Ramajo *et al.,* 2008).

A specification allowing for these spatial regimes in the equation should be considered:

$$\begin{bmatrix} \log(u_{lu}) \\ \log(u_{su}) \\ \log(u_{nu}) \end{bmatrix} = \begin{bmatrix} \log(A_{lu}) & 0 & 0 \\ 0 & \log(A_{su}) & 0 \\ 0 & 0 & \log(A_{nu}) \end{bmatrix} \begin{bmatrix} \eta_{lu} \\ \eta_{su} \\ \eta_{nu} \end{bmatrix} + \\ + \begin{bmatrix} X_{lu} & 0 & 0 \\ 0 & X_{su} & 0 \\ 0 & 0 & X_{nu} \end{bmatrix} \begin{bmatrix} \beta_{lu} & \beta_{su} & \beta_{nu} \end{bmatrix} + \begin{bmatrix} e_{lu} \\ e_{su} \\ e_{nu} \end{bmatrix} \quad (3)$$

In the previous section we have established theoretically and empirically the existence of spatial dependence in unemployment rates, so the suitability of some kind of spatial model should be considered. Furthermore, symptoms of spatial instability are detected in the next section, so we propose different spatial regimes to incorporate discrete heterogeneity.

3.2. Empirical model

Firstly, model [2] has been estimated by means of OLS (Table 3). Both local unemployment rates and accessibility measures have been considered in logarithmic form, but it should be stressed that the use of these variables in levels makes no considerable difference. All the control variables are significant (with the exception of MLF and WI) and the estimated coefficients present the expected signs in accordance with previous theoretical and empirical studies.

The effect of the accessibility to placement offices is significant and negative, the unemployment rate decreases —ceteris paribus— by 0.062% when accessibility rises by 1% [5].

Standard tests have been carried out so as to assess the adequacy of the regression. The Breusch-Pagan test points to heteroskedascity, which in turn is related to the different sizes of the municipalities considered. In any case, since spatial dependences may cause this heteroskedasticity (McMillen, 1992), the result has been interpreted with caution. We may also note that the Kolmogorov-Smirnov test has led us to reject the assumption of normality of the OLS residuals.

Another issue is whether the accessibility variable is endogenous. Wooldridge's score test (1995) has been carried out so as to check the endogeneity of the accessibility variable. This test, whose instruments are geographic (municipality surface) and

[5] Suárez (2011) analyze the sensitivity of the estimated accessibility elasticities according to the possible values of the distance decay parameter.

Table 3. OLS regression of local unemployment rate

	OLS (White)
Intercept	–3.007 (0.073)***
A_i with $\lambda = 0.10$	–0.062 (0.005)***
FLF	0.894 (0.111)***
MLF	–0.051 (0.137)
HH	0.291 (0.019)***
LL	–0.119 (0.015)***
ILLI	3.501 (0.205)***
PRI	–0.075 (0.045)*
SEC	–0.266 (0.054)***
UNI	–2.033 (0.122)***
FOR	–0.529 (0.051)***
WB	0.363 (0.047)***
WI	0.072 (0.048)
WS	0.154 (0.039)***
Breusch-Pagan test	232.3***
Kolmogorov-Smirnov	0.246***
R^2 (adj.)	0.278
Log-likelihood	–2,525.216
AIC	5,080.432

demographic characteristics, is more appropriate when the residuals show heteroskedasticity. In this case, the endogenous regressors are actually exogenous [6]. Hence the OLS estimator is more efficient.

Moran's I is widely used to detect spatial dependences based on OLS residuals. The resulting statistic standard deviation is 41.815***. Here we have used a row-standardized rook contiguity matrix so that $w^s_{ij} = w_{ij} / \sum_j w_{ij}$ when $i \neq j$ and $w^s_{ij} = 0$ when $i = j$.

Nevertheless, it is necessary to analyze the existence of spatial heterogeneity and disentangle it from spatial autocorrelation. Then, equation [3] is estimated by means of OLS. Again, Moran's I statistic is highly significant (43.142***) and points to the existence of spatial autocorrelation in the residuals. Once spatial autocorrelation has been detected, we may proceed to incorporate it into the proposed model. In spatial econometrics, spatial autocorrelation is modeled by means of the relation between the dependent variable Y or the error term and its associated spatial lag, Wy for a spa-

[6] Unless an instrumental variables estimator is really needed, OLS should be used instead. In this case, the robust regression statistic is 1.295 with a p-value 0.255.

tially lagged dependent variable (spatial lag model) and *We* for the spatially lagged error term (spatial error model), respectively.

Only a few papers deal with how to specify a spatial econometric model (see Mur and Angulo, 2009). Then the problem is how to best identify the structure of the underlying spatial dependences in a given data set. This paper relies on widely used strategy (specific to general), which is based on the LM (Lagrange Multiplier) test and its robust version for local misspecifications (Anselin *et al.,* 1996). In this classical approach, the LMERR (Lagrange Multiplier for error dependence) and the LMLAG (Lagrange Multiplier for spatially lagged dependent variable) are compared. If the LMERR is lower than the LMLAG, the spatial lag model should be specified. If not, the spatial error model is to be specified. Florax *et al.* (2003) have developed a hybrid approach based on the robust version of these tests [7].

These tests have been computed on OLS residuals of the previously estimated models. We have also considered different criteria to build the spatial weight matrices that allowed us to analyze the sensitivity of the results [8]. As regards the structure of the spatial effects, three criteria are usually considered in the creation of a spatial weight matrix: contiguity, k-nearest and distance. Firstly, we define a rook contiguity matrix, where $w_{ij} = 1$ if municipalities i and j share a common edge and $w_{ij} = 0$ otherwise. Secondly, we apply a k-nearest neighbors' criterion ($k = 3$, 4 and 5). Then, we obtain a distance-based matrix, where $w_{ij} = 1$ if the distance between i and j is less than d and $w_{ij} = 0$ if $i = j$ or $d > d_{ij}$ ($d = 20$, 30 and 40 km).

We report the values of the LM specification tests using the rook contiguity matrix, since for the rest of the matrices, these tests and their robust versions render the same conclusions. Both LMERR and LMLAG reject their respective null hypothesis of absence of spatial autocorrelation. The LMLAG (2,253.791***) is greater than LMERR (1,839.588***) and consequently a spatial lag of the dependent variable is included in the model. The robust version of these statistics confirms the diagnostic: R-LMLAG (414.607***) and R-LMERR (0.404; p-value = 0.525). Consequently, a spatial lag specification has been chosen and, more specifically, one based on both the economic theoretical framework and the results of the specification test. Similarly, LeSage and Pace (2009) assert that spatial lag models have been used in contexts where there is a theoretical motivation for Y to be dependent on neighboring values of Y. Molho (1995) and Patacchini and Zenou (2007) provide theoretical explanation for the spatial correlation between unemployment rates.

The stability of the regression coefficients (homogeneity) is commonly assessed by means of the Chow test which is adapted by Anselin (1990) to the case of a cross-sectional model with a structure of spatial dependence [9]. The overall spatial Chow test strongly rejects the joint null hypothesis of structural stability (333.77***).

[7] Mur and Angulo (2009), however, point out that the robust and the classical approaches render identical results.

[8] These results bring up one of the unsolved questions in spatial econometrics: the selection of the spatial weight matrix (Fernández *et al.,* 2009).

[9] Mur *et al.* (2009) use a broad notion of spatial heterogeneity and propose several test to detect it.

Maximum likelihood (ML) is the most conventional estimation method for a standard spatial autoregressive model (SAR) where the error terms are assumed to follow a normal distribution. The Generalized Moment Estimator (GME) for the autoregressive parameter in a spatial model, proposed by Kelejian and Prucha (1999), also allows us to solve the problems previously described. They prove that the GM estimator is consistent without the assumption of normality. More recently, Lin and Lee (2010) have shown the robustness of the GMM estimators under unknown heteroskedasticity —a context in which the MLE is usually inconsistent.

Generally speaking, it should be noted that the results are qualitatively similar across the different methods: positive value of the spatial autoregresive parameter and negative value of the accessibility estimated coefficient in the non-urban regime [10].

In Table 4 we include the estimation results by means of ML and GMM using as spatial weight matrix a *k*-nearest neighbor matrix $k = 5$ [11]. The estimated spatial coefficient is 0.538 when the model is estimated by ML, whereas this value is higher (0.769), when the GMM estimation method is used. In both cases, it is highly significant. A possible explanation for this smaller value could lie in the non-normality of the error term and the aforementioned heteroskedasticity problem [12]. Therefore, GMM results are more reliable.

We find that the role of employment offices is especially important in non-urban areas where employment opportunities are limited. The estimated coefficient of the accessibility is negative and significant but it is constrained to –0.0314 (ML) or –0.0176 (GMM). In other words, access to employment offices is more likely to be associated with reductions in local unemployment rates in non-urban areas. In terms of policy welfare, this implies that it is very important for employment offices to locate to in non-urban areas with high needs for employment services in order to bridge the gap between unemployed workers and employers where job opportunities are unclear.

All coefficients of the control variables —except SEC and WS— are statistically significant in the GMM model (non-urban regime). The percentage of university graduates is significant and negative, whereas those of illiterates and also primary education graduates are significant and positive. As expected, the coefficient of primary education graduates is lower than that of illiterates.

With respect to the two other considered regimes (small and large urban) the accessibility variable is not significant. This result is not surprising, and is explained by two reasons. On the one hand, the majority of the urban employment offices have congestion problems so its effect on local unemployment rates may be limited. On

[10] The results obtained by means of 2SLS (available from the authors upon request) and GMM methods are quantitative the same.

[11] The spatial weight matrices defined in section 3 have also considered to analyze the sensitivity of the results. In all the cases, the spatial lag model is pointed out as the more suitable specification.

[12] Lin and Lee (2010) show that the ML estimator is generally inconsistent with unknown heteroskedasticity if the SAR model were estimated as if the disturbances were i.i.d.

other hand, if employment opportunities are higher the role of employment offices could be diminishes.

Finally, the residuals of the spatial lag model have been analyzed to check whether the spatial autocorrelation had been fully removed. The result of the LM test is significant to reject the null hypothesis of no spatial correlation in the residual errors. However, as we explained above, the heteroskedasticity problem points to the specification of a model in which such unknown heteroskedasticity in the error term may be controlled.

Recently, Kelejian and Prucha (2010) and Arraiz *et al.* (2010) have extended the GMM approach to a spatial autoregressive disturbance process with heteroskedasticity innovations. The general form is:

$$\log(u) = \rho W_1 \log(u) + \eta \log(A) + X\beta + e \tag{4}$$

and

$$e = \theta W_2 e + \varepsilon; \tag{5}$$

In this case, heteroskedasticity of unknown form is permitted with $E(\varepsilon_i) = 0$ and $E(\varepsilon_i^2)$. The last column in Table 4 shows the estimation results of this model (GMM-HET). Again, we have obtained a strong spatial dependence between local unemployment rates with a significant spatial effect. The estimated coefficient of the accessibility measure is negative and statistically significant in non-urban areas (–0.0122) and non-significant in small and large urban areas. With respect to the control variables there are some changes: WS is significant and PRI and MLF are not.

However, the interpretation of the parameters is more complicated in models containing the spatial lag of the dependent variable. Any change in the dependent variable for a single area may affect the dependent variable in all the other areas. Thus, a change in one explanatory variable in the municipality *i* will not only exert a direct effect on its own unemployment rate, but also an indirect effect on the unemployment rates of other municipalities. Consequently, the interpretation of the effects on dependent variable *Y* of a unit change in an exogenous variable X_j, the derivative $\partial Y/\partial X_j$, is not simply equal to the regression coefficient since it also takes account of the spatial interdependencies and simultaneous feedback embodied in the model.

As the partial derivative impacts take the form of a matrix $(I - \rho W)^{-1} I\beta_j$, LeSage y Pace (2009) propose new scalar summary measures to collect all these interactions between municipalities so that we may reach a correct interpretation of the spatial models and distinguish between the direct and the indirect impact. Then, the direct impact shows the average response of the dependent variable to independent variables, including feedback influences that arise from impacts passing through neigh-

Table 4. Estimation Results for the Spatial Regimes Spatial Lag Model

	ML			*GMM*			*GMM-HET*		
	Non-urban	Small	Large	Non-urban	Small	Large	Non-urban	Small	Large
Intercept	–1.5588***	–0.2770	–0.1548	–0.9384***	–0.8425**	–1.1355***	–0.6940***	–0.2335	–0.0480
Access	–0.0314***	–0.0018	0.0124	–0.0176***	0.0279	0.0172	–0.0122***	–0.0004	0.0143
ILLI	1.8744***	0.7592	4.5228***	1.1412***	–0.6780	3.1753***	0.9497***	0.2463	2.2868***
PRI	0.0345	–0.1953	–0.0064	0.0805**	–0.6145	0.1200	0.0479	0.1941	–0.0577
SEC	–0.0811**	0.1199	–0.0416	0.0025	0.0258	0.1735	0.0035	0.3841**	0.0449
UNI	–1.6118***	–1.1530**	–1.0679***	–1.1364***	–0.9977*	–0.7868**	–0.8588***	–0.2100	–0.6275***
FOR	–0.3400***	–0.5655***	–0.0669	–0.2232***	–0.3579**	0.0188	–0.1564***	–0.3577***	0.0099
FLF	0.3806***	–0.7780	–0.4286	0.1645**	–2.2189**	–1.0376**	1.1597**	–1.1967**	–0.7421**
MLF	0.1738	2.1996**	1.7915***	0.2603**	2.0410**	2.0918***	0.1119	1.6906***	1.5470***
WI	0.1323***	0.3298**	–0.3514**	0.1421***	0.2594	–0.2713	0.1155***	0.3672***	–0.1256**
WB	0.2630***	0.3721**	0.2261	0.2165***	0.3976**	0.2335	0.1816***	0.2460**	0.1292
WS	0.0793**	–0.1297	–0.2598**	0.0487	–0.1618	–0.2645**	0.0891***	–0.0144	–0.2134**
Rho	0.5386			0.7698***			0.8310***		
Lambda	—			–			–0.6266***		
Spatial Breusch-Pagan	278.885***			282.535***			256.921***		
Kolmogorov-Smirnov	0.2804***			0.2383***			0.2791***		
R^2	0.4724			0.5327			0.5242		
N	6,292			6,292			6,292		
Log-likelihood	–1,472.531			—			—		
AIC	3,021.100			—			—		

bours and back to the municipality itself [13]. The indirect impact tackles the effect that any change in a region has on others, and how changes in all regions affect a region.

These effects can be summarized by their mean. The average total effect of a unit change in X_j is

$$N^{-1}\sum_{ir}^{N}\frac{\partial Y_i}{\partial X_{rj}} = N^{-1}i'\left(I-\rho W\right)^{-1} I\beta_j i \tag{6}$$

and this effect can be partitioned into a direct and an indirect component in all cells of X_j. The average direct impact is given by the mean of the main diagonal of the matrix, hence

$$N^{-1}\sum_{r}^{N}\frac{\partial Y_r}{\partial X_{rj}} = N^{-1}\ \text{trace}\left[\left(I-\rho W\right)^{-1} I\beta_j\right] \tag{7}$$

The difference between the total effect and the direct effect is the average indirect effect of a variable, that is, it is equal to the mean of the off-diagonal cells of the matrix $(I - \rho W)^{-1} I\beta_j$

$$N^{-1}\sum_{r\neq s}^{N}\frac{\partial Y_r}{\partial X_{sj}} = \left(I-\rho W\right)^{-1} I\beta_j i - N^{-1}\ \text{trace}\left[\left(I-\rho W\right)^{-1} I\beta_j\right] \tag{8}$$

Table 5. Direct, indirect and total impact estimations: non-urban municipalities

Accessibility	*Direct*	*Indirect*	*Total*
ML	–0.0346***	–0.0335***	–0.0681***
GMM	–0.0227***	–0.0533***	–0.0760***
GMM-HET	–0.0172***	–0.0549***	–0.0722***

The accessibility to placement offices has a slightly higher (and significant) direct effect than the coefficient estimate. This difference is caused by impacts passing through neighboring regions and back to the region itself. Consequently, a positive feedback effect is obtained.

Even more interesting is the estimation result of the indirect impact, which is significant and three times higher than the coefficient estimate in the GMM model, showing a positive influence of the accessibility to placement offices across the spatial dependences between municipalities. The total impacts are –0.0760 for GMM and –0.0722 for GMM-HET. This means that if accessibility increases by 1%, the unemployment rate decreases —*ceteris paribus*— by 0.0760%/ 0.0722%, respectively.

[13] The main diagonal of higher order spatial weight matrices is non-zero, which allows us to collect these feedback effects.

Thus, the presence of heteroskedasticity has no main effect on the coefficient estimates of this empirical model when GMM and GMM-HET methods are compared. All these approaches have been applied to the study of local unemployment rates and we have found that the accessibility measure helps to reduce them.

4. Conclusions and policy recommendations

In this paper we investigate whether a specific strategy of allocating employment offices and different levels of accessibility to the employment offices can contribute to a reduction of local unemployment rate on the municipality level. Given the limited knowledge about the role of employment offices in Spain, our analysis contributes to this field of research in several ways.

Firstly, from the methodological point of view, the modeling techniques applied in this paper highlight the importance of accounting for spatial dependence and spatial heterogeneity in the analysis of the role of organizations like the Public Employment Services.

Using ML and GMM methods, we have shown a strong spatial correlation between unemployment rates, i.e. that neighborhood influences are very important in labor markets. This view is consistent with other empirical studies such as Molho (1995) and Patacchini and Zenou (2007) and, therefore, the spatial perspective cannot be ignored in the analysis of the Spanish labor market.

Secondly, we have obtained that there are spatial differences across the employment offices in Spain, even though employment offices are located around urban municipalities. We find an inverse relationship between access to employment offices and local unemployment rates in non-urban municipalities.

In addition to that, when we compute the direct and indirect impacts of the accessibility measure on unemployment rates in non-urban areas, the indirect impact is shown to be higher than the estimated coefficient. This, in turn, shows a positive influence on the reduction of unemployment rates across the spatial interactions between municipalities.

In contrast, in urban municipalities this relationship is not clear. It may be due to the congestion problem and the high level of employment opportunities in urban municipalities.

The results suggest that policy makers should strive to improve the accessibility to placement offices, especially in the non-urban municipalities.

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Section Empirical contributions

A Spatial analysis on the relation between accessibility and spatial development for Cross-border regions

Anabela Ribeiro*, Jorge Silva**

ABSTRACT: Cross-border regional development is one of the EU current major concerns. These regions are usually less dynamic socio-economically. Some of them have recently benefited from new roads, which have mainly been funded through the European financial program of Transnational Transport Networks, TEN-T. Using socioeconomic data from the Portugal/Spain cross-border area a model able to measure the relation between accessibility and development in this region is being calibrated. This paper reflects an initial study using Portuguese and Spanish geographical units in the border area for the period 1991-2001 and giving special efforts to the building of similar spatial units in both countries.

JEL Classification: R15, R42, R58, O18, C31.

Keywords: Regional Development, Cross-border Areas, Spatial Regression.

Un análisis espacial de la relación entre la accesibilidad y el desarrollo territorial de las regiones transfronterizas

RESUMEN: El desarrollo regional transfronterizo es, en la actualidad, una de las principales preocupaciones de la UE. Normalmente, estas regiones tienen menos dinámica socio-económica. Algunas de ellas se han beneficiado recientemente de nuevas carreteras, que han sido principalmente financiadas por el programa europeo TEN-T. Utilizando los datos socioeconómicos del área transfronteriza entre Portugal / España, se ha calibrado un modelo para medir la relación entre la accesibilidad y el desarrollo en esta región. Este documento refleja un estudio inicial con unidades geográficas en la zona fronteriza para el periodo 1991-2001. Se destaca también el esfuerzo complementario para la construcción de unidades homogéneas a ambos lados de la frontera.

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1. Introduction

The spatial distribution of activities is the result of opportunities and localization strategies outlined in terms of specific objectives. If we take into account that most human activities involve using and sharing limited resources it is easy to see that the decision processes are complex and involve an important economic component. The acceleration of regional development, particularly in peripheral and border regions —as in our case— seems generally to be associated with substantial capital investment, the allocation of sophisticated technical and scientific resources to production systems, and a thorough renovation of the economy. Building new infrastructure in these areas also leads to significant public investment to make private capital more productive, and it is hoped, therefore, that the expansion of networks and systems will, in the first place, enable firms to operate at lower costs and achieve better performance and, second, mean that the resulting productivity gains will increase the range of regional economic activity. Our geographical working area is considered a peripheral region; it is facing a sharp population decline, weak business dynamics, and its transport infrastructure is referred to as *being little in line with the local development needs*.

Two characteristics of this type of territory can help us better understand these local needs. First, based on census data, there is a significant trend for the number of young people to fall and the elderly population to increase, with particularly disturbing future implications. In fact, although this is *only* a reduction in the younger population, it necessarily implies a future reduction in workforce; this trend means that an increasingly small active population will have *to* support a growing number of elderly people. The region can realistically only establish a trend towards population stabilization if people come from outside, that is, if the territories are attractive, because there is no credible prospect of a change in the sign (negative) of natural increase. And a young potentially active population is essential for regional development. Second, the topography and water courses (as well as political decisions) have always conditioned the structure of the main road network of the area. This situation has changed very little in recent years. Apart from the delay that has been systematically observed in improving some of the main roads crossing the region - essential to both the permeation of the national territory and to penetrating either side of the border - the capillary network has not been properly addressed by the authorities. These networks are doubly important for the integrated development of the region. From an inside point of view it represents more direct links between Portuguese towns. From a wider strategic point of view, it represents links to neighboring Spanish settlements. This latter issue is fundamental to a cross-border cooperation (CBC) pattern which age-old tradition needs to preserve and enhance in order to improve local economic dynamics.

Accessibility in general and the transport infrastructure in particular are fundamental to the integrated development of any region. To achieve this target it is necessary they exist and act as such. However, although some components have not yet gone beyond the virtual planning stage, the region —on both sides of the border— is already endowed with an interesting range of transport infrastructure. One issue here is that not all of these new or improved roads operate at full use of their capacity (or else they do not do so in network). While infrastructure construction and the implementation of transport systems in these regions, which are simultaneously remote and border areas, may be guided by the principle of territorial equity, we are also aware that logic should prevail in local claims; any requests for investment of generic utility should be replaced by more selective interests that are easier to support technically and economically. Whilst it is not possible to eliminate the effects of the past it is nonetheless legitimate to balance any development opportunities in this region with scenarios of more and/or improved accessibility at national, interregional and cross border levels.

These background considerations demonstrate the importance of this subject, although it has not been treated in any depth in the literature. In fact, recent examination of the most prestigious science databases shows that specific papers devoted to this issue are quite rare, and even fewer have focused on cross-border accessibility, and most of these are qualitative in nature. This paper thus aims to provide some new scientific knowledge about the impact of accessibility on sustainable development. A specific cross-border region between Portugal and Spain has been chosen as a case study.

First, and for better understanding of this area dynamics some autocorrelation studies were taken within the Iberian Peninsula. Then, a group of 15 cross-border municipalities was selected. Through a classical regression analysis the above relationship was evaluated, considering only these municipalities' access connections within Portugal. Then the process was repeated but adding information concerning access connections with Spain for those 15 municipalities. Finally some information was included about Spanish municipalities directly connected to the other side of the border, next to the Portuguese municipalities. In a fourth stage this work will be extended to all municipalities on both sides of the entire Portugal/Spain border. This later stage will be developed within a spatial regression framework, with the addition of the «location» variable as an explanatory variable for development.

2. Literature review

Considerable investment has been made in new road infrastructure in recent decades. This investment has mainly been supported by the argument that road links are important tools in improving social and economic cohesion. In Europe the related policies and actions aim to consolidate the Trans-European Transport Networks (TEN-T) and provide closer links between core and peripheral countries (European Commission, 2007). The positive influence of transport infrastructure (through improved accessibility) in development is a widely accepted concept. But the full validity of this concept has not yet been established. The great majority of studies about how accessibility impacts on development apply on a spatially aggregated basis and use methodologies and models such as cost benefit analysis with production functions (Aschauer, 1989), among others. Rietveld and Bruinsma (1998) and Banister and Berechman (2000) report a wide range of approaches. Research in Portugal uses the same aggregated approaches to show that new transport infrastructure positively affects the global Portuguese economic performance (Pereira and Andraz, 2005). The growing complexity of spatial socio-economic interactions has recently called for the use of more disaggregated spatial units and the inclusion of the «location» factor, arguing that the positive effects are weaker when looking at it on a local basis (Mas *et al*, 1996; Guild, 2000). The use of accessibility indicators is an important step forward, as seen in the work of Vickerman (1995), Button (1995), Forslund and Johansson (1995) and Gutiérrez and Urbano (1996) and, more recently, of Lopez and Gutierrez (2008) related to important new European transport infrastructures and consolidating the concept of «potential accessibility». However, the calculation of accessibility is not enough to measure the way it acts as a development factor. Antonio Páez makes some important advances by using the same type of accessibility indicators as variables in a spatial regression analysis framework (Páez, 2004), supported by the spatial econometrics work of Anselin (1988). Besides Paez, the work of Anselin has inspired great number of contributions since the beginning of the millennium, e.g. Mur (2009). The same methodology is now used in recent Portuguese work (Ribeiro, 2009). The number of kilometers of Portugal's network of major roads has increased substantially in the last twenty years (through the TEN-T program), as has happened in many European countries (Santos *et al*, 2009). Consequently, most of the country felt a huge increase in accessibility but the corresponding improvement in development has not matched expectations, since in many areas population continues to decline (Gaspar *et al*, 2002). These negative effects are more pronounced in cross-border areas, where a spatial regression analysis is used to explain to what extent the new accessibility achieved by the new roads has affected population growth at municipality level (Ribeiro *et al*, 2010). Overall, cross-border areas have become increasingly important in the context of European integration, particularly since the recent enlargement. Usually, but not always, peripheral to the main city centers within their country's spatial structure, these regions suffer from chronic development problems (many of them related to centuries of history and changing boundaries). Among other similar programs, the European Commission approved recently (2007) a European program for cross-border cooperation between Spain and Portugal for the period 2007-2013 (*http://www.poctep.eu*). The efforts are now concentrating on improving connectivity and basic infrastructures in the border areas in a new approach aimed at improving competitiveness, promoting employment and enhancing socio-economic and institutional integration in the border regions. Therefore, it is fundamental to analyze how the existing transport infrastructures can do better to meet those objectives. The scientific background (to the relation between accessibility and development) does not go much further than the literature mentioned above, and on cross-border issues it is extremely recent, largely resulting from recent

European funded projects (and mainly qualitative). And there is no article on the application of spatial regression analysis to this subject. In fact, the most prestigious relevant database contains very few articles about cross-border regions, development and accessibility (or transport), (Mesarec and Lep, 2009; Johnson, 2009; Lopez *et al*, 2009). As Portuguese examples, several articles have examined the same type of issues. For example, Silva (2005) and Cavaleiro *et al* (2009). But again, these important studies consider the availability of direct transport infrastructure as the indicator for development and do not analyze the significance of that potential impact. Globally, there seems to be a lack of scientific research on transport infrastructure impact as a spatial development factor for cross border regions.

This paper initiates a process of spatial regression analysis, starting to build up a model to be applied to the entire Portugal/Spain cross-border region that is able to quantify this impact. In fact, the spatial nature of this impact suggests that the use of regression techniques can include the space factor, which is particularly important in the analysis of cross-border territories. Nevertheless these techniques will be fully applied only in further developments of this paper. For now, we hope that this research approach will contribute quite significantly to the scientific information available about the important connection between transport infrastructure and development in cross-border regions. As currently underlined by the European Commission these regions' development represents a strategic factor for the future strengthening of European cohesion, since multi-spatial cooperation is now one of the three main European Union objectives.

3. Study area, data and methodology

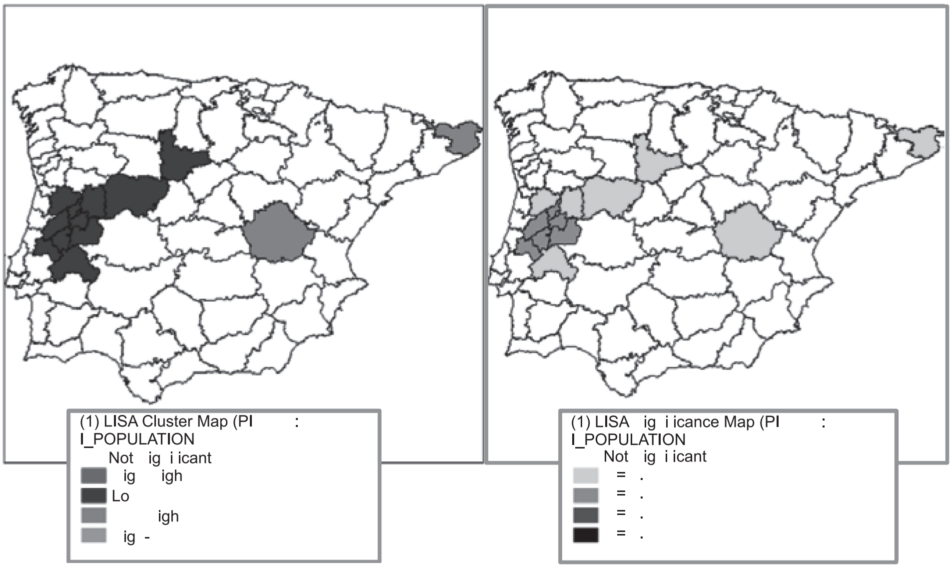
This study is developed in two phases. One at the level of NUT III (including all the Iberian Peninsula) and other at the level of municipalities. The first one, while using Iberian Peninsula NUTIII is developed in order to give focus to the cross border region under appreciation. The second one, at the municipality level for a restrict cross border area is developed in order to give some insight on spatial correlations for this area.

3.1. Iberian Peninsula Autocorrelation Study for NUT III level

Bellow there is a simple spatial autocorrelation analysis for all the Iberian Peninsula (that includes both countries, Portugal and Spain) using NUT III (bigger than the municipalities).

In Figure 1 it is possible to observe the results for population in 2001. Note that the significance map indicates the level of significance of the areas identified either as «clusters» («high-high», «low-low») or «outliers» («high-low», «low-high») (16). The NUT III identified within the group «low-low» (in dark blue), are all contiguous and locate in both sides of the border. From the Portuguese side 9 NUT III are included, and from Spanish side 2 NUT III are included. This is an area where, in the Iberian Peninsula context, it is quite significant (statistically) the low population values and correlated with population values in the neighbors. This autocorrelation occurs precisely where our cross-border region is located.

Figure 1. Lisa cluster and significance maps for population in 2001 in the Iberian Peninsula

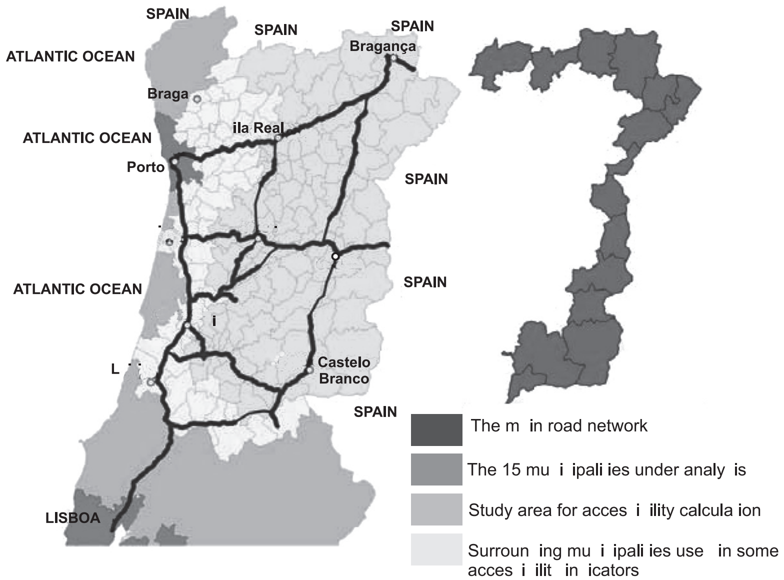


3.2. Cross Border Analysis for 9 NUT III at the municipality level

At this stage a group of 15 Portuguese cross-border municipalities was selected (Figure 2) for the evaluation of the above relationship, considering these municipalities' accessibility connections within the Portuguese territory, using a classical regression analysis. In future stages we will include data from both sides of the border, always taking the municipality as the unit.

Two sets of variables are needed for the regression: those that could reflect development and those that could induce development. The variables that could reflect spatial development are socio-economic (e.g. population variation, if taken as a good proxy for product data, since there is no reliable information on product at municipality level). The variables that could induce development (or not) include population literacy (School Background) and/or accessibility levels (Accessibility); the later one potentially inducing development and closer to transport infrastructure investment. In a previous study (with 86 Portuguese municipalities including the 15 now under analysis), a set of control variables were choose such as unemployment, population

Figure 2. The set of 15 municipalities under study within Portugal mainland



evolution in the previous decade. Only some prove to be the significant. Therefore only some variables were tested in the present study. Variables like population variation and population literacy will be collected from current Census data and/or correlated databases (of particular interest is the Census Data Collection expected within Portuguese territory for 2011, which means an excellent opportunity to enhance the accuracy of our results). The accessibility variables (potential accessibility) are calculated using population and time/distance (calculated from digitalized transport networks). So potential accessibility of a municipality is the total activity (population, product, etc.) reachable within a certain time/distance from that municipality to the others that are part of a certain study area. These transport networks are those appropriate to serve the spatial structure formed by the spatial units selected.

All measures of accessibility used time-distance in minutes. In the case of the variable Acessibility Pt 1991-2001, firstly we calculate the values using the expression $Ai = \sum j$ (Pj/tij 0,5) and data for 1991 [Ai (1991)] and 2001 [Ai (2001)]. In the expression, 0,5 is the impedance factor, a value adapted from other traffic studies in Portugal and for similar areas. Then we calculate the «variation of potential accessibility from 1991 to 2001» for each municipality. The network used was the road and the mode was the car. The influence of congestion on travel time was not considered because we are dealing with interregional accessibility and therefore congestion is not an issue (particularly in those deprived, ultra peripheral areas). The travel times are calculated upon a digitalized network (on a GIS framework) that was built in detail for this specific work area in order to have accessibility variables that indentify local differences. Then we repeated the process but adding information on access connections with Spain for those 15 municipalities. For this a new variable was included to add a specific classification to each of the 15 municipalities, according to the number and type of its connections with the Spanish side of the border. Table 1 describes the number and type of all those connections. It also shows a classification we imposed on each type of connection, i.e., from Motorway ($T = 7$) —on the left, to Railway ($T = 1$)— on the right. Although a railway is not a road access it still exists and adds real connection between both opposite sides of the border. For road infrastructures the authors used the Michelin Maps Ranking, 2010 Edition; for the railway they choose the lowest priority because, based on official statistics, quite there is no local/regional use of this infrastructure, either for passengers or goods purposes.

Table 1. Number and type of cross-border connections of each municipality

Units (from North to South)	*Motorways (T=7)*	*Internat. Road (T=6)*	*Interreg. Road (T=5)*	*Surfaced Road (T=4)*	*Unsurfaced Road (T=3)*	*Road Subject to Restriction (T=2)*	*Railway (T=1)*
Montalegre	–	–	–	3	–	–	–
Chaves	–	1	–	–	–	–	–
Vinhais	–	–	–	1	–	–	–
Bragança	–	1	1	1	–	–	–
Vimioso	–	–	–	1	–	–	–
Miranda do Douro	–	–	1	2	1	–	–
Mogadouro	–	–	1	–	–	–	–
Freixo de Espada à Cinta	–	–	–	1	–	–	–
Figueira de Castelo Rodrigo	–	–	1	–	–	–	–
Almeida	1	–	–	1	–	–	1
Sabugal	–	–	–	–	–	–	–
Penamacor	–	–	1	–	–	–	–
Idanha-a-Nova	–	–	1	2	–	–	–
Castelo Branco	–	–	–	–	–	–	–
Vila Velha de Rodão	–	–	–	–	–	1	–

Using all these data a new variable might then be built, arranging the municipalities in order of their importance in terms of the number and type of cross-border connections with Spain, as in Equation 1:

*Connection 2010i = (n.º of Motorwaysi * 7) + (n.º of International Roadsi * 6) + (n.º of Interregional Roadsi * 5) + (n.º of Surfaced Roadsi * 4) + (n.º of UnSurfaced Roadsi * 3) + (n.º of Roads Subject to Restrictionsi * 2) + (n.º of Railwaysi * 1)* (1)

This variable, called Connection 2010, led to the following classification (Table 2):

Table 2. Municipalities in *Connection 2010* order

Municipalities	*Connection 2010 (classification)*
Sabugal	0
Castelo Branco	0
Vila Velha de Rodão	2
Vinhais	4
Vimioso	4
Freixo de Espada à Cinta	4
Mogadouro	5
Figueira de Castelo Rodrigo	5
Penamacor	5
Chaves	6
Montalegre	12
Almeida	12
Idanha-a-Nova	13
Bragança	15
Miranda do Douro	16

This variable represents «actual» connections and a special note must be made on that. How can we compare present connections with population evolution between 1991 and 2010? The answer relies on the fact that all the new connections are part of a National Road Plan known since 1985 and therefore able to produce changes associated with the expectations of the local development it generates. In a final analysis for this stage, we developed the same type of analysis but considering socio economic data from the other side of the border. Within that purpose, Spanish population growth was considered for the same period (1991-2001), and for the geographical areas in the border with the 15 Portuguese municipalities. In this point we needed to develop a previous geographical analysis aggregating Spanish municipality's data into artificial geographical areas (that can be compared in size with the Portuguese ones, because Spanish municipalities are generally much smaller). Besides the variable Connection 2010 (which is naturally the same for the two sides of the border), we do not had at this stage information about population literacy or detailed accessibility variables for Spain, to develop the exact same type of regression for the Spanish side. Therefore, a simple accessibility variable (time distance to the national capital - DistCap) was calculated for both sides of the border, which could be used as a control variable in the Spanish regressions (this variable is taken as «actual» accessibility, in 2010, because it is assumed that the new roads were built during the decade 1991-2001, therefore inducing development during this period).

There will be one more stage in the near future, as mentioned earlier: to extend this work to all municipalities located in both sides along the entire Portugal/Spain border, adding new variables.

4. Analisys

Within the framework of regression analysis and using all data selected for the Portuguese cross-border municipalities under analysis, the modeled relations (between the variables that reflect development and the ones with the potential to induce development) will hopefully add scientific weight to knowledge on significant spatial development tendencies for the region. Accessibility variables enter in the regression as independent ones, therefore as variables potentially able to induce development. The program used was the GeoDa which assumes that firstly we run an OLS regression and secondly, if spatial autocorrelation is present on residuals, we run a SLM (Spatial Lag Model) or a SEM (Spatial Error Model), both using a Maximum Likelihood Estimation. In this paper, because of the above explanation about the lack of data and the particularities of the geographical units, only the OLS was run. This OLS model results include a Lagrange test for spatial autocorrelation on the residuals. Nevertheless these results must be taken with special care since a set of 15 municipalities is not enough to produce sufficiently robust results. Therefore, and once the complete data base is built (gathering data from Portugal and from Spain) new and more significant analysis will be taken.

So, as previously mentioned, next points refer: *a)* to the use of Portuguese socio-economic and accessibility data, *b)* to the inclusion of variable Connection 2010 in the previous analysis, and *c)* to the use of some available Spanish socio-economic and accessibility data, keeping *Connection 2010* as a common variable. In this later analysis, the Spanish regression was also compared with the Portuguese identical regression, i.e.:

Assuming a relationship in which nothing exists beyond the border:

Population Pt 1991-2001 = f (Acessibility Pt 1991-2001; School Background Pt 1991) (2)

Where: Population Pt 1991-2001 and Acessibility Pt 1991-2001 respectively represent population variation and potential accessibility variation between 1991 and 2001; and the School Background Pt 1991 represents the highest education level achieved by the population in 1991 (proportion of population with an University level/degree).

The following results were obtained (Table 3).

Table 3 shows that when high education level increase 1%, population increases too by around 6.02%; but when potential accessibility level increases 1%, the population decreases 0.18%. Which means that besides the fact that all variables are significant, population with higher education in 1991 seems to have more impact on population increase than variations in potential accessibility between 1991 and 2001. Of course a figure of 0.18% is too low, but even so it has a negative sign which it is

Table 3. Relationship in which *nothing* exists beyond the border

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Probability*
CONSTANT	–22.4829	2.0010	–11.2350	0.0000
School Background Pt 1991	6.0230	0.8488	7.0970	0.0001
Acessibility Pt 1991-2001	–0.1790	0.0838	–2.1357	0.0540

$R^2 = 0.81$.

not a good prognosis for this group of municipalities. In addition, taking into account its socio-economic characteristics, this result was expected: if the territory does not have enough infrastructures to ensure welfare the population will try to leave the territory as soon as appears accessibility increases and/or improves.

While testing for spatial autocorrelation, it was possible to find out that there is some evidence on autocorrelation on the residuals, indicating that a spatial error model should be estimated (Table 4).

Table 4. Relationship in which *nothing* exists beyond the border - Spatial Analysis

Test	*Value*	*Probability*
Moran's I (error)	–2.0700	0.0380
Lagrange Multiplier (lag)	1.0540	0.3045
Robust LM (lag)	0.0145	0.6990
Lagrange Multiplier (error)	4.4520	0.0349
Robust LM (error)	3.5470	0.0597
Lagrange Multiplier (SARMA)	4.6010	0.1002

Adding data concerning the above mentioned cross-border connections:

Population Pt 1991-2001 = f (Acessibility Pt 1991-2001; School Background Pt 1991; Connection Pt Sp 2010) (3)

Where: the new variable Connection PtS p 2010, represents the importance of cross-border connections with Spain, in 2010, as mentioned in Table 2.

The following results were obtained (Table 5):

Table 5. Relationship including cross-border connections

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Probability*
CONSTANT	–21.2265	2.2248	–9.5409	0.0000
School Background Pt 1991	6.3370	0.8731	7.2584	0.0000
Acessibility Pt 1991-2001	–0.2083	0.0858	–2.4270	0.0336
Connection Pt Sp 2010	–0.2518	0.2092	–1.2037	0.2540

$R^2 = 0.84$.

The results from Table 5 are similar to the previous case. But, besides the fact that the new variable (Connection 2010) is not significant, we may add to the general conclusion that when the cross-border connections are improved by 1%, the population decreases 0.25%. Anyway, we can again see that enhanced accessibility within the Portuguese territory and more cross-border connections will combine to contribute to a decrease of population. Again, it was possible to find some evidence on the existence of autocorrelation in the residuals (Table 6):

Table 6. Relationship including cross-border connections - Spatial Analysis

Test	*Value*	*Probability*
Moran's I (error)	–2.3730	0.0176
Lagrange Multiplier (lag)	0.5876	0.4433
Robust LM (lag)	0.5826	0.4453
Lagrange Multiplier (error)	5.3230	0.0210
Robust LM (error)	5.3180	0.0211
Lagrange Multiplier (SARMA)	5.9056	0.0522

Adding data concerning Spanish population and accessibility to the capital:

Population Sp 1991-2001 = f (Dist Cap Sp 2010; Connection Pt Sp 2010) (4)

Where: the new variable Dist Cap Sp 2010, represents the time distance to the Spanish Capital, Madrid, in 2010.

The following results were obtained (Table 7):

Table 7. Relationship including Spanish population growth, accessibility to the Spanish capital and cross-border connections

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Probability*
CONSTANT	0.0429	0.1568	0.2734	0.7892
Dist Cap Sp 2010	–0.0008	0.0006	–1.1855	0.2588
Connection Pt Sp 2010	–0.0001	0.0033	–0.0293	0.9771

$R^2 = 0.12$

From this analysis we can conclude that neither of the variables used as independent is significant. Accounting for the fact that they are both accessibility related variables, this means that population growth in the Spanish side is both independent from the existence of connections with Portugal and from the distance to the national capital, Madrid.

Again, it was possible to find some evidence on the existence of autocorrelation in the residuals but without robustness (Table 8):

Table 8. Relationship including Spanish population growth, accessibility to the Spanish capital and cross-border connections - Spatial Analysis

Test	*Value*	*Probability*
Moran's I (error)	–1.6957	0.0899
Lagrange Multiplier (lag)	3.6177	0.0572
Robust LM (lag)	0.3212	0.5709
Lagrange Multiplier (error)	3.3087	0.0689
Robust LM (error)	0.0121	0.9123
Lagrange Multiplier (SARMA)	3.6298	0.1629

In order to further confirm this result, the analysis was repeated but for Portuguese data:

Population Pt 1991-2001 = f (Dist Cap Pt 2010; Connection Pt Sp 2010) (5)

Where: the new variable Dist Cap Pt 2010, represents the time distance to the Portuguese Capital, Lisbon, in 2010.

So the following results were obtained (Table 9):

Table 9. Relationship including Portuguese population growth, accessibility to the Portuguese capital and cross-border connections

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Probability*
CONSTANT	–12.0262	9.9643	–1.2069	0.2507
Dist Cap Pt 2010	0.0024	0.0365	0.0655	0.9488
Connection Pt Sp 2010	0.1415	0.4934	0.2946	0.7733

$R^2 = 0.009953$.

As in the previous analysis, population growth in the Portuguese side is both independent from the existence of connections with Portugal and from the distance to the national capital, Lisbon. These results are in line with previous ones. In fact Connection 2010 never was significant, potential Accessibility was significant but with a inverse relation (the bigger the accessibility the smaller the population growth), and the only determinant variable in Population growth was the School Background of resident population.

Again, it was possible to find some evidence on the existence of autocorrelation in the residuals but without robustness (Table 10).

Further analyses should investigate deeply these conclusions, measuring more precisely the «perverse» accessibility effect for cross border regions. For these future analyses, a more accurate definition of comparable geographical areas in both sides of the border is desirable, a work absolutely needed for investigation and for cross-border cooperation projects. This is the first and main objective of further steps.

Table 10. Relationship including Portuguese population growth, accessibility to the Portuguese capital and cross-border connections - Spatial Analysis

Test	*Value*	*Probability*
Moran's I (error)	–1.9743	0.0483
Lagrange Multiplier (lag)	5.1258	0.0236
Robust LM (lag)	1.3724	0.2414
Lagrange Multiplier (error)	5.3035	0.0213
Robust LM (error)	1.5502	0.2131
Lagrange Multiplier (SARMA)	6.6760	0.0355

5. Conclusions

This work's main objective is to build a model able to measure the relation between accessibility and development for all the municipalities in the Portugal/Spain cross-border area. This scientific opportunity results from the observation of huge road infrastructure investment, often indicated as being little in line with the local development needs in peripheral regions that are currently facing sharp population decline and weak business dynamics.

At the same time, and since this subject is of so much importance, it is surprising that very few studies have focused on quantitatively measuring the complex relationship between accessibility and development.

This study has selected the particular case of cross-border regions, since these are usually the most depressed areas in both countries. It will be developed in four main stages and this paper deals with the first two. First a group of 15 cross-border municipalities was selected (developing a study on autocorrelation with the identification of autocorrelation behaviors for some variables within the Iberian Peninsula at the NUT III level). Through a classical regression the above relationship was evaluated, considering only these municipalities' access connections within Portugal. Then the process was repeated but adding information concerning access connections with Spain for those 15 municipalities.

In the third stage we intend to add data from the Spanish municipalities directly connected to the other side of the border, next to the Portuguese municipalities. In a fourth stage this work will be extended to all municipalities on both sides of the entire Portugal/Spain border.

For neither of the countries, neither of the accessibility variables seemed to have influence or be related with population evolution. Since these network modifications occurred in the last 20 years it would be expected that population evolution (somehow reflecting more accessible and attractive territory) would have grow. But this relation does not seem to be relevant.

So far, the results suggest that increased accessibility within the countries and good connections with Portugal/Spain, respectively, are less relevant for local development than school background, or are insignificant. Moreover, an increase in national potential accessibility or in connection seems to have a negative influence on population increase.

These results show that locally, and particularly for cross-border municipalities, accessibility seems to be an irrelevant factor in development. The fourth stage of this analysis (see above) will help to consolidate the conclusions that have been drawn in this paper as the launching pad for this important analysis.

The spatial trend under these processes will also be further analyzed using a complete Spatial Regression process and identifying the local differences in the relation between accessibility and development.

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Section Empirical contributions

Investigaciones Regionales

Spatial Hedonic Pricing Models for Testing the Adequacy of Acoustic Areas in Madrid, Spain

José-María Montero *, Gema Fernández-Avilés **, Román Mínguez **

ABSTRACT: Road traffic noise is one of the main concerns of large cities. Most of them have classified their territory in acoustic areas and have constructed strategic noise maps. From both sources we have elaborated seven types of acoustic neighbourhoods according to both their noise gap in regard to the legal standard and the percentage of population exposed to noise. A spatial Durbin model has been selected as the strategy that best models the impact of noise on housing prices. However, results for Madrid do not confirm the hedonic theory and indicate, as one of the possibilities, that the official acoustic areas in Madrid could be incorrectly designed.

JEL Classification: C21, Q51, Q53.

Keywords: Acoustical area, road traffic noise, strategic noise map, spatial hedonic pricing models.

Modelos espaciales de precios hedónicos para contrastar la adecuación de las áreas acústicas en Madrid, España

RESUMEN: El ruido derivado del tráfico es una de las principales preocupaciones de las grandes ciudades. La mayoría de ellas han clasificado su territorio en áreas acústicas y han elaborado mapas estratégicos de ruido. A partir de ambas fuentes hemos creado siete tipos de vecindarios acústicos según su alejamiento del estándar legal y el porcentaje de población afectada. El modelo espacial de Durbin ha demostrado ser el que mejor modeliza el impacto del ruido en Madrid, ciudad objeto de estudio. Sin embargo, los resultados obtenidos no confirman la teoría hedónica y, como una de las posibles explicaciones, sugerimos que las áreas acústicas oficiales pudieran estar mal delimitadas.

Clasificación JEL: C21, Q51, Q53.

Palabras clave: Área acústica, ruido de tráfico, mapa estratégico de ruido, modelos espaciales de precios hedónicos.

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1. Introduction

Noise has always disturbed people's lives, but the situation has worsened recently, particularly in large metropolitan areas, as a result of industrial development, night-time leisure activity and an increase in vehicular traffic. Noise is considered acoustic pollution when it implies discomfort, risk or harm to people, the carrying out of their activities or goods of any nature.

The European Commission states that the noise caused by transport and industrial activity is one of the primary environmental problems in Europe. According to the European Commission (EC, 2002) it is reducing the health and quality of life of nearly 25% of the EU's population (80 million people). In addition, some 170 million European citizens live in «grey areas», that is to say, areas where noise levels range from 55 to 65 dB(A) during the day. According to the World Health Organization (WHO), 20% of European citizens are exposed to more than 65 dBA during the day and 30% are exposed to levels of noise pressure in excess of 55 dBA at night. Furthermore, we cannot ignore the economic factor that acoustic pollution entails, as noise generates costs. Social expenditure caused by the noise of vehicular traffic in the EU is estimated to range from 30,000 to 46,000 million euro a year, approximately 0.4% of the GDP of the EU member states (Ayuntamiento de Madrid, 2010).

As regards noise at night (basically due to leisure activity), large cities no longer sleep at night and there are an increasing number of activities that take place at night: street cleaning, rubbish collection, delivery of goods and even offices (call centres). But public holidays and weekends are the main problem as a result of the number of recreational activities on offer. The noise made by nocturnal leisure undoubtedly causes the most discomfort. And this is not only due to when it occurs, but also because recreation centres are normally concentrated in areas of the city that are primarily residential.

Combating noise involves studying and analysing several perspectives (Ayuntamiento de Madrid, 2010): i) What are the sources of noise? ii) What factors influence the emission of noise? iii) What factors influence the spread of noise? iv) What is the time dimension of noise? v) Which areas are affected by noise?

Noise, especially that derived from road traffic is problematic for at least two reasons: i) increasing transportation of goods and people means higher noise levels and ii) as road traffic is related to human activity and needs, much of it occurs in areas where people live, work, go to school, etc. According to Nijland *et al.* (2003) and Andersson *et al.* (2010), the latter means that today's urban development will lead to noise being a bigger problem in the future unless efforts are made to mitigate the problem.

Noise can adversely affect both human hearing and other aspects of people's health. As regards the former, the most worrying in large cities is a temporary or permanent rise in our absolute threshold of hearing. In reference to the latter, noise can cause, among other adverse effects, the loss of privacy, degradation of suburbs affected by this problem and the depreciation of property, particularly housing. Therefore, it is no surprise that economists have developed a number of procedures that provide reasonable estimates of the monetary value of acoustic externalities and that the European Commission has developed projects to combat noise, including SILENCE, HARMONOISE-IMAGE, SMILE and QCITY.

As stated in Nelson (2008), economic valuation methods are divided into two categories: revealed preference methods such as the hedonic price method for housing values; and stated preference (SP) methods such as contingent valuation surveys. Revealed preference methods exploit the fact that there are private markets that are complementary. The main alternatives to hedonic valuation are survey methods that ask respondents to state their willingness to pay for environmental improvements, including the contingent valuation method, contingent ranking, conjoint analysis and other SP models. Notwithstanding, survey-based methods have both theoretical problems and the empirical difficulty of asking survey respondents questions concerning long term changes in noise level exposure that they have not in general experienced (Lake *et al.,* 2000). In contrast, our review of the literature suggests that the HP method is robust and appropriate for estimating values for road traffic-related noise.

We focus on the impact of acoustic pollution on the depreciation of property using spatial hedonic strategies. But our approach to the problem of noise in large cities, as far as we know, is completely new. The base of our approach is acoustic areas, which are a relatively new concept in large cities. An acoustic area is defined by the gap between the level of noise exposure and the level of noise considered acceptable given the classification of the area (residential, industrial, leisure...). This approach has the advantage of deflating the amount of noise that can be considered a consequence of living in a specific area of a large city. In this sense, this approach is different to the inclusion of noise levels (measured or perceived) in hedonic (spatial or not) pricing models. Even the objective we pursue is different: while in traditional hedonic specifications the objective is to estimate the willingness for quiet, we aim to both verify whether the acoustic areas are correctly or erroneously delimitated and also identify those areas that need urgent measures to combat noise in order to avoid a rapid depreciation of properties. Unfortunately, the results obtained suggest that the acoustic areas are not correctly delimitated.

The article is structured as follows: after this introductory section, section 2 includes the literature review. Section 3 outlines the process to delineate quiet and conflict areas in Madrid. Section 4 is devoted to spatial hedonic pricing models. Section 5 describes the case study, reports the main results of this research and ends with a policy analysis. Section 6 concludes.

2. Literature review

Gamble *et al.* (1974) is cited as the first major study to apply HP methods to road traffic noise. They studied US interstate highways in four communities in New Jersey, Virginia and Maryland. Other early work includes HP studies of traffic noise for Washington DC (Nelson, 1975, 1978), Chicago (Vaughan and Huckins, 1975) and Toronto (Taylor *et al.,* 1982). Early European studies include a 1974 study for Stockholm by Hammar and a study of Copenhagen by Hjorth-Andersen (1978).

Since these pioneer studies, as expected, extensive literature on HP studies for airports and road traffic noise was published (see Nelson, 2008, and the references therein). The literature on the valuation of noise declined substantially in the 1990s, but it has witnessed a renaissance over the last ten years due to the advent of GIS methods, computerised data, the popularity of spatial econometric methods and increasing concern and awareness on behalf of citizens in regard to environmental problems and quality of life.

In the last decade, without aiming to provide an extensive review, it is worth highlighting the following works: Wilhelmsson (2000), who analyses the impact of noise stemming from vehicular traffic on the value of houses in a suburb in Stockholm (Sweden). More specifically, the results obtained show that every extra decibel of noise, housing prices record an average decrease of 0.6%, while a house located in a noisy area is worth, on average, 30% less than another in a quiet area. Lake *et al.* (2000) conducted a case study based on over 3,500 property sales in Glasgow, Scotland and suggested that property prices were depressed by 0.20% per decibel increase in road noise. Bickel *et al.* (2003) estimate the resource costs, opportunity costs and disutility caused by transport noise impacts in Sweden. They review the existing literature and find that the Noise Sensitivity Depreciation Index ranges from 0.08% to 2.22%. Nelson (2008), one of the most prolific researchers on the topic, includes an extensive research outline on spatial and non-spatial hedonic pricing models including noise as a regressor. Dekkers and van der Straaten (2009) build a spatially-explicit hedonic pricing model in Amsterdam based on three sources of traffic noise (road, railway and aircraft noise), simultaneously. They conclude that a higher noise level means, *ceteris paribus,* a lower house price. In addition, air traffic has the largest price impact, followed by railway traffic and road traffic. They find a noise reduction of 1 dB leads to a decrease in price of 1.459 Euro per house, resulting in a total gain of 574 million Euros for a 1 dB decrease in noise. Montero *et al.* (2010) construct a composite (pollution and noise) index using DP2 distance and then apply kriging to match the monitoring station observations to census data, which are more numerous. The kriging process allows them to estimate the spatial dependence of the composite index and classify the neighbourhoods of Madrid according to the values of the foregoing index. Andersson *et al.* (2010) examine the effect of road and railway noise (objective measures) on property prices in the municipality of Lerum, close to Gothenburg in the west of Sweden (36,000 inhabitants and a population density of 138 inhabitants per km^2). Their results from a spatial hedonic price model (although they do not detect spatial dependencies) are in line with the evidence from the acoustic literature which has shown that individuals are more disturbed by road than railway noise, but contradicts recent results from a hedonic study on data from the United Kingdom (Day *et al.,* 2007). Baranzini *et al.* (2010) compare the use of perceived and measured noise in a hedonic housing model in Geneva, Switzerland, and confirm convergence in the perceived and measured noise variables. In their case study, a HPM using measured noise data provides turns out to be just as accurate as those that use subjective data. Finally, Nikolaos *et al.* (2011) survey the main issues in the literature on the real estate market and evaluate the effect of some externalities including noise on real estate through a detailed literature review in both Europe and the United States.

3. Acoustic areas, strategic noise maps and quiet and conflict areas

We propose an HP strategy for estimating the value of quiet, but including a new indicator as a regressor: an indicator based on the adequacy of the level of noise to the legal standard for the area. This indicator measures the gap between measured noise and the level of noise considered appropriate according to the activities that take place in a specific area. This gap is weighted with the percentage of affected population.

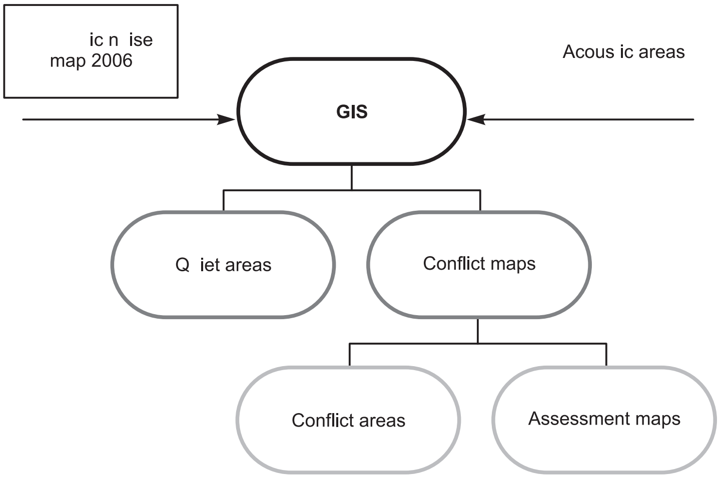
The main advantages of this type of indicator are as follows:

i) It considers the complete set of locations in a city rather than just a sample of them.
ii) It takes into account whether the area is residential, industrial, cultural, recreational, etc. Therefore, it takes into account the trade-off between the characteristics of the area, economic activity and noise.
iii) This type of indicator can be included in a spatial hedonic pricing model without provoking errors-in-variables problems.
iv) The indicator can be adapted for both the linear and non-linear effects of noise on housing prices.

Acoustic areas are a way of classifying territory according to noise. They delimitate the zones of the city with the same objectives in terms of acoustic quality. More specifically, they can be defined as parts of the city where the legislation sets specific targets according to the predominant utilisation of the land (activities that take place in that area). Seven types of acoustic areas are defined in Law 37/2003 according to the predominant use of land: residential, industrial, leisure and spectacles, services, health, schools and culture, affected by transportation infrastructures, and natural spaces. On the other hand, the Strategy Noise Map (SNM) provides comparable information about acoustic values across the city. Finally, the locations where acoustic levels exceed the quality target are known as «conflict areas».

According to art. 14.4 RD 1367/2007 a «conflict area» is a region of the city where the objective values of noise that guarantee acoustic quality are exceeded. Conflict areas have been identified by implementing the database of the SNM for Madrid, 2006 in a GIS, together with the legal standards of noise (day, evening and night) set by RD 1367/2007. In contrast, a «quiet area» is a region where the level of noise is, at least, 5 dB below the acoustic quality objective defined for such an area. Figure 1 summarises the process of evaluating acoustic quality.

Figure 1. Assessment process of acoustic quality (Madrid)



Taking the above evaluation of acoustic areas in Madrid as a starting point, and taking into account both the affected population and the degree of exposure to noise, we have classified the neighbourhoods of Madrid as follows:

Table 1. Criteria to classify neighbourhoods

	Classification	*Degree of exposure to noise*	*Percentage of affected population*
Type 1	Quiet area	Low	Under 20%
Type 2	Quiet area	Low	Above 20%
Type 3	Area not exceeding the legal standard	–	–
Type 4	Conflict area where noise only slightly exceeds the legal standard	Low	Under 20%
Type 5	Conflict area where noise greatly exceeds the legal standard	High	Above 20%
Type 6	Conflict area where noise greatly exceeds the legal standard	High	Under 20%
Type 7	Conflict area where noise greatly exceeds the legal standard	High	Above 20%

Under the assumption that homebuyers have a reasonable knowledge of the area where they intend to buy a property, that is to say, they have a reasonable idea about the main features of the neighbourhood, including noise, our objective is to estimate willingness to pay for living in a quiet area, or the noise discount for living in a conflict area.

This approach will test the adequacy of the acoustic areas in Madrid. If acoustic areas are well delimited, there is expected to be a premium for living in a quiet area and a penalty in prices of dwellings located in conflict areas. Of course, the size of the penalty is expected to increase with the level of exposure to noise relative to the objective for the area.

In addition, a secondary but also interesting goal is to examine the relationship between densely populated areas and conflict areas, because if it is strong and positive, decision makers should adopt new measures to correct this externality.

The statistical distribution of noise is described by showing the levels of dBA that are exceeded 10%, 50% and 90% of the time: L10 (peak level), L50 (median), and L90 (background). The decibel (dB) is measured on a logarithmic scale. A ten-fold increase in sound intensity is equivalent to a 10 dB increase, or roughly double the perceived loudness. Sound levels are weighted to account for human ability to hear sounds at different frequencies, e.g., the A-weighted sound level is used to describe sounds stemming from transportation. Representative sound levels are: *a)* quiet suburban street (50 dBA); *b)* conversational speech at 3 feet (60 dBA); *c)* freight train at 100 feet (70 dBA); and d) busy city intersections (80 dBA).

4. Methods: Spatial hedonic pricing models

As mentioned in the introductory section, hedonic models are the usual strategy for estimating the impact of noise on housing prices. In case of dealing with acoustical areas (or neighbourhoods), this specification corresponds to the equation:

$$y_i = \alpha + \sum_{i=1}^{n} \lambda_j N_j^{(i)} + z_i^T \delta + \varepsilon_i \qquad i = 1,\ldots,n, \qquad j = 1,2,4,5,6,7 \tag{1}$$

where y_i represents the log of the price of the i-th dwelling, $N_j^{(i)}$ are binary variables the value of which is one when such a dwelling is sited in the j-th type area (the third category of noise is eliminated to prevent multicollinearity), $z_i^T = (z_{1i}, z_{2i}, \ldots, z_{ki})^T$ includes the k individual and areal characteristics of the i-th dwelling, α is the intercept of the equation and ε_i is a random disturbance that is assumed to distribute as $N(0,\sigma_\varepsilon^2)$.

The difference of impacts on housing prices between a type of acoustic area and the reference area is given by $\dfrac{\partial y_i}{\partial N_j^{(i)}} = \lambda_j$.

The way N_j is included in the model goes beyond linearity and allows for more flexible modelling.

It is a well-known fact that under the assumptions of homoskedasticity, non-autocorrelation and multivariate normal distribution of the vector of random disturbances, the OLS estimation method provides both BLUE estimates of the model parameters and the estimated variance of such parameters.

However, model (1) does not take into account the spatial argument, that is to say, the existing spatial dependencies among the prices of dwellings. As has been shown in the literature (Anselin, 1988), the omission of spatial effects can result in estimators being inefficient and, what is worse, inconsistent, regardless of the estimation method. In order to capture the existing spatial dependencies in the prices of dwellings, following Le Sage and Pace (2009), the specification we propose is the spatial Durbin model (SDM). We chose this model because it is quite general and robust. In fact, the usual spatial specifications —spatial autoregressive models (SAR) and spatial error models (SEM)—, are particular cases of the SDM. In addition, the SDM provides consistent estimates for the majority of spatially correlated data generating processes.

The SDM is given by the following matrix equation:

$$y = \rho Wy + \alpha i_n + X\beta + WX\gamma + \varepsilon \qquad \varepsilon \sim N(0, \sigma_\varepsilon^2 I_n) \tag{2}$$

where y is a $(n \times 1)$ vector including the observations of the logarithms of the house prices, X is a $(n \times k)$ matrix comprising the binary variables that indicate the type of acoustic area —according to both the gap between the legal standard and the level of noise and also the percentage of affected population— as well as the observations of the individual and areal characteristics associated to each dwelling and other spatial variables such as noise, surface, condition, mean mortgage in the neighbourhood, etc., i_n is a $(n \times 1)$ unit vector for the intercept (removed from X to avoid problems of exact multicollinearity in the estimation) and W is the $(n \times n)$ spatial weights matrix. Obviously, Wy and WX capture the spatial lags corresponding to the dependent variable and those included in X, respectively. On the other hand, ρ is a spatial parameter that measures the existing spatial dependence of the dependent variable, α is the intercept parameter, σ^2 is the variance of the disturbance under homoskedasticity and β and γ are $(k \times 1)$ vectors of parameters associated to the independent variables and their lags, respectively. Restrictions $\rho = 0$ and $\gamma = 0$ in the SMD lead to the non-spatial hedonic model (1).

As we know, the specifications that include the spatial lag of the endogenous variable, Wy, as a regressor, produce an endogeneity bias, because the spatial lagged variable is correlated to ε. However, under the assumption of multivariate normal distribution of disturbances, the parameters of the model, $\theta = (\rho, \alpha, \beta, \gamma, \sigma_\varepsilon^2)^T$, can be estimated using the maximum likelihood (ML) procedure. For this purpose, as well as for computing spillovers, following Le Sage and Pace (2009), we first re-write (2) as:

$$y = (I_n - \rho W)^{-1}[\alpha i_n + X\beta + WX\gamma] + (I_n - \rho W)^{-1}\varepsilon \qquad \varepsilon \sim N(0, \sigma_\varepsilon^2 I_n) \tag{3}$$

It is important to note that spatial spillovers (effects of changes in independent variables on the dependent variable) are not given by any vector of parameters directly in SDM. This is why —once again following Le Sage and Page (2009)— we express equation (3) as follows:

$$\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} = \sum_{r=1}^{k+1} \begin{pmatrix} S_r(W)_{11} & S_r(W)_{12} & \cdots & S_r(W)_{1n} \\ S_r(W)_{21} & S_r(W)_{22} & \cdots & S_r(W)_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ S_r(W)_{n1} & S_r(W)_{n2} & \cdots & S_r(W)_{nn} \end{pmatrix} \begin{pmatrix} x_{1r} \\ x_{2r} \\ \vdots \\ x_{nr} \end{pmatrix} + V(W) i_n \alpha + V(W)\varepsilon, \quad \varepsilon \sim N(0, \sigma_\varepsilon^2 I_n) \tag{4}$$

where

$$\begin{aligned} V(W) &= (I_n - \rho W)^{-1} \\ S_r(W) &= V(W)(I_n \beta_r + W\gamma_r) \end{aligned} \tag{5}$$

Now, we can compute both the direct and indirect effects, respectively, of a change in x_{ir} and x_{jr} on y_i as:

$$\frac{\partial y_i}{\partial x_{ir}} = S_r(W)_{ii} \qquad \text{and} \qquad \frac{\partial y_i}{\partial x_{jr}} = S_r(W)_{ij} \tag{6}$$

Both impacts are non-linear functions of the estimated parameters and, in addition, depend on the parameters associated to the regressor X_r as well as on ρ.

As the magnitude of the impact of a variable X_r generally differs across regions, Pace and Le Sage (2006) define the Average Direct Impact (ADI), Average Total Impact (ATI) and Average Indirect Impact (AII) of regressor X_r as follows:

$$\begin{aligned} ADI &= n^{-1} \text{ trace } \left(S_r(W)\right) \\ ATI &= n^{-1} i_n^T \left(S_r(W)\right) i_n \\ AII &= ADI - ATI \end{aligned} \tag{7}$$

Finally, one of the main advantages of the SDM is that if we set some restrictions in this model, it is possible to obtain other well-known spatial models. Setting $\gamma = 0$ leads to the SAR model, and by setting $\gamma = \rho\beta$ we obtain the SEM. As the SDM framework nests those models, it is robust under different specifications. Another advantage is that once the SDM, SAR and SEM have been estimated by ML, we can perform LR tests to select the appropriate specification.

In summary, for comparative purposes, we will estimate the hedonic house prices model using OLS and ML, depending on whether or not the spatial argument is included in the analysis.

5. Case study: Madrid

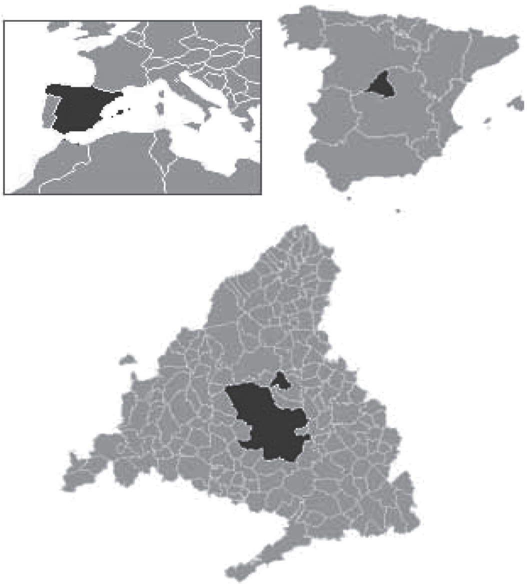
5.1. Housing market and noise

Madrid (the capital of Spain) is the third most populous city in the European Union (pop. 6,271,638 in 2009, 3,213,271 of which live in the city). Like other capitals in the world, Madrid is the city where Government institutions, the Parliament, embassies, main museums, central offices of the most relevant companies, etc., are located. This has made Madrid a large city covering 60,430.76 ha, together with a large peripheral metropolitan area with more than five million inhabitants that it is closely related to. Obviously, these relations imply movement and a large number of trips and regular flows of both population and also goods, etc., which has led to a complex transportation system.

More specifically, Madrid has both a dense ring road network (M-30, M-40, M-45 and M-50) and a dense radial highway network. Both networks have enormously improved accessibility to emerging industrial and high economic activity areas, resulting in competitiveness and dynamism. However, as a negative consequence of the above positive factors, road traffic has become the main source of noise.

In addition, Madrid has the fourth largest European airport and is the centre for train communications (half a thousand trains enter Madrid from the 10 most important Spanish cities, as well as from Paris and Lisbon). Freight transportation by train is also really important in Madrid. Every day 400 trains enter and leave the city, transporting 150,000 tons of commodities. In fact, Madrid has the largest inland maritime customs centre in Europe.

Figure 2. Location of Madrid



It is therefore no surprise that the number of vehicles in Madrid has increased by 5.6% over the last decade, amounting in 2010 to a total of 1,917,382. This implies 1,202.5 vehicles per km and 683.5 vehicles per 1,000 inhabitants. Two million drivers enter and leave the city on a daily basis. So, car pressure is increasing as well as its negative impacts on noise.

As a result of the economic development of Madrid and the increase in population, construction (especially residential construction) has become an extremely important industry for the economy of Madrid as a whole. According to the Spanish Regional Accounts, 2009, this sector contributes 8.6% of total GDP. Madrid is the city with the largest housing stock in Spain —11.5% of the total, with a percentage of home ownership of 78.7% (2,275,188 out of 2,890,229)— and is also the main housing market: in 2009 some 53,513 housing transactions were completed in Madrid (Spanish Housing Office). The highest housing prices in the country are also registered in Madrid.

As for noise, Madrid was the first city to establish regulations aimed at combating noise. The first Spanish law to specifically combat acoustic pollution was enacted in 1969. However, only the noise generated by industry and citizen activities and behaviour were considered up to the 1990s, environmental noise being omitted [1]. This shortfall was overcome through Appendix I of the Integrated Pollution Prevention and Control Act 16/2002, of July 1st. But it was not until the enactment of the Noise Act 37/2003 of November 17th that a nationwide law regulating this problem existed. This law was later completed by the Royal Decrees 1513/2005 and 1367/2007, which expound on it.

Acoustic quality objectives and immission limits are established in accordance with acoustic areas. The Noise Act defines an acoustic area as a territorial area, delimited accordingly by the competent authority, which has the same acoustic quality objective.

Finally, the Action Plan for Acoustic Pollution in Madrid was drawn up in 2009 with the objective of complying with the demands established in EU legislation and the Noise Act. This plan expressly recognises that the main source of noise in the city is vehicular traffic.

The SNM for Madrid provides both the levels of noise across the city and the amount of people affected by the different intervals of noise. The latter is core information to assess how serious the problem is and to give priority to areas where a large number of citizens are affected. As can be seen in Table 2, the percentage of population exposed to an L_{den} above 65 dBA is 14.9%. In the night time, the percentage of population affected by L_n levels above 55 dBA is 41.7%.

Table 3 reports the percentage of population exposed to more than 65 dBA (L_{den}) in some of the largest European cities and the corresponding percentage in the night time when the threshold is $L_n > 55$ dB. The data come from the Communication

[1] Environmental noise is defined as undesirable or harmful exterior noise caused by human activity, including the noise made by vehicular, rail and air traffic and industrial dispatches.

Table 2. Population exposed to noise according to noise intervals

L_{den} *intervals*					
55-60	60-65	65-70	70-75	> 75	Total population affected
482,800	623,600	389,200	85,400	9,100	1,590,300
L_n *intervals*					
50-55	55-60	60-65	65-70	> 70	Total population affected
636,100	462,400	169,400	32,200	1,400	1,301,500

Table 3. Percentage of population exposed to L_{den} > 65 dB and L_n > 55 dB

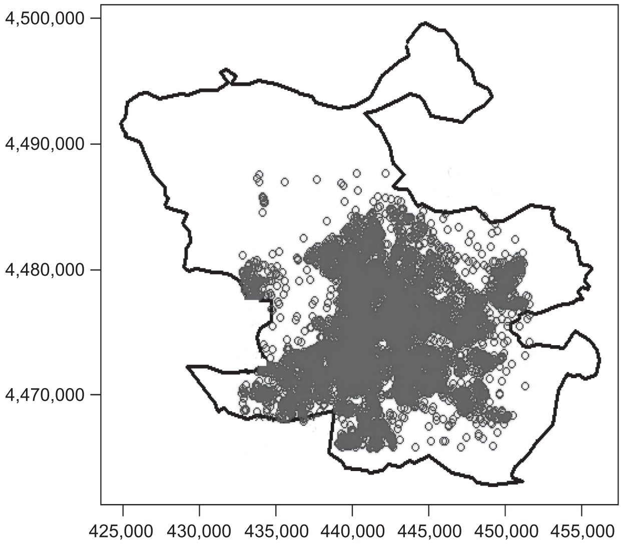
	Population	L_{den} *> 65 dB*	L_n *> 55 dB*
		% pop. > 65 dB	*% pop. > 65 dB*
Warsaw	1,704,717	42.8%	47.5%
Budapest	2,650,230	25.7%	29.9%
Bucharest	2,082,000	24.0%	28.0%
Hamburg	2,040,000	18.1%	24.7%
Greater London Urban Area	8,278,251	15.6%	19.9%
Madrid	3,238,208	14.9%	10.2%
Greater Manchester Urban Area	2,240,230	14.5%	7.1%
Berlin	3,331,249	8.2%	6.6%
West Midlands Urban Area	2,284,093	5.6%	6.5%
Rome	2,546,804	5.3%	5.2%

Information Resource Center Administrator (CIRCA) *http://circa.europa.eu/Public/irc/env/d_2002_49/library*, a collaborative platform between European Administrations and member states on acoustic cartography required by Directive 49/2002/EC.

5.2. Data sets

The issue of housing prices remains unresolved in Spain. This is the reason we have constructed our own database for Madrid. The final database we have created contains information about the price and 33 characteristics of 11,796 owner-occupied single family homes. Figure 3 shows the location of the observed dwellings. The database was created from the sales that took place in Madrid in the first quarter of 2010. As far as we know, it is the largest database ever used to analyse the Madrid housing market. It is important to note that the sample accounts for 90% of the sales in that quarter. The list of variables we have used mirrors the usual set used in the literature (see Table A in the appendix). Most of them have been codified as categorical to allow for more flexibility in the specification of the model. This allows for non-linearities between the different levels of each variable.

Figure 3. Location of observed houses



Source: Own elaboration based on a proprietary data base.

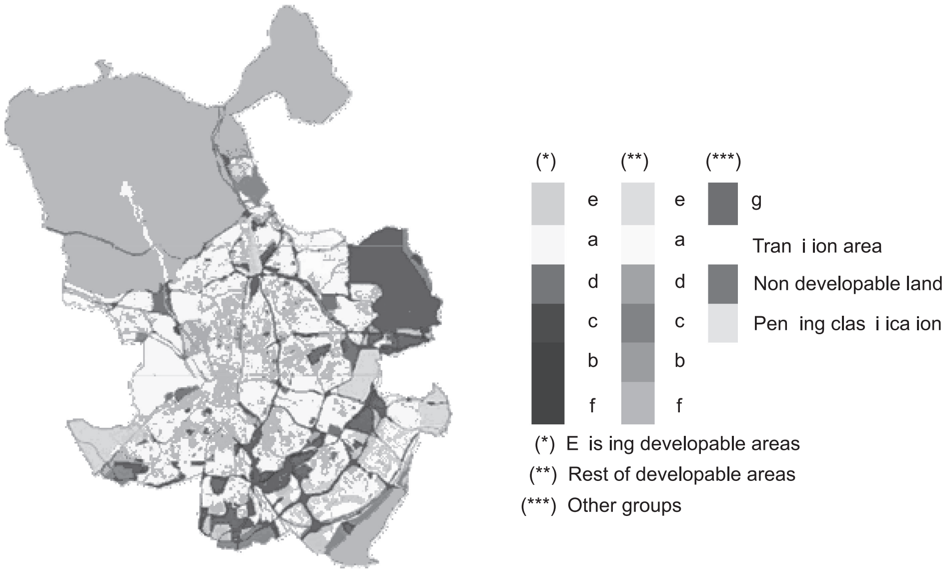
As for the data relative to noise, they were provided by the Department of Quality, Control and Environmental Assessment at the Madrid Council. As stated in section 3, conflict areas are obtained by implementing the data from the SNM (2006) in a GIS together with the daytime, evening and night-time legal standards set by the RD 1367/2007. Quiet areas are the zones where the level of noise is at least 5 dB below the legal standard for such an area. Figure 4 shows the acoustic areas of the city and Figure 5 contains the SNM for Madrid, while Figure 6 reports the classification of neighbourhoods according to noise exposure and population affected that we use in this article.

5.3. Results and policy analysis

Of course, the simplest (or better direct) expectation one could have is that the noise level reduces housing prices. But one could also assume some other more complex possibilities, depending on the urban model of the area under study, which would lead to examine the expected 'net effects' of noise and other core variables that influences housing prices.

In our case, as our starting point is official acoustic areas, and they are supposed to have been defined according to the activities that take place in a specific area, our

Figure 4. Acoustic areas (RD 1367/2007)



Type	*Characteristics*
a	Residential use
b	Industrial use
c	Recreational use and shows
d	Predominance of tertiary use, different to type C
e	Predominance of health, educational and cultural use that require special protection from acoustic pollution
f	Sectors of the territory affected by the general network of transport infrastructures
g	Natural landscapes that require special protection from acoustic pollution

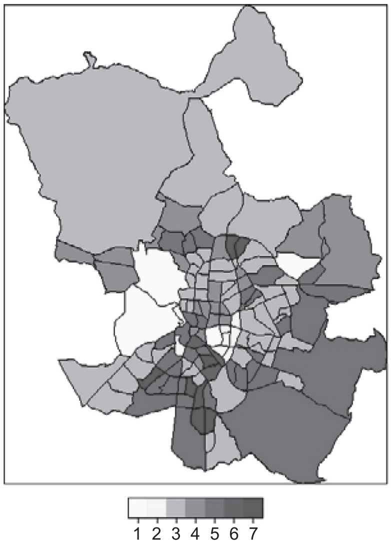
Source: Ayuntamiento de Madrid (2010), pp. 28 and 29.

Figure 5. Strategic Noise Map (2006)

Type of area	*Indexes of noise (Target)*		
	L_d *(7:00 am-7:00 pm)*	L_d *(7:00 pm-11:00 pm)*	L_d *(11:00 pm-7:00 am)*
e	60	60	50
a	65	65	55
d	70	70	65
c	73	73	63
b	75	75	65
f	Indeterminate	Indeterminate	Indeterminate
g	Indeterminate	Indeterminate	Indeterminate

Source: Ayuntamiento de Madrid (2010), p. 9.

Figure 6. Type 1 to Type 7 neighbourhoods in Madrid



Source: Own elaboration based on Department of Quality, Control and Environmental Assessment at the Madrid Council.

prior expectations are a relative premium for quietude in Type 1 and Type 2 neighbourhoods (with respect to the Type 3 one), and a relative penalty for noise in Type 4 to Type 7 zones (again with respect to the reference neighbourhoods).

As for results, we first obtain ordinary least squares (OLS) estimates for a non-spatial hedonic model (Table 7, first column) and test for the presence of spatial autocorrelation in the residuals using the usual Lagrange Multiplier test statistics for error and lag dependence (Table 4). This and the rest of econometric models have been computed using the Spatial Econometrics Toolbox written in Matlab by Le Sage (1999) and the spdep library written in *R* by Bivand (2010).

Table 4. Lagrange multiplier diagnostics for spatial dependence

	LM-Lag	*LM-Lag Rob.*	*LM-Err*	*LM-Err Rob.*
OLS	438,477 (0.00)	73,886 (0.00)	400,977 (0.00)	36,387 (0.00)

* LM-lags test a non-spatial hedonic model (null hypothesis) versus a SAR model (alternative hypothesis). LM-Err test a non-spatial hedonic model (null hypothesis) versus a SEM (alternative hypothesis). In both cases, we display the test statistic, the asymptotic distribution under H_0 being a $\chi^2_{(1)}$, together with the associated *p*-value.

From the first column of Table 7 we can deduce that low noise has a substantial impact on prices in a Type 1 quiet neighbourhood compared to the reference ones where noise matches the legal target (Type 3). Moving from a Type 3 to a Type 1 neighbourhood implies an increase in price of dwellings of 6.5% due to quietude. However, this is not the case of a Type 2 neighbourhood. Despite quietude, a Type 2 neighbourhood unexpectedly penalises housing prices for quietude (1.7%) with respect to the reference neighbourhoods. Also unexpectedly, housing prices in conflict neighbourhoods where noise only slightly exceeds the legal standard have a premium for noise, irrespective of whether the population affected by an excess of noise over the legal standard for the zone is more or less than 20% of their total population. The premium for noise is even higher in a Type 6 neighbourhood (South and South-Eastern parts of the city and highly affected by road traffic noise). Finally, a Type 7 neighbourhood —a conflict area where noise greatly exceeds the legal standard and with a high percentage of their population affected by noise—, records a slight depreciation for noise with respect to the reference neighbourhoods, but not significant. Obviously, when interpreting the above results it must be taken into account that in the OLS model the spatial dependencies of dwelling prices are not considered. The rest of the coefficients of the model display the signs initially expected.

As indicated in Table 4, there is strong evidence of spatial dependence in the hedonic model. This suggests the specification of a spatial Durbin model (SDM) to capture this dependence (eq. 2). The reasons to choose the SMD are both, theoretical and statistical. From the theoretical point of view, it can be argued that the SDM is a quite general model that includes spatial lags both of the dependent variable and also the regressors. Given that home buyers are not atomistic agents (as decision makers) acting in isolation, but they interacts (its preferences, utility, etc.) with other heterogeneous agents in the system in the form of social norms, neighborhood effects, copy-catting and other peer group effects, SDM can be considered an optimal specification to take into account the above mentioned interactions (see Anselin, 1999, p. 2, and the references therein, and Anselin and Lozano-Gracia, 2008, pp. 14-15, for details). In addition, the inclusion of spatial lags both of the dependent variable and also the regressors makes SDM especially suitable to compute the spillovers; what is more, the SDM allows for a functional form of spillovers quite more flexible than other strategies based on a distance decay criterion.

It is possible to specify a more general model, as the spatial autoregressive model with autoregressive disturbances (SARAR model), by incorporating spatial dependence in the disturbance term, but: *a)* the spillovers would be the same (for the same vector of parameter values) and, *b)* the results of Moran's I and Geary' C tests obtained with the SDM residuals ($I = -1.2323$, p-value = 0.2178, and $C = -1.2126$, p-value = 0.2253) do not suggest the existence of spatial autocorrelation in the disturbance term. This is why, for the sake of simplicity, we have selected the SDM. In addition, as SDM nests other well known particular spatial specifications as SAR and SEM, this allows for testing whether those parsimonious specifications are preferred to SDM or not. It must be taken into account that the estimates of the SDM are consistent even in the case that the data generating process were the corresponding to the above more parsimonious models. From the statistical point of view, on the one hand we reject the specification of a SARAR model on the basis of the above results of Moran's I and Geary's C tests, and on the other hand, as the SAR and SEM spatial models are individual cases of the general SDM, we can proceed performing likelihood-ratio (LR) tests, the null hypothesis being the suitability of the restricted model (SAR or SEM) in comparison to the general SDM. Table 5 shows the result of those tests, which reject the null hypothesis in both cases, indicating the preference for the SDM model ahead of the rest. Table 6 displays other statistical information justifying our choice of the SDM.

Table 5. LR tests for selecting models

LR TESTS (ML estimation)		
SAR(H_0) - SDM(H_1)	220.63	(0.00)
SEM(H_0) - SDM(H_1)	255.47	(0.00)

* Likelihood ratio tests: The nested (SAR or SEM) model vs. the more general model (SDM). The asymptotic distribution of the test statistic is a χ^2 with degrees of freedom equal to the number of restrictions imposed by the corresponding nested model. The values in parentheses are the p-values associated to each test statistic.

Table 6. Estimated Hedonic House Price Models

	Non-spatial Models	*Spatial Models*		
	OLS	*SDM*	*SAR*	*SEM*
n	11,796	11,796	11,796	11,796
σ	21.27%	20.62%	20.83%	20.83%
$p(M)$	40	80	41	41
AIC	–3.09	–3.14	–3.13	–3.13
Log Likelihood		5,916.56	5,806.24	5,788.82
ρ		0.231 (67.10)	0.214 (61.49)	0.239 (27.98)

$p(M)$ represents the number of parameters in the model.

In order to specify the spatial econometric model we deal with, we have used a spatial weights matrix that takes into account the six closest neighbours. As usual, the weights matrices are used in row-standardised form. Nevertheless, we have checked that results do not vary significantly when other weights matrices are used (matrices with a different number of neighbours, Delaunay triangles from a Voronoi tessellation, etc.). As SDM includes the spatial lagged variables, we focus on spillovers (Table 7) instead of the coefficients of the regressors.

We must underline that the spillover measures the effect of a change in the regressor x_j on the dependent variable, this effect being divisible into changes due to the observation itself (direct effects) and those caused by neighbouring observations (indirect effects). As such spillovers are generally different for each observation $i = 1,\ldots,n,$ our results refer to the average values of the spillovers for all observations. In order to take into account the uncertainty regarding the parameters estimated when calculating the spillovers, 1,000 simulations are performed using different values for parameters each time. These values are obtained from the asymptotic distribution of the estimators, that is, in each simulation the values $\gamma = (\rho,\beta^T,\theta^T)^T$ are obtained by extracting a value from the distribution $N\left(\hat{\gamma};\widehat{VAR}(\hat{\gamma})\right)$ where $\hat{\gamma}$ represents the vector of parameters estimated in the SDM model and the matrix $\widehat{VAR}(\hat{\gamma})$ is the corresponding estimated variance-covariance matrix (Le Sage and Pace, 2009).

Note that ρ, which measures spatial dependence in this specification, is significant and positive. The absolute value of ρ (0.231) is in line with other research on noise and air pollution. With respect to the impact of the types of neighbourhood considered (according to the level of noise relative to the legal standard for the site) on the price of dwellings, results are similar to those obtained in the above non-spatial regression. Nevertheless, some differences can be appreciated. Results reported in Table 7 confirm that low noise has a substantial impact on price in Type 1 quiet neighbourhoods compared to the reference neighbourhoods where noise matches the legal target (Type 3). Moving from a Type 3 to a Type 1 neighbourhood implies an increase in the price of dwellings of 10% due to quietude. However, there is no significantly different impact on price for quietude when Type 2 and Type 3 neighbourhoods are considered. Unexpectedly, conflict neighbourhoods where noise only slightly exceeds the legal standard have an extra price for noise irrespective of whether the population affected by an excess of noise over the legal standard for the area is above or below 20% of their total population. These Type 4 and 5 neighbourhoods are next to the main ring road of the city (M30), a very busy road, and in relation to a Type 3 neighbourhoods, the extra price for exposure to noise is certainly similar in both types of areas. That 'premium for noise' is higher in Type 6 neighbourhoods (high level of noise with respect to the legal standard and low percentage of people exposed to noise): 5.9%. Finally, in Type 7 neighbourhoods, conflict areas where noise greatly exceeds the legal standard and a high percentage of their population is affected by noise, do not record a significant impact for noise with respect to the reference neighbourhood (Type 3). As in the non-spatial case, the rest of the coefficients of the model display the signs initially expected.

The unexpected results for neighbourhoods with noise levels over the legal standard are a consequence of large indirect spillovers, which in Type 6 neighbourhoods largely compensate the direct externalities (with the opposite sign) and in Type 7 zones are certainly similar to direct spillovers. In Type 4 and Type 5 areas indirect spillovers practically coincides with total ones (albeit they are not significant).

The direct spillovers show the expected sign for non quiet areas (a penalty for noise deviating from the legal standard that increases with the percentage of population affected), but are not significant in all Types of neighbourhood.

The reason of the low magnitude of direct effects, irrespective of the type of neighbourhood, could be attributed to the use of both, lags in the dependent variable and lags in the regressors. As is known, a consequence of the inclusion of a large number of lagged reggresors is more room for indirect effects.

The reason why the indirect effects only display the expected pattern in quiet areas could be that noisy neighbourhoods are surrounded by quiet ones and areas with a small gap between the legal standard and the level of noise are next to areas where there is a large gap and areas where the level of noise is at least 5 db(A) below the legal standard.

Results do not change substantially when the SAR or SEM specifications are implemented (Table 7). The main differences in regard to the SDM estimates are: i) the willingness to pay for quietude in a Type 1 neighbourhood decreases from 10% to 5-6%; ii) the impact of moving from the reference neighbourhoods to a quiet Type 2 neighbourhood is a reduction in price of approximately 2.5%; iii) the extra price for moving from the reference neighbourhoods to a Type 6 neighbourhood (where noise greatly exceeds the legal standard) drops from 5.9% to 2.4% with SAR model and 3.5% with the SEM; and iv) the extra price for moving from a Type 3 to a Type 7 neighbourhood turns into a slight penalty.

Table 7. Total, direct and indirect spillovers according to type areas

	OLS	*SDM*			*SAR*			*SEM*
		Total	*Direct*	*Indirect*	*Total*	*Direct*	*Indirect*	
	Coeff. (t-stat)	*Coeff. (t-stat)*	*Coeff. (t-stat)*	*Coeff. (t-stat)*	*Coeff. (t-stat)*	*Coeff. (t-stat)*	*Coeff. (t-stat)*	*Coeff. (t-stat)*
Type 1 Area	0.0653 (5.07)	0.1003 (5.08)	–0.0278 (–0.90)	0.1281 (3.51)	0.0602 (3.84)	0.0476 (3.82)	0.0126 (3.78)	0.0487 (3.14)
Type 2 Area	–0.0169 (–1.77)	0.0009 (0.07)	–0.0344 (–0.96)	0.0353 (0.92)	–0.0250 (–2.05)	–0.0198 (–2.06)	–0.0053 (–2.02)	–0.0250 (–2.13)
Type 4 Area	0.0275 (3.78)	0.0278 (2.68)	0.0083 (0.37)	0.0195 (0.79)	0.0151 (1.66)	0.0119 (1.66)	0.0031 (1.66)	0.0249 (2.79)
Type 5 Area	0.0213 (4.09)	0.0287 (4.02)	0.0015 (0.09)	0.0272 (1.51)	0.0204 (3.08)	0.0161 (3.08)	0.0043 (3.02)	0.0170 (2.65)
Type 6 Area	0.0464 (3.78)	0.0594 (3.38)	–0.0244 (–0.64)	0.0837 (1.96)	0.0237 (1.53)	0.0187 (1.53)	0.0049 (1.52)	0.0349 (2.34)
Type 7 Area	–0.0034 (–0.36)	0.0068 (0.52)	–0.0400 (–1.44)	0.0468 (1.54)	–0.0054 (–0.45)	–0.0043 (–0.45)	–0.0011 (–0.45)	–0.0113 (–0.98)

* Direct and total spillovers for the non-spatial and SEM models coincide with the β_i coefficients of the corresponding models. There are no indirect spillovers in these models. For the SDM and SAR models the spillovers (direct, indirect and total) are computed using equation (10). The values in brackets are the *t*-statistics of the coefficients.

On a note apart, it is no surprise that indirect effects on SDM are larger than in SAR. The reason is that in the SAR specification $\gamma_r = 0$ and, since the indirect effects are located off-diagonal terms of $S_r(W)$, they are multiplied by ρ and powers of ρ. As the estimated value of ρ is 0.21, the indirect effects are small. However, in SDM γ_r is not null and the spillovers are expanded in the form:

$$\begin{aligned} S_r(W) &= \left[I_n + \rho W + \rho^2 W^2 + \ldots\right]\left(I_n\beta_r + W\gamma_r\right) \\ &= I_n\beta_r + W\gamma_r + \rho W\beta_r + \rho W^2\gamma_r + \rho^2 W^2\beta_r + \rho^2 W^3\gamma_r + \ldots \end{aligned} \quad (8)$$

Note that in the above equation the term $W\gamma_r$ specifically affects to the off-diagonal values of $S_r(W)$. Note also that such values are not weighted by ρ. As a consequence, the indirect effects tend to be much larger in SDM than in SAR.

The main findings that derive from the above estimated models lead firstly to the question of whether the acoustic areas defined by the RD 1367/2007 are well defined, because a premium for noise is not in agreement with the hedonic theory.

The second possibility assumes that the acoustic areas are well defined but, as there is no discussion regarding the spatial dependence of dwelling prices and such dependence immediately leads to spatial hedonic pricing specifications, indirect effects are the cause of the unexpected result. Indeed, including spatial lags in the hedonic pricing model implies taking into account adjacent locations to that where the impact of a specific amenity is estimated. That usually results in substantial indirect impacts and, as the different acoustic areas defined in the RD 1367/2007 spread right across the city, indirect impacts are large and could display the opposite sign to direct effects and, as a consequence, more than offset the direct spillovers. As a result, the sign and sometimes the magnitude of total impacts do not agree with the hedonic theory. If this second possibility is the right one, the following question arises: the acoustic areas that home buyers include in their utility function coincide with the acoustic areas defined in the RD 1367/2007? In the case of a negative response, subjective areas should be considered in the analysis to explain the impact of noise on the price of dwellings. But in that case a serious problem looms in future. As a set of measures is going to be implemented to reduce noise in the areas where legal standards are exceeded and to maintain quietude in quiet areas, if official acoustic areas do not match home buyers' perceptions, indirect impacts will lead to high prices of dwellings in locations where noise exceeds the legal standard due to their proximity to quiet areas or areas where the level of noise matches the legal standard. As the Plan designed for Madrid Council to improve the level of acoustic pollution insists, the opinion of citizens is core information. As such, we recommend redesigning the acoustic areas according to citizens' perception of noise.

The third and last possibility is that the proposed spatial strategies are not appropriate for estimating the impact of noise on housing prices. The weakest point of the model is probably the contiguity matrix. Some anisotropic patterns of contiguity could be considered for noise impact estimation purposes, and that pattern should probably be different depending on the area of the city. In this way, the indirect effects will be more realistic and will not so clearly shadow the direct spillovers.

In any case, irrespective of the adequacy of the acoustical areas, in light of the magnitude of the indirect effects it is clear the importance of the noise conditions of adjacent neighbourhoods in the willingness to pay for quietude.

6. Conclusions

One of the consequences of noise, especially road traffic noise, is the depreciation of houses located in neighbourhoods exposed to levels of noise that exceed the legal standard for such areas.

As road traffic is related to human activity and needs, much of it occurs in areas where people live, work, go to school, etc. And these kinds of activities can be expected to increase in the future, making noise an even greater problem in the future unless steps are taken to mitigate it. It is important to bear in mind that the impact of noise on housing prices can result in the degradation of the neighbourhood and the city being divided by housing prices.

The construction of acoustic areas and strategic noise maps, as well as the estimation of the noise depreciation index, are core instruments for addressing future efforts to mitigate the noise problem and avoid the degradation of the most affected neighbourhoods. That is one of the reasons why economists have developed a number of procedures that provide reasonable estimates of the monetary value of acoustic externalities and that the European Commission has developed projects to combat noise, including SILENCE, HARMONOISE-IMAGE, SMILE and QCITY, among others.

However, in Madrid the neighbourhoods that exceed the legal standard for noise, regardless of the percentage of population exposed to excessive noise, have a «premium for noise» that could be concealing the degradation of the neighbourhood. This premium for noise is due to the indirect effects that arise from the proximity between noisy areas and quiet areas in the city. In most aspects, Madrid could be considered a concentric city and indirect effects, which have been shown to be certainly relevant, are very difficult to interpret.

Three possible explanations for our unexpected finding are proposed. The first refers to the inadequacy of the acoustic areas defined in the RD 1367/2007. The second is that the acoustic areas that home buyers include in their utility function do not coincide with the acoustic areas defined in the RD 1367/2007. And the third, closely related to the above mentioned concentric disposition of the city, focuses on the pattern of the contiguity matrices included in the spatial hedonic specifications. In our opinion, an anisotropic pattern of contiguity could be considered for noise impact estimation purposes and should probably be different depending on the area. Of course, this is a promising and challenging avenue of research.

In spite of the above possibilities, we should not forget that, as stated in Chay and Greenstone (2005) for air quality, exogenous differences in noise gaps with respect to the legal standard are extremely difficult to isolate because the «true» relationship between the type of area (according to the above mentioned gap) and the price of properties may be obscured in cross-sectional analysis by unobserved determinants of housing prices that co-vary with such a gap. This question remains unanswered.

Finally, special attention should be paid to citizen perception of noise, because to the extent that legal and perceived acoustic areas do not match, the policy measures proposed in the Plan designed for Madrid Council to mitigate acoustic pollution will fail to avoid the degradation of the South-East peripheral areas of the city, which have a high percentage of population exposed to levels of noise clearly above the legal standard for such areas.

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Appendix

Table A. Variable names and descriptions

Variable name	*Description*
Dependent variable	
Price	House price
Variable of interest	
Type 1 Area	Quiet area (% of affected pop. under 20%)
Type 2 Area	Quiet area (% of affected pop. above 20%)
Type 4 Area	Conflict area where noise slightly exceeds the legal standard
Type 5 Area	Conflict area where noise greatly exceeds the legal standard
Type 6 Area	Conflict area where noise greatly exceeds the legal standard
Type 7 Area	Conflict area where noise greatly exceeds the legal standard

Table A. *(Continue)*

Variable name	*Description*
House characteristics	
Pollution	Census based pollution perception
Crime	Rate of crime
Good condition	Indicator variable for good condition
Flat	Indicator variable for flats
Studio-apartment	Indicator variable for studios
Top-floor flat	Indicator variable for top-floor flats
House	Indicator variable for houses
Age	Age of the housing
Ground level	Indicator variable for ground level
Floor 1^{st}	Indicator variable for floor 1^{st}
Floor 2^{nd} - 3^{rd}	Indicator variable for floor 2nd and floor 3^{rd}
Floor 4^{th} - 5^{th}	Indicator variable for floor 4th - 5^{th}
Floor 6^{th} or more	Indicator variable for floor 6th or more
Baths	Number of bathrooms
Garage	Indicator variable for parking space
Lift	Indicator variable for lift
Air conditioning	Indicator variable for central air conditioning
Swimming pool	Indicator variable for swimming pool
Monthly mortgage	Monthly mortgage
Areal characteristics	
.30	Indicator for housing which are inside of M-30
M.30.2	Indicator for housing which are close to the M-30
Shopping area	Indicator for houses in the shopping area
Historical quarter	Indicator for houses in the historical quarter
Built up area	Number of square meters of built up area
Density pop. distr.	Population density in the district
Children (% distr.)	Percentage of children below 14 years
Immigrants (% distr.)	Percentage of immigrants in the district
Mortgage reference area	Mean mortgage in the area

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Section Empirical contributions

Spatial Causality. An application to the Deforestation Process in Bolivia

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Manuel Ruiz *** Horacio Villegas *

ABSTRACT: This paper analyses the causes of deforestation for a representative set of Bolivian municipalities. The literature on environmental economics insists on the importance of physical and social factors. We focus on the last group of variables. Our objective is to identify causal mechanisms between these factors of risk and the problem of deforestation. To this end, we present a testing strategy for spatial causality, based on a sequence of Lagrange Multipliers. The results that we obtain for the Bolivian case confirm only partially the traditional view of the problem of deforestation. Indeed, we only find unequivocal signs of causality in relation to the structure of property rights.

JEL Classification: C21, C50, R15.

Keywords: Risk of deforestation, Bolivia, municipalities, causality.

Causalidad espacial. Una aplicación al proceso de deforestación en Bolivia

RESUMEN: Este trabajo analiza las causas de la deforestación para un conjunto representativo de municipios bolivianos. La literatura sobre economía ambiental insiste en la importancia de los factores físicos y sociales. Nos centramos en el último grupo de variables. Nuestro objetivo es identificar los mecanismos causales entre estos factores de riesgo y el problema de la deforestación. Con este fin, se presenta una estrategia de análisis para identificar mecanismos de causalidad espacial, basada en una secuencia de los multiplicadores de Lagrange. Los resultados que obtenemos para el caso de Bolivia confirman sólo parcialmente la visión tradicional del problema de la deforestación. De hecho, sólo encontramos

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signos inequívocos de causalidad en relación con la estructura de los derechos de propiedad.

Clasificación JEL: C21, C50, R15.

Palabras clave: Riesgo de deforestación, Bolivia, municipios, causalidad.

1. Introduction

In the last few years, deforestation has become one of the hop topics on the research agenda of Economics and Environmental Economics. As it is generally acknowledged, damages to the environment have a great long run impact on the welfare conditions because of their effects on biodiversity reduction, natural resources depletion, climate change and soil degradation, among other factors (Kaimowitz and Angelsen, 1999). This is particularly relevant for Bolivia, where hundreds of thousands of hectares of rainforests and woodland are lost every year.

Different arguments have been used to explain this process. On the one hand, it is agreed that ploughing for agricultural purposes is in detriment of the woodland mass (Pacheco, 2004). At the same time, the improvement of transport infrastructures and demographic pressure increase the risk of deforestation. The lack of a well-defined property rights structure is another factor that facilitates the rainforest wasting. Some other physical or environmental factors also have a strong impact where deforestation takes place.

In this respect, Bolivia is a very interesting case as, approximately, 50% of the country is still grassland and rainforest. However, pressure for the transformation of the wilderness has increased significantly in the last few decades. The objective of our paper is to study the existence of causality mechanisms between the list of variables usually identified as factors of risk. The available deforestation indicators correspond for a set of 91 Bolivian municipalities that pertain to four departments, Beni, Pando and part of La Paz and Santa Cruz. These municipalities represent 60% of Bolivian territory and 40% of the population.

The peculiar aspect of our work is that we would like to go a bit further from the pure concept of dependence between risk factors and deforestation indices. In this sense, it must be remembered that a (spatial) econometric model relates a set of variables, trying to find their structure of dependence. However nothing is said in what respects to possible causality mechanisms between them. Causality is a central topic in mainstream econometrics that requires of a specific treatment but, surprisingly, this topic has had a very limited impact on the field of spatial econometrics using pure cross-sections (Weinhold and Nair, 2001, Hurlin and Venet, 2001, Hood *et al.,* 2008, or Tervo, 2009, for the case of spatial panel data). One of the purposes of this paper is to address the problem of spatial causality.

The paper is structured as follows: Section 2 provides a brief overview of the problem of deforestation and its consequences for the case of Bolivia. The Third section presents the problem of causality is a spatial cross-section and proposes some solution. The Fourth section contains the results of the application of causality analysis to the data for the Bolivian municipalities. Main conclusions appear in Section 5.

2. Deforestation: the Bolivian case

In the last decades Bolivia has registered an exponential increase in deforestation. In the period of time between 1975 and 1993 a deforestation rate of 0.3% was produced, equivalent to the disappearance of 168,012 hectares of forests per year (Wachholtz, 2006). Between 1993 and 2000, the average increased to 270,000 hectares (Rojas *et al.,* 2003) and 280,000 hectares per year for the period 2004 to 2005.

In the previous data, we only consider the cases of deforestation that affected to a minimum of 5 hectares. Muñoz (2006) estimates that if the clearings of less than 5 hectares are taken into account, the number can easily reach half a million hectares per year. In per capita terms, a study lead by Andersen and Mamani (2009) found that the deforestation rates in Bolivia represent around 320 m^2/person/year, which is 20 times greater than the world average (16 m^2/person/year). This is one of the highest per capita deforestation rates in the world.

On the other part, according to the National Institute for Agrarian Reform (INRA, 2011), in 6 of the 8 Bolivian *ecoregions* (climatic systems with specific traits) more than 50% of its territory appears under the denomination of Communitarian Land of Origin. The areas where there are greater private ownership rights are the Integrated Central North, the Bosque Tucumano Boliviano, the Chaco and, in less scale, the Gran Chiquitania. The communitarian ownership rights are concentrated in the regions of the Amazon, the Bosque Tucumano Boliviano and the Chaco.

Finally, according to the United Nations Program for Development (PNUD, 2008), currently, the fringe that is suffering a greater pressure of deforestation is found between 142 masl[1] and 283 masl which explain the severe damages suffered in the departments of Pando, Beni and Santa Cruz. Deforestation has had, up to now, an smaller impact in the most elevated regions, as in the Humid Plateau of the Central Andes, in Yungas and in the Bosque Tucumano Boliviano. On the other hand, the pressure has been very intense in the regions of the Integrated Central North and the Chaco, due to their favorable conditions for agrarian and livestock production. The same process is beginning to occur now with the Amazon and the savannahs of Beni, although the typical seasonal floods of this zone slow the transformation of the forest into agrarian land (Lambin, 1997).

3. A procedure for testing spatial causality

Causality is one of the key issues in Economics to the extent that, for example, Heckman (2000) claims that «*the definition of causal parameters*» has been one of

[1] «Masl» means «meters above sea level».

the major contributions of Econometrics. There is a huge literature devoted to the topic where we can find different methods and approaches to the analysis of causality (Hoover, 2004). However, it is a bit surprising the little impact that this topic has had in a spatial context (we can only cite the work of Blommestein and Nijkamp, 1983). Recently, Herrera (2011) addressed the question of causality in a purely spatial context offering an updated perspective and new proposals. This section partly follows his suggestions.

Indeed, causality is not as simple as it seems, even in a time dimension: common causes, counterfactuals, non-experimentality, etc are problems that appear regularly in the literature. Difficulties increase in space where the first problem is to define the meaning of the term. For the sake of simplicity, let us think in the case of only two variables. We agree with the operational definition of Herrera (2011): *variable x causes variable y, in a spatial setting, if the first variable contains unique information in relation to the second variable, once we have taken into account all the information existing in the Space related to y*. Consequently, we are going to use the term causality in information.

There are three points that need to be addressed when testing for causality between variables in pure spatial cross-sections, as it appears in Figure 1.

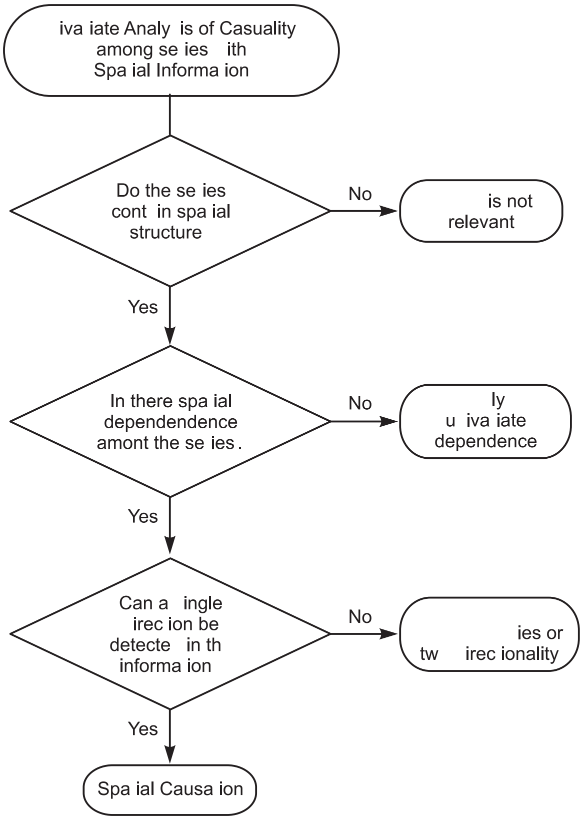
i) The role of the Space: if the variables are spatially independent then it would be preferable to use a traditional approach to the problem (Heckman, 2000, or Pearl, 2009).
ii) The relation between the variables: if the two variables were independent it would not make sense to talk about causality.
iii) Assuming that Space is relevant and that the variables are related, causality in information implies that there is a one-way information flow between the two variables.

The first step means testing for the assumption of spatial independence of the data of each variable, for which a certain formalization of Space would be needed. In this sense, we follow the usual reasoning in terms using a finite sequence of weighting matrices, specified on a priori basis. Then, some of the well-known test of spatial dependence can be applied to each series (like the Moran's I, the Lagrange Multiplier, etc.). The results of this first step should be consistent: the same weighting matrix must intervene in the spatial structure of each series [2] and the hypothesis of spatial independence must be rejected for the two variables. In other words, Space should be relevant for the two variables and the spatial topology must coincide.

The second step, dependence between the variables, is a necessary condition to observe causality. In this case, we need a test of spatial dependence between the variables that takes into account the spatial structure of both series. The bivariate Moran's I_{yx} is a Mantel-type coefficient (Mantel, 1967), adapted by Wartenberg (1985) as an index to measure the spatial cross-correlation between two variables. Assuming that

[2] We mean that the same weighting matrix must be chosen as the *optimal spatial operator* (Herrera *et al.,* 2011) in order to account for the spatial dependence of each series.

Figure 1. Testing for causality between spatial series



the two variables are observed in R different locations, the expression of this statistic is as follows:

$$I_{xy} = \frac{\sum_{j=1}^{R}\sum_{i=1_{i\neq j}}^{R} y_i w_{ij} x_j}{S_0\sqrt{Var(y)\,Var(x)}} \tag{1}$$

where w_{ij} is the (i, j)-th element of the weighting matrix W and S_0 the sum of all the elements of W; Var(y) and Var(x) refer to the (estimated) variance of the series y and x. The distribution function of the I_{yx} statistic is unknown.

Czaplewski and Reich (1993) obtain its moments, $E(I_{yx})$ and $V(I_{yx})$, over all possible R! random permutations of the pairs $\{y_s; x_s\}_{seS}$, being S the set of locations whose cardinality is R. For moderate to large sample sizes (in any event, $R > 40$), the authors proposed the statistic: $T_{xy} = \frac{I_{xy} - E(I_{yx})}{\sqrt{V(1_{yx})}}$, which is distributed, approximately, like a standard normal distribution. The null hypothesis of no correlation is rejected when $|z_{xy}| > N_{\alpha/2}$, where $N_{\alpha/2}$ is the critical value corresponding to the standardized normal value that leaves a probability of $\alpha/2$ on the right. Below we present another test for spatial independence, based on Lagrange Multipliers.

The purpose of the third step is to detect the direction of causality, if present, between the two variables. Following usual practice in time series analysis, we are going to specify an unrestricted spatial vector autoregressive model (SpVAR) to complete the testing strategy. Let us remind that the optimal weighting matrix, W, has been chosen before. For simplicity, we assume that the spatial dependence of both series is of the first order:

$$\left.\begin{aligned} \left[I_R - \rho_{yy}W\right]y + \left[\beta I_R + \rho_{yx}W\right]x + \eta_y = u_y \\ \left[\theta I_R + \rho_{xy}W\right]y + \left[I_R - \rho_{xx}W\right]x + \eta_x = u_x \end{aligned}\right\} \tag{2}$$

where $\{\rho_{yy}; \rho_{yx}; \rho_{xy}; \rho_{xx}\}$ are parameters of (crossed) spatial dependence, I_R is the identity of order R, y and x $(R \times 1)$ vectors of observations of the variables of interest, $\{\eta_y; \eta_x\}$ are two vectors of deterministic terms of order $(R \times 1)$ and $\{u_y; u_x\}$ random vectors. More compact:

$$AY + \eta = u \tag{3}$$

where Y is a $(2R \times 1)$ vector such that $Y' = [y'; x']$. The μ vector is also of order $(2R \times 1)$: $\eta = [\eta_y; \eta_x]$; for simplicity, let us assume that the non-deterministic component of both series consist of only a constant, so $\eta = m \otimes l$, being l an $(R \times 1)$ vector and m a (2×1) vector of means $[m_y; m_x]$. The error vector is composed of two sub-vectors of order (R × 1): $u' = [u_y'; u_x']$, which is normally distributed $u \sim N(0, \Xi)$, where:

$$\Xi = \begin{bmatrix} \sigma_y^2 I_R & 0 \\ 0 & \sigma_x^2 I_R \end{bmatrix} = \begin{bmatrix} \sigma_y^2 & 0 \\ 0 & \sigma_x^2 \end{bmatrix} \otimes I_R = \Sigma \otimes I_R \tag{4}$$

Moreover, A is a $(2R \times 2R)$ matrix with the following structure:

$$A = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \rightarrow \begin{cases} A_{11} = I_R - \rho_{yy}W \\ A_{12} = \beta I_R + \rho_{yx}W \\ A_{21} = \theta I_R + \rho_{xy}W \\ A_{22} = I_R - \rho_{xx}W \end{cases} \tag{5}$$

Assuming normality, the log-likelihood function is:

$$L(Y;\Psi) = -\frac{R}{2}\ln(2\pi) - \frac{R}{2}\ln|\Sigma| + \ln|A| - \frac{\left[AY - \eta\right]'\left(\Sigma \otimes I_R\right)^{-1}\left[AY - \eta\right]}{2} \tag{6}$$

With $\Psi' = \left[\rho_{yy};\beta;\rho_{yx};\eta_y;\sigma_y^2;\rho_{xx};\theta;\rho_{xy};\eta_x;\sigma_x^2\right]$. The score vector is

$$l(\Psi) = \begin{bmatrix} \partial L/\partial\rho_{yy} \\ \partial L/\partial\beta \\ \partial L/\partial\rho_{yx} \\ \partial L/\partial\eta_y \\ \partial L/\partial\sigma_y^2 \\ \partial L/\partial\rho_{xx} \\ \partial L/\partial\theta \\ \partial L/\partial\rho_{xy} \\ \partial L/\partial\eta_x \\ \partial L/\partial\sigma_x^2 \end{bmatrix} = \begin{bmatrix} (1/\sigma_y^2)(y'W'u_y) - tra_{11}W \\ -(1/\sigma_y^2)(x'u_y) + tra_{21} \\ -(1/\sigma_y^2)(x'W'u_y) + tra_{21}W \\ -(1/\sigma_y^2)(l'u_y) \\ -(R/2\sigma_y^2) + (u'_y\, u'_y/2\sigma_y^4) \\ (1/\sigma_x^2)(x'W'u_x) - tra_{22}W \\ -(1/\sigma_x^2)(y'u_x) + tra_{12} \\ -(1/\sigma_x^2)(y'W'u_x) + tra_{12}W \\ -(1/\sigma_x^2)(l'u_x) \\ -(R/2\sigma_x^2) + (u'_x\, u_x/2\sigma_x^4) \end{bmatrix} \tag{7}$$

where $tr(-)$ is the trace operator, $a_{11} = \left[A_{11} - A_{12}A_{22}^{-1}A_{21}\right]^{-1}$, $a_{12} = -a_{11}A_{12}A_{22}^{-1}$, $a_{21} = -$
$= -A_{22}^{-1}A_{21}a_{11}$ and $a_{22} = A_{22}^{-1} + A_{22}^{-1}A_{21}a_{11}A_{12}A_{22}^{-1}$.

Using the framework of the SpVAR of (2), we can test: (1) independence between the series and (2) direction of causality (in information) between the series. Independence between the two series corresponds to the following null hypothesis:

$$\left.\begin{array}{ll} H_0: & A_{12} = A_{21} = 0 \\ H_1: & A_{12} \vee A_{21} \neq 0 \end{array}\right\} \tag{8}$$

The score vector (reordered according to the parameters in the null hypothesis) evaluated under the same null hypothesis of (8) becomes:

$$l(\Psi)_{|H_0} = \begin{bmatrix} \partial L/\partial\rho_{yx} \\ \partial L/\partial\beta \\ \partial L/\partial\rho_{xy} \\ \partial L/\partial\theta \\ \partial L/\partial\rho_{yy} \\ \partial L/\partial\eta_y \\ \partial L/\partial\sigma_y^2 \\ \partial L/\partial\rho_{xx} \\ \partial L/\partial\eta_x \\ \partial L/\partial\sigma_x^2 \end{bmatrix}_{|H_0} = -\begin{bmatrix} (1/\sigma_y^2)(x'Wu_y) \\ (1/\sigma_y^2)(x'u_y) \\ (1/\sigma_x^2)(y'Wu_x) \\ (1/\sigma_x^2)(y'u_x) \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} \lambda_0 \\ \lambda_1 \end{bmatrix} \tag{9}$$

Being $\lambda_0' = -\left[\dfrac{x'Wu_y}{\sigma_y^2} \; \dfrac{x'u_y}{\sigma_y^2} \; \dfrac{y'Wu_x}{\sigma_x^2} \; \dfrac{y'u_x}{\sigma_x^2} \right]'$ and $\lambda_1' = -[0 \;\; 0 \;\; 0 \;\; 0 \;\; 0 \;\; 0]'$.

The Lagrange Multiplier is the quadratic form of the score vector on the inverse of the information matrix, both (vector and matrix) should be evaluated under the null hypothesis of (8). Combining these results, we obtain the expression of the Multiplier than enables us to test independence between the two series:

$$LM_I = \lambda_0' I^{11} \lambda_0 \underset{as}{\sim} \chi^2(4) \tag{10}$$

where I^{11} is the inverse of the variance-covariance matrix of vector λ_0, whose expression can be found in equation (3.4.85) of Herrera (2011) [3]. Therefore, to test the assumption of no correlation:

$$H_0 : \{x_s\}_{s \in S} \text{ and } \{y_s\}_{s \in S} \text{ are uncorrelated processes}$$

The decision rule for the LM_I test with a confidence level of $100(1-\alpha)\%$ is:

— *If* $0 \leq LM_1 \leq \chi^2_\alpha(4)$ *the null hypothesis of (8) cannot be rejected.*
— *If* $LM_1 > \chi^2_\alpha(4)$ *reject the null hypothesis of (8).*

Assuming that the null hypothesis of independence in the bivariate system of (2) has been rejected, the next step refers to the non-causality hypothesis. This is a double-lap exam: first we test that one variable, let us say *x,* does not cause in information the other, *y*; then we change the order, testing that *y* does not cause, in information, to *x*. The null hypothesis of the first combination (*x* does not cause *y*) is:

$$\left.\begin{matrix} H_0 : A_{12} = 0 \\ H_1 : A_{12} \neq 0 \end{matrix}\right\} \tag{11}$$

The score vector, evaluated under the null hypothesis of (11), is:

[3] Briefly I^{11} is a sub-matrix of the information matrix of the bivariate system of (2). As it is usual with the Lagrange Multipliers, the information matrix should be evaluated under the null hypothesis, in this case, of (8).

$$l(\Psi)_{|H_0} = \begin{bmatrix} \partial L/\partial\rho_{yx} \\ \partial L/\partial\beta \\ \partial L/\partial\rho_{xy} \\ \partial L/\partial\theta \\ \partial L/\partial\rho_{yy} \\ \partial L/\partial\eta_y \\ \partial L/\partial\sigma_y^2 \\ \partial L/\partial\rho_{xx} \\ \partial L/\partial\eta_x \\ \partial L/\partial\sigma_x^2 \end{bmatrix}_{|H_0} = -\begin{bmatrix} (1/\sigma_y^2)(x'Wu_y) + trA_{11}^{-1}A_{21}A_{22}^{-1}W \\ (1/\sigma_y^2)(x'u_y) + trA_{11}^{-1}A_{21}A_{22}^{-1} \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} \gamma_0 \\ \gamma_1 \end{bmatrix} \tag{12}$$

Where:

$$\gamma_0' = -\left[\frac{x'W'u_y}{\sigma_y^2} + trA_{11}^{-1}A_{21}A_{22}^{-1}W \quad \frac{x'u_y}{\sigma_y^2} + trA_{11}^{-1}A_{21}A_{22}^{-1} \right]$$

$$\gamma_1' = [0 \;\; 0 \;\; 0 \;\; 0 \;\; 0 \;\; 0 \;\; 0 \;\; 0]'$$

In a more compact notation, the Lagrange Multiplier obtained for the null hypothesis of (11) is:

$$LM_{NC} = \lambda_0' I^{11} \lambda_0 \underset{as}{\sim} \chi^2(2) \tag{13}$$

Once again, I^{11} is the inverse of the variance-covariance matrix of the γ_0 vector (expression (3.4.127) of Herrera, 2011). Consequently, to test the null hypothesis of:

$$H_0 : \{x_s\}_{s\in S} \text{ does not cause } \{y_s\}_{s\in S} \tag{14}$$

The decision rule for the LM_{NC} test with a confidence level of $100(1-\alpha)\%$ is:

— *If* $0 \leq LM_{NC} \leq \chi_\alpha^2$ (2) *the null hypothesis of (11) cannot be rejected.*
— *If* $LM_{NC} > \chi_\alpha^2$ (2) *reject the null hypothesis of (11).*

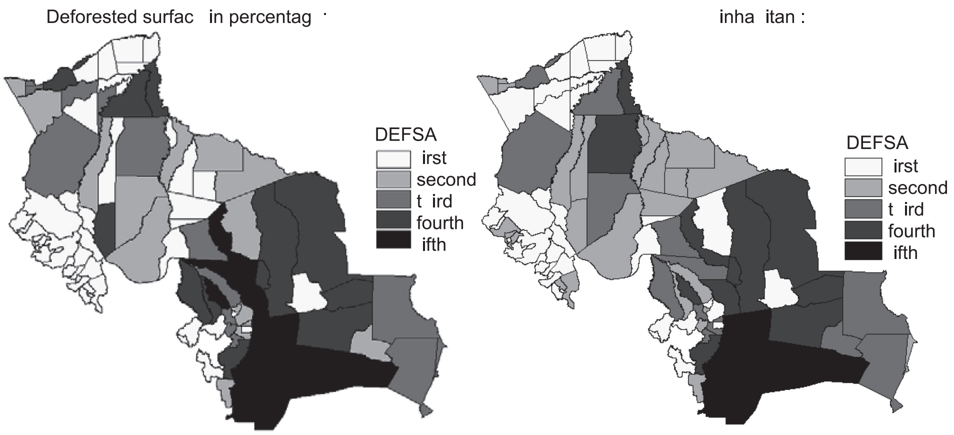
4. Deforestation in the Bolivian municipalities. A spatial approach

In this section, we apply the techniques developed previously to the information available on deforestation for a set of 91 Bolivian municipalities in the period 2004-2007. These municipalities belong to the departments of Bendi, 19 of them, Pando, 16, 23 come from the department of La Paz and 34 from Santa Cruz. They are selected according to data availability (we could not find information for the other 222 Bolivian municipalities). Figure 2 shows the spatial layout of the municipalities included and not included in the study.

Figure 2. Bolivian municipalities in the deforestation study

Figure 3 depicts the indices of deforestation for these municipalities, using the quantiles of the distribution frecuencies. The variables represented are the percentage of the land surface of each municipality classified as deforested in 2007 according

Figure 3. Deforestation indices in the Bolivian municipalities



to Rojas *et al* (2003), variable DEFSA, and the number of deforested hectares per inhabitant in the respective municipality, variable DEFPA. The spatial distribution of these data is what we are trying to explain.

There is an overall consensus in relation to the factors that are inducing the deforestation process (Kaimowitz and Angelsen, 1998). Some of them pertain to the block of physical environmental characteristics like rainfalls, temperature, climate instability, etc. However, we are interested in the impact of *human factors* in the sense that they reflect the consequences of social decisions in relation to economic growth, social organization, property rights, etc.

Due to statistical restrictions, we only have information for a limited number of risk factors: accessibility, measured in terms of density of principal and secondary roads per square kilometre (variable DECAT), population pressure, measured by the population density per Km^2 (variable DEPOB), urbanization, estimated by means of the percentage of population settled in rural areas, variable DEPOR, and property rights, as percentage of the municipality land surface privately owned, variable PROPI. The spatial distribution of the four variables, once again in quantiles, is shown in Figure 4.

Figure 4. Deforestation in the Bolivian municipalities. Risk factors

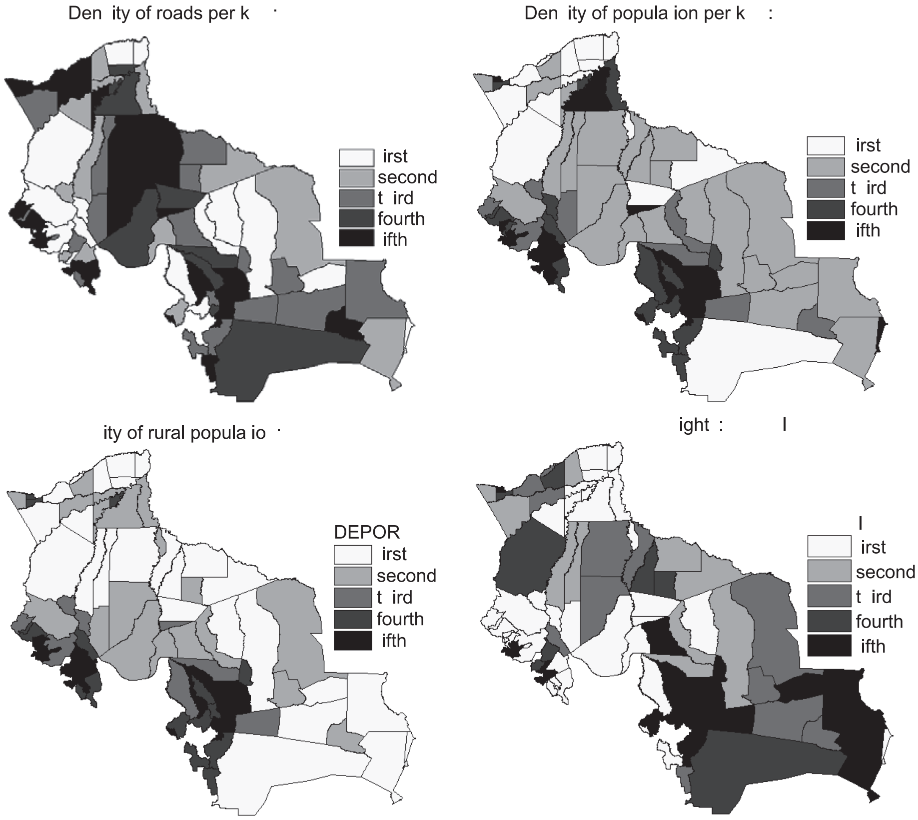


Table 1 presents some data for this group of variables. One important question to note is the great heterogeneity of the municipal records. For example, the average percentage of land classified as deforested is 2.03% for the 91 municipalities, but the figures range from 0.02% to 14.1%. The set of municipalities include cases with a very low density, 0.14 inhabitants per square kilometre, and others densely populated, with 1,175 inhabitants per square kilometre. The disparities in other indices such as road density or property rights structure are even greater. Moreover, all the variables are affected by severe non-normality problems. This is an important issue here because the strategy designed involves the use of maximum likelihood estimators, in which the assumption of normality plays a crucial role. Therefore in the following, we use the data in logarithms (transformed variables are identified with the symbol *l* before the respective code; the problems with the assumption of normality are corrected).

Table 1. Deforestation indices: Descriptive statistics

Variables	μ	η	*Min.*	*Max.*	σ	α	κ	*SW*	*I*
DEFSA	2.03	0.58	0.02	14.1	3.23	2.17	4.21	0.64 (0.00)	0.58 (0.00)
DEFPA	0.69	0.25	0.00	10.5	1.33	5.06	32.29	0.49 (0.00)	0.15 (0.01)
DEPOB	25.60	3.87	0.14	1,175.0	126.65	8.46	73.45	0.17 (0.00)	0.04 (0.04)
DEPOR	5.88	1.99	0.09	41.3	8.73	2.20	4.71	0.68 (0.00)	0.50 (0.00)
DECAT	98.75	82.66	0.00	330.7	59.81	–1.42	2.61	0.90 (0.00)	0.29 (0.00)
PROPI	30.44	6.18	0.00	100.0	39.75	–0.94	–0.87	0.71 (0.00)	0.10 (0.03)

μ: Mean; η: Median; σ: Standard deviation; Min.: Minimum value; Max.: Maximum value; α: Skewness, κ: Kurtosis; SW: Shapiro-Wilks statistic; MI: Moran's I statistic. In parenthesis, *p*value.

Furthermore, as shown by the Moran index, there is a strong positive spatial dependence structure in the data of deforestation. This test of spatial independence is highly significant in all the cases. The weighting matrix employed to solve the test corresponds to the row-standardized version of the four nearest-neighbours (the conclusion of dependence is robust to the specification of the *W* matrix and, also, to the log transformation). The same matrix has been used in the causality analysis that follows.

As can be seen is Table 2, the linear correlation between the six indices of deforestation is medium to low. Except for two cases, DEFPA-DEFSA and LDEPOR-LDEPOB, the correlation coefficients are smaller than 0.5 in absolute value, although mostly of them are statistically significant (13 of the 15, at the usual significance level of 5%), with a predominance of positive scores (12 out of 15).

Table 2. Deforestation indices: Correlation matrix

	DEFPA	*LDEPOB*	*LDEPOR*	*LDECAT*	*LPROPI*
DEFSA	0.509	0.377	0.275	0.378	0.463
DEFPA		–0.093	–0.581	–0.071	0.051
LDEPOB			0.881	0.431	0.362
LDEPOR				0.421	0.376
LDECAT					0.314

95% confidence interval: (–0.21; 0.21).

All these data confirm, as expected, the relevance of the spatial dimension in the problem of deforestation. The role of the Space appears even more important when we consider bivariate spatial relationships. Table 3 shows the results of the bivariate Moran's test, I_{yx}, and the Lagrange Multiplier, LM_I, for the assumption of spatial independence between the deforestation indicators and the risk variables. The results of the LM_I test in relation to the percentage of land surface deforested, DEFPA, are clearly anomalous. According to the simulations reported by Herrera (2011), the Lagrange Multiplier is more sensitive to the presence of outliers. The log-transformation is an smoothing transformation, useful for correcting non-normality problems, but probably not enough for the case of the Multiplier.

Table 3. Measures of bivariate spatial dependence

	LM_I		I_{yx}	
	LDEFPA	*LDEFSA*	*LDEFPA*	*LDEFSA*
LDEPOB	0.11 (0.99)	5.84 (0.21)	–3.15 (0.00)	2.98 (0.01)
LDEPOR	0.57 (0.97)	11.37 (0.00)	9.22 (0.00)	13.52 (0.00)
LDECAT	6.09 (0.19)	209.1 (0.00)	–7.24 (0.00)	2.02 (0.02)
LPROPI	14.81 (0.01)	22.93 (0.00)	16.96 (0.00)	3.46 (0.00)

*p*value in parenthesis.

Table 4 presents the results of the final step in our discussion of spatial causality. These results correspond to the Lagrange Multipliers of expression (13), LM_{NC}, whose null hypothesis is non-causality (in information). As indicated in Section 3, the results of this test are only relevant in the case that, previously, the assumption of spatial independence between series has been rejected. Furthermore, the identification of a certain direction of causality, in information, between the variables is subjected to the simultaneous fulfilment of two clauses: the null hypothesis of non-causality should be rejected in one direction nut no rejected in the opposite direction.

Table 4 shows that, in relation to the indicator of per capita deforestation, LDEFPA, the test is non-conclusive in two cases. The population pressure, LDEPOB, and

Table 4. Causality results. Lagrange Multipliers, LM_{NC}

	LDEFPA		*LDEFSA*	
	→	←	→	←
LDEPOB	0.87 (0.64)	0.90 (0.64)	2.99 (0.22)	33.83 (0.00)
LDEPOR	8.31 (0.02)	5.74 (0.05)	11.60 (0.00)	262.46 (0.00)
LDECAT	2.75 (0.25)	0.03 (0.99)	14.10 (0.00)	68.36 (0.00)
LPROPI	12.61 (0.00)	5.41 (0.07)	13.82 (0.00)	5.73 (0.06)
*p*value in parenthesis	→ : Causality is from the variable on the left to the variable on the right.		← : Causality is from the variable on the right to the variable on the left.	

the indicator of accessibility, LDECAT, do not cause deforestation, whereas urbanization, LDEPOR, and the structure of property rights, LPROPI, do cause this variable. The null of non-causality from LDEFPA to each of the four risks of deforestation cannot be rejected in any case, at a 5% level of significance (the conclusion is very tight with respect to LDEPOR and LPROPI).

Rejections of the null tend to predominate in the case of the percentage of land surface deforested in each municipality, LDEFSA. This is the case of LDEPOR and LDECAT, where the null of non-causality is rejected in both directions. According to the framework of Section 3, we cannot identify a unique direction for the information flow which prevents us of using the term causality (in information). On the contrary, the density of population, LDEPOB, appears to be caused by the deforestation process. Once again, property rights, LPROPI, emerge as a cause factor in the problem of deforestation

5. Final conclusions

Deforestation is an issue of great interest, particularly in regions that have preserved their environmental diversity; this is the case for most of South America in general, and Bolivia in particular. The literature on deforestation insists on the importance of physical variables related, for example, to climate and territory and other variables associated to social effects; human settlements, road infrastructure, and property rights are regularly identified as deforestation risk factors.

Our analysis has focused on the statistical part of the relationship, ignoring other aspects of the discussion. The problem that we consider is whether it is possible to detect causality relationships, in information, with a single cross-section of data and no time perspective. In this case, we wonder what occurs with the deforestation data available for a representative group of Bolivian municipalities.

The answer is positive to the first question: it is possible to develop a method for testing causality using purely spatial data. The strategy that we proposed is based on a sequence of Lagrange Multipliers obtained from a spatial VAR system. The application of this strategy to the data available confirms only part of the traditional approach to the deforestation problem. Our conclusions can be summarised as follows:

— The variable with the greatest causal impact on the deforestation problem is the structure of property rights.
— Deforestation is found to be the cause of population distribution, as measured by population density.
— Other variables such as accessibility, measured through road density, or the importance of rural settlements do not appear to have a precise causal effect on deforestation.

It is important to note that the above results do not define the type of impact of the causal variables on the deforestation indices. The evidence available enables us to say, for instance, that an increase in private or communal land tenure will have a causal impact in the deforestation process. The same can be said of the relationship between deforestation and population density. The quantification of these relationships, in the sense of being able of forecasting tendencies, is in this project's future research agenda.

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Section Empirical contributions

Public Capital and Regional Economic Growth: a SVAR Approach for the Spanish Regions

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ABSTRACT: Recently, a significant share of the empirical analysis on the impact of public capital on regional growth has used multivariate time-series frameworks based on vector autoregressive (VAR) models. Nevertheless, not as much attention has been dedicated to the analysis of the long-run determinants of regional growth processes using multi-region panel data and applying panel integration and co-integration techniques. This paper estimates the dynamic domestic effects of public infrastructure using a structural vector autoregressive (S-VAR) methodology for the Spanish regions. From a methodological point of view, the paper contains several features that can be viewed as a contribution to the existing empirical literature. First, the important issues of the stationarity of the data and the existence and estimation of cointegrating relationships in the long-run are addressed in the context of the analysis of panel data. Secondly, the long-run cointegrating production function is embedded within structural vector error correction (S-VEC) short-run models to produce consistent estimates of impulse responses, contrary to many researchers who have estimated unrestricted VAR models in levels or VAR models in first differences. The estimates reveal new results with respect to the previous empirical evidence.

JEL Classification: C32; E62; H54; R53.

Keywords: Public capital, regional growth, VAR methodology, Spain.

Capital Público y Crecimiento Económico Regional: un enfoque SVAR para las Regiones Españolas

RESUMEN: Recientemente, un porcentaje significativo de los estudios empíricos que analizan el impacto del capital público sobre el crecimiento económico regional ha utilizado series temporales multivariantes basadas en modelos de vectores autoregresivos (VAR). En este contexto, no se ha prestado demasiada atención al

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análisis de los determinantes a largo plazo de los procesos de crecimiento regional utilizando paneles de datos multi-regionales y aplicando técnicas de integración y cointegración para paneles. Este trabajo estima los efectos domésticos dinámicos de las infraestructuras públicas utilizando una metodología de vectores autorregresivos estructurales (S-VAR) para las regiones españolas. Desde el punto de vista metodológico, el trabajo contiene distintas características que pueden ser vistas como una contribución a la literatura empírica existente. Primero, las importantes cuestiones de la estacionaridad de los datos y de la existencia y estimación de relaciones de cointegración en el largo plazo son abordadas en el contexto del análisis de los datos de panel. En segundo lugar, en los modelos de corto plazo de vectores de corrección de error estructurales (S-VEC) se tiene en cuenta la función de producción de cointegración en el largo plazo para producir estimaciones consistentes de las respuestas a impulsos; esto es contrario a lo que hasta ahora han hecho muchos investigadores, que han estimado modelos VAR sin restringir en niveles, o modelos VAR en primeras diferencias. Las estimaciones muestran resultados nuevos con respecto a la evidencia empírica previa.

Clasificación JEL: C32; E62; H54; R53.

Palabras clave: Capital Público; Crecimiento Regional; Metodología VAR; España.

1. Introduction

The role of public capital investment has been a critical component of the policy agenda focused on enhancing regional growth. Permanent changes in public capital investment could have important effects on regional economic activity. The theoretical arguments pointing to the role of public capital on economic development are embodied in many of the «New Growth Theory» (NGT) and «New Economic Geography» (NEG) models. These models challenge traditional Neo-Classical Growth Models, which predicted regional convergence without a specific theoretical consideration of the role of public capital: steady-state income per capita is assumed to be independent of the initial conditions, no matter the size of the inherited differences in capital stock.

In contrast, endogenous growth theory was based on the existence of increasing returns and positive externalities (Romer, 1986, 1990; Lucas, 1988, 1993), where the existence of increasing returns could be explained by an intensive investment in knowledge, human capital or infrastructure (e. g., Barro, 1990). In this theoretical context, Barro and Sala-i-Martin (1992) analyzed the growth effects of the flow of productive government spending, while Turnovsky (1997) and Aschauer (2000) considered the growth effects of the stock of public capital. Therefore, the stock of public infrastructures could be among the significant variables conditioning the level and growth of regional productivity, and thus government policy —through its expenditure programs on public capital over space— would have the potential to affect the long-run growth rate of a regional economy.

On the other hand, in the early 1990s, the NEG models provided explanations for the formation of a large variety of economic agglomerations in geographical space (Fujita and Krugman, 2004). This new line of research emphasizes the interaction among increasing returns to scale, transportation costs (broadly defined) and the movement of productive factors. According to Fujita and Thisse (2002), public expenditure is fundamental in both the reduction of transport costs and in the supply of local public goods, playing a key role in the critical trade-off between increasing returns and transport costs. The general belief is that public capital could increase the productivity of private factors, thereby generating a significant impact on growth. Accordingly, it becomes essential (from a policy evaluation point of view) to have a quantifiable measure of the impact of public investment on the growth performance of receiving economies.

There exist a number of studies (see, among others, Kamps, 2005, and Roca-Sagalés and Sala, 2010, for a comprehensive review) in the literature that documents the effects of public capital on economic growth. Initially, earlier studies (Aschauer, 1989, and Barro, 1990) and the following set of studies have concentrated mostly on country case studies. Lately, a second set of studies (with earlier work from Munnell, 1990) has focused on regions within a country. These econometric studies have shown the importance of spillover effects as potential factors that may affect regional growth. However, an overwhelming amount of research has focused on the measure of spillover effects in the analysis of the aggregate effects of the public capital provision at the regional level (see, for example, Holtz-Eakin and Schwartz, 1995; Boarnet, 1998; and Pereira and Roca-Sagalés, 2003). Adopting this perspective, spillover effects, understood as positive or negative externalities derived from the impact of the public capital provision in a region, would have to be considered when investigating the effects of public capital in one region on the production of other regions.

In sum, the evaluation of the aggregate effects of public capital should contemplate the existence of both direct (domestic) and indirect (spill over) effects. For a region, domestic effects are the effects derived from public capital installed in the region itself, while than spillover effects are derived from public capital installed outside that region. Even then, the issue of domestic effects has been ignored the recent contributions try to improve the measurement of the spillover effects of public capital. Empirical results and policy implications from the existing literature based on spillover effects to regional economies should be complemented, taking into account the own specificities and constraints of such regions derived from the analysis of domestic effects.

In the present paper, the effects of public capital for the 17 regions that make up Spain are measured using a «structural» VAR (S-VAR) approach. The dynamic effects will be considered from a domestic perspective [1]. From a methodological point of view, the paper contains several innovative features that can be viewed as a contribution to the existing empirical literature. First, the important issues of the stationarity of the data and the existence and estimation of cointegrating relationships in the long-run are addressed in the context of the new tools proposed recently

[1] This article is complementary to Márquez *et al.* (2010), where the spillover effects of one-time innovations in the public capital installed in a given region on the economic growth of the other Spanish regions (cross-border effects) are estimated by using «bi-regional models».

for the analysis of panel data [2]. In this sense, to date, none of the existing studies of the impact of public capital investment on the economic growth performance using multi-region panel data has applied panel integration and cointegration techniques to analyze the long-run determinants of regional growth processes. Secondly, based on the integration and cointegration results, the long-run cointegrating production function is embedded within structural vector error correction (S-VEC) short-run models to produce consistent estimates of impulse responses, in contrast to many researchers who have estimated unrestricted VAR models in levels or VAR models in first differences. These models might produce inconsistent estimates of the impulse response functions.

The results could assist in formulating economic policies, complementing the approach shown in Márquez *et al.* (2010), where it is possible to identify the regions where the spillover effects originate. From these findings, the regions that are able to generate spillover effects on other regions are determined, deepening the understanding of the spatial and temporal dynamics of the location of further public investment.

The results on the impact of public capital on regional economic growth in the present paper are somehow unexpected in comparison to previous research findings on the Spanish regional economies. A main determinant of these results is the inclusion in the short-run regional models of an error correction term derived from the estimation of a joint steady-state relationship for the Spanish regional system. The use of the pooled mean group methodology to obtain the estimation of the production function of the regional economic system as one cointegrating vector allowed for cross-section specific heterogeneity in the coefficients of the short-run parameters of the regional VAR models (see Pesaran *et al.*, 1999). Thus, the stability of the regional models in the short-run is ensured by means of an error correction mechanism that takes into account the information of the joint regional equilibrium in the long run.

Departing from the standard method used until now, the application of this empirical approach would be helpful in simulating the domestic effects generated by regional public capital investment in a region on output, employment, and private performance in the same region. The results that were obtained involve both positive and negative domestic effects from public capital. Another contribution derives from the analysis of the spatial distributions of the estimated domestic effects: the long run effects of public capital on private capital show a strong geographic pattern and reveal the presence of positive spatial dependence.

In section 2, a succinct review of the theoretical and empirical literature on public capital and economic growth is presented, with special reference to the Spanish regional case. In section 3, a brief description of the data properties is provided and the empirical results are reported and discussed. The final section summarizes the paper's major findings and offers some policy prescriptions.

[2] To separate the long run behaviour from the short run dynamics it is necessary that the variables under consideration are nonstationary [typically integrated of order one, $I(1)$], so that the errors from the long-term cointegrating relationships could be stationary.

2. Public capital and regional economic growth

Public capital has been considered an important instrument of regional policy (see de la Fuente and Vives, 1995). Previous research about the role of public capital in economic growth could be systematized considering different perspectives (see Romp and de Haan, 2007 for a survey of the extensive literature): the definition and scope of the public capital variable; the division between country and regional level studies; the main approaches (production functions, cost functions and VAR/VECM models); and the level of aggregation of the data (data over specific sectors or data over all sectors).

Authors like Aschauer (1989), García-Mila and McGuire (1992) and Munnell (1992), among others, have applied neoclassical production functions. Their findings provide a diversity of results, making it difficult to obtain any definitive conclusions. Further, several inconsistencies have been reported. The single-equation regression model used by Aschauer has potential econometric problems like spurious regression due to non-stationarity of the data, possible misspecification of the production function, endogeneity and/or the direction of causality from public capital to productivity. With respect to the problem of the spurious regression, cointegration theory provides a means of approaching this problem, taking into account the non-stationarity problem. The missing variables problem makes reference to the possible omission of relevant variables like those indicated by NGT (e. g., knowledge, human capital, R&D investment, etc.). Finally, the direction of causality, that is, the possible influence from economic growth on public capital, causing a problem of endogeneity, is one of the main drawbacks of the production function approach.

Alternatively, the cost function approach (see, for example, Ezcurra *et al.,* 2005 for the Spanish case) measures the impact of public capital on economic growth in terms of cost-savings benefits. This approach evaluates whether costs decrease with public capital provision. The cost-function approach is more flexible than the production-function approach, and this is its main advantage. Nevertheless, the requirement of data for the cost-function approach is greater than in the case of the production-function approach.

More recently, in the context of the VAR models, the impulse response analysis has been used as a fundamental tool to simulate the effect that an unexpected change of the public capital would have on another variable, for example, on the value of regional production. The use of the VAR approach to test the significance of the dynamic effects of public capital on economic growth presents some advantages. According to Kamps (2005), this approach allows for the existence of indirect links between the variables under investigation. In addition, if the number of long-run (cointegrating) relationships are tested and estimated consistently, the vector error correction (VEC) models would produce consistent estimates of impulse response functions. With respect to the empirical literature where the VAR methodology has been used to simulate the effects of unexpected changes in the public capital on regional macroeconomic variables for the case of the Spanish regions, a few studies like Pereira and Roca-Sagalés (1999, 2001) can be found. Further, Pereira and Roca-Sagalés (2003) and Roca-Sagalés and Sala (2006) have investigated the existence of regional spillover effects of public capital formation in the economic regional system of Spain.

Regional economic growth could be affected by public capital through different mechanisms. The most direct way is the consideration of public capital as a factor of production (see Sturm, 1998). The effects derived from the interactions between public capital and private capital would be another way. In this sense, the existence of a positive effect of public investment on private capital accumulation was obtained by Martínez-López (2006) for the Spanish regions over the period 1965-1997. On the other hand, the new economic geography (Krugman, 1991; Fujita *et al.,* 1999) suggests that public capital may affect regional economic growth through its influence on transport costs. More public capital (specially transport infrastructure) could have an important impact on market access (see, for example, Redding and Venables, 2004, or Head and Mayer, 2004). Good access to large markets (high market access) may prove to be critical in the explanation of regional economic performance.

Finally, it is important to highlight that the distinction between short- and long-run effects of public capital is important in regional economic analysis. There is no reason to believe that public capital has the same spatial impact whether in terms of sign or magnitude of its effects in both the long- and the short-run. In this sense, and with respect to the long-run effects of public investment, Baxter and King (1993) note that an unexpected (permanent) increase in public investment will induce a response of output. This long run response will be both direct and indirect (derived from the supply-side effect generated by private capital and labor). On the other hand, considering the short run effects of public investment, Baxter and King (1993) declare that an unexpected (permanent once it occurs) shock in the stock of public capital will imply a transition of the economy to the new steady state. During this transition, the stock of public capital accumulates, increasing the output. This accumulation involves a governmental absorption of resources that could generate some interactions. As a result, the rising stock of public capital will alter the stock of private capital and labor through the change of the marginal product. Obviously, this theoretical difference between short- and long-run effects has important empirical implications as demonstrated example, by Moreno *et al.* (2002) who determined the short- and long-run effects of public infrastructure in the context of manufacturing industries in the Spanish regions using aggregated cost functions. In summary, one might venture to say that public capital could be a complement or substitute with respect to private capital and employment, conditioning the pattern of the output responses; further, the response could be different in the long- and short-run.

As documented in the literature on the effects of public infrastructure, although there is a general consensus of the need for a certain level of public capital, the results obtained are inconclusive. The studies analyzing the impact of public capital on regional output and regional productivity generally point to the effectiveness of public capital as a tool for regional policy; some examples are provided in order to reveal the different conclusions that have been derived to date. Destefanis and Sena (2005), in studying the Italian case, concluded that public capital had positive effects, at least in some Italian regions. Karada *et al.* (2004) used a vector autoregression (VAR) model to estimate long run accumulated elasticities of private sector variables with respect to public capital in the seven geographical regions of Turkey. These authors showed evidence of the positive effects of public capital on private output in five of the seven regions. However, for some regions, public capital crowds out private sector inputs. Sloboda and Yao (2008) analyzed interstate spillovers of private capital and public spending in the United States; they detect crowding out effects among the 48 contiguous states for the period 1989-2002.

For the Spanish economy, the general perception is the existence of positive effects such as Cantos *et al. (*2005), Ezcurra *et al.* (2005), Moreno *et al.* (2002), Boscá *et al.* (2002), Mas *et al.* (1996). Other studies such as Gorostiaga (1999) and González-Páramo and Martínez (2003) do not show significant effects of public capital stock on economic growth. In the literature, it is argued that the non significant effect of public investment in economic growth is due to the existence of spillover effects. Thus, Salinas-Jiménez (2004), obtains positive effects for the Spanish case, but only if spillover effects were taken into account.

3. The dynamic domestic effects of public capital on the Spanish regions: new evidence from structural VAR models

This section describes an empirical application analyzing the domestic effects of public capital for the Spanish regions. This empirical section is organized as follows. First, the Spanish data used to implement the S-VAR approach are presented. Secondly, panel integration tests are applied to this data set, and the results of the unit roots analysis are reported. Next, panel cointegration tests are employed to test for cointegration, and the results on the estimation of the long-run equilibrium cointegrating relationship are presented. Finally, individual S-VEC short-run models are first presented and then estimated, and the results of an impulse response analysis based on a set of identifying assumptions are shown.

3.1. Spanish regions and data

Spain is composed of 17 regions and Ceuta and Melilla —two Spanish North African cities— that constitute the so-called Autonomous Communities [3]. In the present work, only the 17 regions in Spain are analyzed (see Figure 1). The Spanish regional system has a marked economic core-periphery pattern, with an unequal

[3] The Autonomous Communities have achieved the status of self-governed territories, sharing governance with the Spanish central government within their respective territories.

economic geography. Traditionally, the peninsular economic periphery is comprised of Castilla-León, Castilla-La Mancha and Extremadura while Madrid, País Vasco, Cataluña and Valencia make up the economic core. Galicia, Andalucía, Murcia, Islas Baleares and Islas Canarias are also considered as «peripheral» regions; while Navarra, La Rioja, and Aragón may be considered as «core» regions. Finally, Asturias and Cantabria are historical «core» regions, but currently experiencing significant industrial restructuring processes.

Figure 1. Spanish Regions

Accordingly, the panel data-set contains 17 regions over the period 1972-2000; for each region, the variables used are the public net productive capital stock (*PK*), the private net capital stock (*K*), the number of employed persons (*E*), and the real Gross Added Value (*Y*). The regional series for *Y* have been drawn from the Instituto Nacional de Estadística (INE) of Spain and from the Hispadat database (see Pulido and Cabrer, 1994, and Cabrer, 2001) and the time series for *PK*, *K* and *E* have been taken from the Instituto Valenciano de Investigaciones Económicas (IVIE) of Spain. The regional public capital stock comprises public capital owned by the local, regional and national administrations, including transport infrastructures (roads, ports, airports and railways), water and sewage facilities and urban structures.

Table 1 displays selected summary indicators for the 17 Spanish regions, presenting some relevant data about the geographical distribution of the aforementioned variables for the (approximately) three decades comprising the database (1972-1980, 1981-1990 and 1990-2000). As the table shows, there are clear regional disparities in the geographical distribution of output, employment, and private and public capital stocks. These sharp disparities could be shown, for example, in the case of two regions like Madrid and Extremadura. Madrid has an area corresponding to 1.6% of the Spanish regional system. During the first (third) sub-period, Madrid produced 15.7% (16.6%) of the aggregate output, with 12.1% (13.7%) of the total employment, 15.4% (15.3%) of the private capital stock and 10.6% (10.0%) of public capital stock of Spain. Conversely, Extremadura, with 8.3% of the total area, during the first (third) sub-period accounted for only for 1.7% (1.8%) of the Spanish output, with 2.7% (2.3%) of the total employment, 1.8% (1.9%) of private capital and 3.1% (3.3%) of public infrastructures of Spain.

Table 1. Basic data for Spanish regions

Regions	*Area*	*GAV*			*Employment*			*Private Capital*			*Public Capital*		
	% km²	*1972-1980*	*1981-1990*	*1990-2000*	*1972-1980*	*1981-1990*	*1990-2000*	*1972-1980*	*1981-1990*	*1990-2000*	*1972-1980*	*1981-1990*	*1990-2000*
AN	17.36	14	13.55	13.86	14.43	14.07	14.61	11.83	12.41	13.04	14.95	15.56	17.21
AR	9.45	3.35	3.46	3.31	3.36	3.37	3.25	3.16	3.18	3.15	5.57	5.01	4.09
AS	2.1	3.19	2.9	2.44	3.28	3.05	2.55	3.28	2.92	2.5	3.29	3.35	3.3
BA	0.99	2.12	2.27	2.27	1.77	1.96	2.14	2.36	2.52	2.94	1.46	1.47	1.56
CB	1.04	1.28	1.28	1.24	1.45	1.39	1.29	1.68	1.48	1.34	1.32	1.49	1.59
CL	18.59	6.61	6.36	5.81	7.11	6.95	6.29	6.11	6.41	6.07	10.25	9.05	7.95
CM	15.74	3.85	3.72	3.57	4.34	4.25	4.11	3.43	3.8	3.93	5.67	5.4	5.52
CN	1.48	2.77	3.46	3.72	3.18	3.53	3.93	2.88	3.14	3.49	3.63	3.89	4.05
CT	6.36	18.63	18.07	18.86	16.7	16.61	17.65	21.13	20.06	19.3	14.98	13.73	13.5
CV	4.61	9.52	9.88	9.79	9.7	10.02	10.32	10.02	11.03	11.43	8.43	8.77	9.03
EX	8.25	1.74	1.85	1.81	2.74	2.49	2.32	1.84	2.07	1.87	3.07	2.96	3.33
GA	5.86	5.75	5.91	5.57	9.52	9.13	7.4	5.31	5.45	5.32	5.77	6.32	6.85
MA	1.59	15.68	15.95	16.64	12.05	12.89	13.67	15.44	14.96	15.34	10.61	10.63	9.99
MU	2.24	2.14	2.3	2.33	2.35	2.48	2.64	2.16	2.3	2.51	1.69	2.15	2.39
NA	1.94	1.68	1.69	1.67	1.39	1.43	1.51	1.38	1.36	1.5	1.93	2.04	1.96
PV	1.4	7.09	6.61	6.34	5.9	5.66	5.61	7.42	6.25	5.56	6.3	6.79	6.71
RI	1	0.61	0.74	0.76	0.73	0.73	0.7	0.58	0.66	0.7	1.09	1.38	0.96
SPAIN	100	100	100	100	100	100	100	100	100	100	100	100	100

3.2. Testing for panel unit roots and cointegration, and estimation of the long-run equilibrium production function

The empirical analysis begins with an evaluation of the stationarity of the four variables of the database using panel unit root tests starts [4]. All panel tests used are based on the null hypothesis of the presence of a unit root in the series, with the exception of Hadri's (2000) test, whose hypothesis is that the series are stationary. The tests differ from each other in the restrictions imposed on the autoregressive process of each of the panel series. Thus, the tests of Levin, *et al*. (2002), Breitung (2000) and Hadri (2000) impose a common persistence parameter to all the series. Therefore, if the null were rejected, the alternative would be that all the series are simultaneously stationary for the first two tests and non-stationary for the latter. Alternatively, the tests of Im, *et al*. (2003) and the Fisher-type tests suggested by Maddala and Wu (1999) allow for the autoregressive parameter to change freely among the different regional variables under consideration. Therefore, the alternative hypothesis in these cases is the presence of a non-null proportion of stationary series of the total. The latter set of tests seem more appropriate from an empirical point of view as they impose less restrictions on the data generating process.

A general overview of the statistics, presented in Table 2, shows the evidence to clearly favor the hypothesis that the four basic variables considered behave as non-stationary variables, with a unit root at least for a non-negligible fraction of the 17 regions of the panel. Indeed, only for the variable *K,* in logs, do the test statistics show

Table 2. Unit root tests for log *Y*, log *E*, log *K* and log *PK*

	Log Y	*Log E*	*Log K*	*Log PK*
Null: Unit root (assumes common unit root process)				
Levin-Lin-Chu	2.201	8.162	–3.785 ***	3.445
Breitung	–2.424 ***	8.341	–2.487 ***	3.078
Null: Unit root (assumes individual unit root process)				
Im-Pesaran-Shin	0.026	8.381	–4.560 ***	0.993
Maddala-Wu ADF-Fisher	31.217	0.659	91.173 ***	26.392
Maddala-Wu PP-Fisher	40.984	0.971	96.893 ***	17.617
Null: No unit root (assumes common unit root process)				
Hadri	3.790 ***	9.371 ***	7.306 ***	6.634 ***

Notes: 1) Probabilities for Fisher tests were computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality; 2) An * (**) [***] indicates rejection of the null hypothesis at the 10% (5%) [1%] significance level based on the appropriate critical values; 3) Exogenous variables: Individual effects, individual linear trends; 4) Automatic selection of lags based on MAIC criterion: 0 to 4; 5) Newey-West bandwidth selection using Bartlett kernel.

[4] The use of panel unit root tests is justified by the results from recent studies [see Banerjee (1999), Baltagi and Kao (2000) or Breitung and Pesaran (2008), among others], which suggest that unit root tests based on panel data are more powerful than those based on individual data.

evidence favorable to the hypothesis of stationarity of the corresponding time series (in Table 2, a deterministic linear trend is included in all the specifications, but if not, the unit root hypothesis is clearly not rejected in this particular case). Since the test results generally support the unit root hypothesis, from now it is assumed that all time series under consideration (all in log values) are integrated of order one. This makes it possible to distinguish between short-run and long-run relations, and to interpret the long-run relations as cointegrating relationships.

To analyze the existence of cointegration between the four variables considered, three panel tests were applied. Two of them, those of Pedroni (1999, 2004) and Kao (1999), are residual-based tests that assume a single cointegrating vector; while the third test, of Maddala and Wu (1999), allows for multiple cointegrating relationships [5]. On the other hand, not all the tests used assume the same degree of individual heterogeneity; while the Pedroni and Maddala-Wu statistics allow the coefficients of each cointegration relation to vary freely for each region, the Kao approach assumes panel homogeneity.

The estimates of the various cointegration statistics are presented in Tables 3, 4 and 5. As a general assessment of the values presented in these tables, one can deduce that there is considerable evidence pointing to the existence of cointegration between the real GAV and the input-production variables for the panel of 17 Spanish regions. Thus, in the case of the Pedroni statistics, all the three versions of the PP and ADF statistics strongly reject the non-cointegration hypothesis. The Fisher type and Kao statistics also corroborate the existence of a stable long-run relationship. Therefore, the overall evidence is consistently in favor of the existence of an aggregate production function as a long-run equilibrium relationship [6].

Table 3. Pedroni panel cointegration tests (Null Hypothesis: No cointegration)

	ν – stat	*ρ – stat*	*PP – stat*	*ADF – stat*
Alternative hypothesis: common AR coefs. (within-dimension)				
Unweighted panel stats	0.964	–0.907	–5.187 ***	–5.353 ***
Weighted panel stats	–1.426	–0.684	–5.635 ***	–6.453 ***
Alternative hypothesis: individual AR coefs. (between-dimension)				
Group-mean stats		0.795	–4.525 ***	–4.542 ***

Notes: 1) All of the panel and group statistics have been standardized by the means and variances given in Pedroni (1999) so that all reported values are distributed as N (0,1) under the null hypothesis of no cointegration; 2) The panel-stats weighted statistics are weighted by long run variances (Pedroni, 1999, 2004); 3) An * (**) [***] indicates rejection of the null hypothesis at the 10% (5%) [1%] significance level based on the appropriate critical values (1.28, 1.64 and 2.33, respectively); 4) For the semiparametric *PP* tests the Newey-West (1994) rule for truncating the lag length for the kernel bandwidth has been used, and for the parametric *ADF* tests a step-down procedure starting from $K = 2$ has been used; 5) The residuals have been estimated using the least squares estimator.

[5] See Gutiérrez (2003) for a Monte Carlo analysis of the statistical properties of these tests.

[6] With respect to the Maddala-Wu results, it is known that the Johansen tests —the kernel of the Maddala-Wu statistics— for the second and subsequent cointegrating vector suffer from substantial size distortions and tend to find multiple cointegrating vectors when the ratio of data observations to the number of parameters is relatively small (Maddala and Kim, 1998). This might explain the non rejection of the hypothesis of the presence of two cointegrating vectors both in maximal eigenvalue and trace statistics.

Table 4. Kao panel cointegration test (Null Hypothesis: No cointegration)

	t – stat
ADF	–4.347 ***

Notes: 1) Probability has been computed assuming asymptotic normality; 2) An * (**) [***] indicates rejection of the null hypothesis at the 10% (5%) [1%] significance level based on the appropriate critical values; 3) Trend assumption: No deterministic trend; 4) Lag selection: Automatic 2 lags by SIC with a max lag of 2; 5) Newey-West bandwidth selection using Bartlett kernel; 6) The residuals have been estimated using the least squares estimator.

Table 5. Maddala and Wu Fisher-type panel cointegration tests [Null Hypothesis: number (r) of cointegration relationships]

	Trace – stat	*Max.eigen. – stat*
$r = 0$	221.10 ***	185.00 ***
$r \leq 1$	76.26 ***	56.99 ***
$r \leq 2$	44.76	40.22
$r \leq 3$	44.96 *	44.96 *

Notes: 1) Probabilities have been computed using asymptotic Chi-square distribution; 2) An * (**) [***] indicates rejection of the null hypothesis at the 10% (5%) [1%] significance level based on the appropriate critical values; 3) Trend assumption: Linear deterministic trend; 4) Lags interval (in first differences): 1 to 1.

The next step is to estimate the parameters of the detected long-run equilibrium production function. The estimated steady-state relationship has the following expression:

$$y_{it} = \beta_{0,i} + \beta_1 e_{it} + \beta_2 k_{it} + \beta_3 pk_{it} + \beta_4 t + v_{it} \tag{1}$$

where $y = \log Y$, $e = \log E$, $k = \log K$ and $pk = \log PK$. As shown, long-run homogeneity of input elasticities is assumed [7], fixed-region effects ($\beta_{0,i}$) are permitted in order to control for time-invariant regional heterogeneity, and a temporal trend (t) is introduced to take into account the time evolution of the technical progress [8]. Given the homogeneity of slopes hypothesis assumed in the above specification, the estimated relation must be interpreted as an average long-run equilibrium production function for the panel of 17 Spanish regions.

With respect to the technique chosen to estimate the equilibrium relationship, and given that ordinary least squares (OLS) estimates of the long-run model would

[7] We also perform the long-run analysis on a region-by-region basis using the Johansen approach. Not surprisingly (due to the short span of data available at the single-region level), the Johansen individual-estimates of the long-run parameters were mixed and noisy, with some coefficients appearing as implausible. The poor results obtained in this case compels us to impose the homogeneity assumption in the estimation of the long-run equilibrium production function [see, among others, the works of Pesaran *et al.* (1999) and Baltagi *et al.* (2000) that consider the issue of pooling in detail, asking the question «To pool or not to pool?»].

[8] Also, introducing a trend in the long-run relation ensures that the deterministic trend properties of the VEC models estimated later remain invariants to the cointegrating rank assumptions (Pesaran *et al.*, 2000).

suffer from asymptotic bias (Kao and Chiang, 2000), the so-called Dynamic Seemingly Unrelated Cointegrating Regressions (DSUR) method proposed by Mark *et al.* (2005) was used. This method allows for the efficient simultaneous estimation of panel cointegrating relationships with correlated disequilibrium errors, working with panel data in which, as in our case, the cross-sectional dimension is small or about the same order with respect to the length of the time series.

The results of the DSUR estimation of the average long-run production function are presented in Table 6. According to these results, the elasticity of employment is around 0.35. Private capital and public capital show elasticities estimated to be 0.32 and 0.10, respectively. In terms of statistical significance, magnitude and theoretical plausibility, the estimates obtained from the DSUR are very consistent, and are well within the range of estimates obtained by other authors. In this sense, one could point to the work of Kamps (2005) and Romp and de Haan (2005), among others, who have summarize information on international studies that have analyzed the dynamic effects of public capital, while Boscá *et al.* (2004) and Mas and Maudos (2005) present surveys of the Spanish experience about this topic.

Table 6. DSUR estimates for $y_{it} = \beta_{0,i} + \beta_1 e_{it} + \beta_2 k_{it} + \beta_3 pk_{it} + \beta_4 t + v_{it}$

$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$
0.348 *** [0.025]	0.315 *** [0.029]	0.102 *** [0.022]	0.010 *** [0.001]

Notes: 1) Cross-section SUR standard errors are given in brackets; 2) An * (**) [***] indicates rejection of the null hypothesis at the 10% (5%) [1%] significance level based on the appropriate *p*-values.

3.3. Region-specific and short-run S-VEC models

In the empirical strategy, an explicit distinction is made between the long-run properties of the regional economies (associated in our case with the cointegrating production function suggested by the economic theory and tested and estimated in the previous sub-section) and the short-run dynamics of the regional system. In this sense, the modeling approach assumes that macroeconomic or regional economic theories are not explicit enough to propose specific relationships that might exist between the input and output regional variables over short time horizons. Hence, a parsimonious and flexible econometric specification is used that attempts to account for the complex dynamic relationships that drive the short-run regional behavior. Specifically, the short-run dynamics of each region are modeled within a VAR framework using S-VEC models that drive the dynamics of adjustment of the input and output variables of each region to the long-run equilibrium across-regions.

These hypotheses allow estimation and testing of the domestic properties of the different region-specific models, analyzing the dynamics of the transmission of shocks from public capital to the rest of state variables (private capital, employment and output).

The reference individual S-VEC model for the region i ($i = 1,2,...,17$) is given by:

$$A_i(L)\Delta X_{it} + C_i Z_{it} = E_{it} \quad , \quad A_{i0}E_{it} = B_i U_{it} \tag{2}$$

where $X_{it} = (pk_{it}, k_{it}, e_{it}, y_{it})'$ is the vector of endogenous variables; $Z_{it} = (1, \hat{\upsilon}_{i,t-1})'$ is the vector of predetermined variables, given in the empirical application by an intercept and the lagged estimated error correction term corresponding to the equilibrium relationship presented in Table 6; $E_{it} = (e_{it}^{pk}, e_{it}^{k}, e_{it}^{e}, e_{it}^{y})'$ is the canonical errors vector from the reduced form; and $U_{it} = (u_{it}^{pk}, u_{it}^{k}, u_{it}^{e}, u_{it}^{y})'$ is the structural errors vector [9]. Matrix $A_i(L) = \sum_k A\_K_i L^k$ includes in our application a maximum of four lags, the optimal lag determined by the standard selection criteria AIC, HQ and SC, where the higher lag order is chosen based on these three information statistics.

With respect to the identification of the structural innovations, a standard recursive Cholesky-type decomposition scheme was used assuming that the relation between the canonical errors and the structural disturbances is given by the equation $A_{i0}E_{it} = B_i U_{it}$, where:

$$A_{i0} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ a_{21}^i & 1 & 0 & 0 \\ a_{31}^i & a_{32}^i & 1 & 0 \\ a_{41}^i & a_{42}^i & a_{43}^i & 1 \end{bmatrix} \qquad B_i = \begin{bmatrix} b_{11}^i & 0 & 0 & 0 \\ 0 & b_{22}^i & 0 & 0 \\ 0 & 0 & b_{33}^i & 0 \\ 0 & 0 & 0 & b_{44}^i \end{bmatrix} \tag{3}$$

This identification scheme has the following implications: i) innovations in public investment affect contemporaneously private capital, employment and real output, but the reverse is not true, ii) shocks to private capital affect contemporaneously the employment and real GAV, but the reverse is not true, and iii) unanticipated changes in employment affect contemporaneously the real GAV, but employment does not react contemporaneously to shocks in regional output. Therefore, the identified shocks are not subject in any case to the reverse causation problem.

3.4. Are there significant domestic effects of public capital formation in the Spanish regional system?

Tables 7 and 8 show summary information about the domestic effects of shocks in public capital installed inside each region displaying, respectively, the short-run and long-run elasticities of private capital, employment and real GAV obtained from

[9] To facilitate the interpretation of the estimated impulse responses, the endogenous variables (in logs) of the structural VEC models have been multiplied by 100. In this case, the accumulated impulse responses provide the percentage change in the level of the respective variable.

the seventeen regional S-VEC models considered [10]. These estimates generate respectively the 0 year point and 25 year point percentage change in private capital, employment, and output per one-percentage point (impact or long-run) change in public capital. Each point estimate in the tables is marked (or not) with an asterisk depending on the corresponding 68% confidence interval that does not include zero [11].

Table 7. Short-run effects of public capital (individual region models)

Region	*Private capital*	*Employment*	*Real GAV*
Andalucía	0.12 *	0.59 *	0.59 *
Aragón	0.34 *	0.49 *	–0.27 *
Asturias	–0.10 *	–0.25	–0.49 *
Baleares	0.01	0.45 *	0.46 *
Cantabria	–0.21 *	–0.01	–0.09
Castilla-León	–0.23 *	0.18	–1.05 *
Castilla-La Mancha	0.09 *	0.35 *	0.93 *
Canarias	0.37 *	0.60 *	0.73 *
Cataluña	–0.14 *	–0.21 *	0.32 *
Comunidad Valenciana	0.06	0.07	0.29 *
Extremadura	0.05	–0.21	0.11
Galicia	0.10 *	–0.10	0.32 *
Madrid	0.05	0.23	0.58 *
Murcia	0.01	0.41 *	–0.01
Navarra	–0.07 *	0.02	–0.16 *
País Vasco	–0.02	–0.21 *	–0.10
La Rioja	0.04 *	0.52 *	0.26 *

Note: A (*) denotes that the corresponding 68% Hall percentile confidence interval does not include zero. The confidence intervals for individual regions are computed using a bootstrap procedure with 1,000 replications.

[10] They are obtained by dividing the impact or long-run response of private capital, employment, and real GAV to a shock to public capital, respectively, by the impact or long-run response of public capital to a shock to public capital. In the computations, we set the response horizon $T = 25$ (since from the simulations it was possible to verify that for all regions the impulse responses converged to their long-run levels before 15 years) to ensure that for all regions the impulse responses have converged to their long-run levels.

[11] The confidence intervals have been computed using Hall's percentile interval bootstrap procedure described in Breitung *et al.* (2004), and are based on 1,000 bootstrap replications.

Table 8. Long-run effects of public capital (individual region models)

Region	*Private capital*	*Employment*	*Real GAV*
Andalucía	–0.04 *	0.27 *	0.31 *
Aragón	0.32 *	0.01	–0.31 *
Asturias	–0.87 *	–0.65 *	–1.92 *
Baleares	0.66 *	0.20	–0.14 *
Cantabria	–0.15 *	–0.08	0.48 *
Castilla-León	–0.28 *	0.57 *	–0.09
Castilla-La Mancha	–0.15 *	0.02	0.12
Canarias	0.62 *	0.35 *	0.11
Cataluña	0.05	–0.52 *	0.32 *
Comunidad Valenciana	0.18 *	0.48 *	0.59 *
Extremadura	–0.55 *	0.34 *	0.04
Galicia	–0.42 *	–0.32 *	–0.47
Madrid	0.28 *	–0.17	–0.07
Murcia	0.27 *	0.51 *	0.83 *
Navarra	0.11	0.15 *	0.15 *
País Vasco	–0.44 *	–0.46 *	–0.43 *
La Rioja	0.15 *	0.32 *	0.20 *

Note: A (*) denotes that the corresponding 68% Hall percentile confidence interval does not include zero. The confidence intervals for individual regions are computed using a bootstrap procedure with 1,000 replications.

Overall, the estimated effects suggest a highly significant pattern of responses of regional private capital, employment and output to innovations in public capital located in the region itself. The regional effects of innovations in public infrastructures on output, employment and private capital are now considered.

Starting from the effects on output, the short-run real GAV effects of public capital (Table 7) show significantly positive responses in nine of the seventeen cases. This output response is statistically significant and negative in four regions located in the medium-upper zone of Spain (Aragón, Asturias, Castilla-León and Navarra), whereas four regions have no significant output responses (Cantabria, Extremadura, Murcia and País Vasco). For these regions exhibiting negative output responses, a possible explanation is that labor and private capital are altered by the rising stock of public capital. In other words, public capital and private capital could be substitutes in the short run, crowding out employment.

Regarding the long-run responses of output to a shock to public capital installed inside the regions (Table 8), the general pattern is similar to the short-run responses: the results show that seven responses are significant and positive, four responses are significant and negative (Aragón, Asturias, Baleares and País Vasco), and six cases are not significant. The new steady state shows that, as in the case of the short-run, Aragón and Asturias have negative responses on output.

The results reported in Tables 7 and 8 also show that all the significant and positive short- and long-run output elasticities are smaller than 1, indicating that an increase in public capital of a one percent will imply a less than one short- or long-run increase in the real GAV. The more than proportional negative output effects of public capital in Castilla-León (in the short term) and Asturias and País Vasco (in the long run) may be explained by the substitution effect of public capital on private output in these regions, accompanied by a negative elasticity of employment in the last two regions.

As general conclusion, the results would indicate that public capital is productive for most regions, indicating that public capital and private capital are complements in the long-run. Comparing our estimates with those (long term) reported in Pereira and Roca-Sagalés (2003), and considering both significance and sign of the elasticities, the present study only has the same results in 7 of the 17 cases; specifically in the cases of Andalucía, Asturias, Cantabria, Cataluña, Comunidad Valenciana, Galicia and Murcia. This lack of consensus between these results could be explained by two factors: the use of a different sample (1970-1995 in the case of the cited reference and 1972-2000 in the present paper) and a different methodology (in this paper VEC models in levels are used to produce consistent estimates of impulse responses, whereas in Pereira and Roca-Sagalés VAR models in first differences are used which might produce —due to the non consideration of cointegration properties in the estimated systems— inconsistent estimates of impulse response functions).

As regards the short-run responses of employment to a shock to public capital (Table 7), there are only two regions for which the short-run effects of public capital are negative and significant: Cataluña and País Vasco. In the rest of the regions, seven regions have significant and positive short-run effects, while eight regions have no significant effects. In the long run (Table 8), the results indicate that public capital and employment are complements (significant and positive effects) for eight regions and present substitute characteristics for four regions, while the rest (five regions) have no significant effects.

The estimates for private capital elasticities are less conclusive, since in the short-run they are positive for six regions and negative in the case of five regions. For the rest of the regions, these short-run measures are not statistically significant. In the long-run, the pattern is similar: significant and positive elasticities in the case of seven regions, significantly negatives in the case of eight regions, and no statistically significance in the rest of the remaining two regions. This would indicate that private capital and public capital could act as both complements and substitutes in the long-run.

In summary to this point, the long-term effects of public capital formation installed inside the Spanish regional system could lead to an increase in the long-run in both the regional real GAV and the regional employment. Nevertheless, if the aim is to increase private capital in the long-run, there is no empirical evidence that an increase in public capital would generate the required response from the private sector.

3.5. Discussion

From the empirical literature, the impact of public capital on private capital is complex and uncertain. From a theoretical perspective, and in the framework of a production function where the public capital stock is introduced as a separated input, it is possible to establish three different relationships between public capital and private capital. In short, they could be complementary, independent or direct substitutes (see, for example, Ramírez, 2000).

If public capital is complementary to private capital, an increase in public capital will increase output directly. In addition, public capital will increase private capital investment directly while public capital will increase output indirectly (stimulating positively the marginal productivity of the private capital stock). Finally, as public capital increases the amount of both private and public capital per worker, the marginal productivity of labor increases, increasing output.

In the case where public capital and private capital are independent, an increase in public capital will generate a positive effect on output and the marginal productivity of labor in the public sector only.

If public and private capital are direct substitutes, an increase in public capital formation will raise output directly. Nevertheless, there will exist a negative effect on the marginal productivity of private capital and labor that could counterbalance the positive effects.

Under the aforementioned relationships, we can say that public capital is complementary to private capital in 3 Spanish regions (Comunidad Valenciana, Murcia, and Rioja); public capital is independent to private capital in 2 Spanish regions (Cataluña and Navarra), and there is a direct substitution effect for the case of 8 Spanish regions (Andalucía, Asturias, Cantabria, Castilla-León, Castilla-La Mancha, Extremadura, Galicia and País Vasco). Finally, for the rest of the Spanish regions (Aragón, Baleares, Canarias and Madrid), from our results it is not possible to classify the type of relationships between public and private capital.

The empirical findings of this paper would suggest that increases in public capital in core Spanish regions would raise the marginal productivity of private capital thereby inducing higher rates of private investment spending. On the other hand, public capital investment in peripheral regions can be substituted directly for private capital investment. These results for peripheral regions could retard future regional economic growth. Effectively, the detected crowding out effects could act as a penalty in peripheral regions if they operate in key sectors of the regional economy such as basic industries and agriculture.

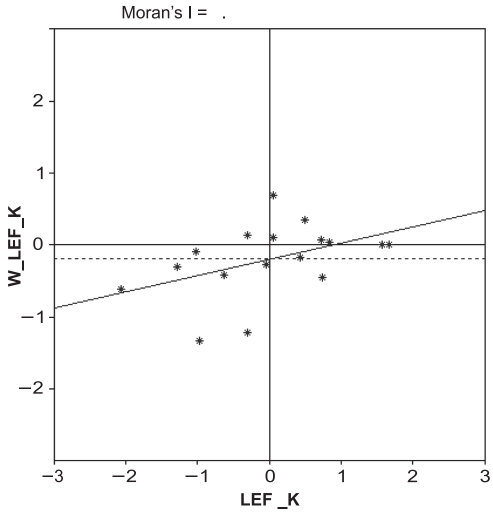
Another additional goal of this discussion is to enlarge the empirical analysis of the detected effects by means of the consideration of the spatial dimension. In this sense, the geographic dimension of the different estimated effects were explored by using an exploratory spatial data analysis (ESDA) approach. This analysis will help with the identification of the type of spatial pattern present in the distribution of regional effects. All computations were carried out by using SpaceStat 1.91 (Anselin, 2002), GeoDA (Anselin, 2003) and ArcView GIS 3.2 (ESRI, 1999) software packages. First, global spatial autocorrelation was tested by using Moran's I statistic (Cliff and Ord, 1981), $I = \frac{N}{S_0} \frac{z'Wz}{z'z}$, where N is the number of regions, $S_0 = \sum_i \sum_j w_{ij}$, z_{it} is the effect of public capital in region i for the t cases considered in deviation from the mean, W was defined expressing for each region (row) those regions (columns) that belong to its neighborhood. Formally, $w_{ij} = 1$ if regions i and j are neighbors, and $w_{ij} = 0$ otherwise. This simple contiguity matrix ensures that interactions between regions with common borders are considered. For ease of economic interpretation, a row-standardized form of the W matrix was used. Thus, the spatial lags terms represent weighted averages of neighboring values.

The values of I for five of the six different effects were well below the expected value for this statistic under the null hypothesis of no spatial correlation. It appears that these effects are not spatially correlated, since their statistics are not significant. Nevertheless, for the case of the long-run effects of public capital on private capital, the Moran's I reveals the existence of a strong and statistically significant degree of positive spatial dependence in the distribution of regional effects. Figure 2 shows the spatial distribution of long-run effects of public capital on private capital. Figure 3 provides a clearer view of the spatial autocorrelation in these regional effects through the Moran scatterplot, showing a strong geographic pattern and revealing the presence of positive spatial dependence.

Figure 2. Long-run regional effects from public capital on private capital

Note: LEF_K denotes long-run regional effects from public capital on private capital.

Figure 3. Morans' I of long-run regional effects from public capital on private capital



Note: LEF_K denotes long-run regional effects from public capital on private capital; W_LEF_K denotes the spatial lag of LEF_K. For the calculated Moran's I, p-value = 0.024.

Both figures show a strong geographic pattern, revealing the presence of spatial heterogeneity in the form of two spatial clusters of rich and poor regions, with the rich regional economies' cluster including the regions within the triangle area comprising the axis País Vasco-Cataluña, Cataluña-Valencia and Valencia-País Vasco plus the capital, Madrid, and the islands (Baleares and Canarias); whereas the rest of the regional system could be characterized as the Spanish «periphery» with less economic activity and a much lower level of per capita income.

4. Summary and conclusions

The effects of public capital on economic growth have received a great deal of attention in the recent economic literature. Within the approaches that have been applied to assess the impact of public infrastructures, this paper estimates the dynamic domestic effects of innovations in public capital using a structural vector autoregressive (S-VAR) methodology for the Spanish regions.

From a methodological point of view, the work contains different innovative features with respect to the previous studies using S-VAR models. First, recently developed panel integration and cointegration tests are used to examine the long-run determinants of aggregate regional production. Thereafter, using a two-step approach (*a la* Engle and Granger, 1987) the detected cointegrating relation is first estimated and then the residuals from the long term relationship are used to estimate individual region-specific structural vector error-correction (S-VEC) models. Thus, the domestic dynamic properties of the estimated S-VEC models are investigated via impulse response functions that portray the effects of shocks to the public capital installed in one region on the rest of variables of the region. As a general conclusion, the long-term effects of public capital formation installed inside the Spanish regional system could lead to an increase in the long-run in both regional real GAV and employment. Nevertheless, if the aim is to increase private capital in the long-run, there is no empirical evidence about the appropriateness of stimulating private capital through an increase in public capital as an adequate policy measure. In the short-run, private capital and public capital could act as both complements and substitutes, although employment seems to receive a predominantly positive stimulus in the short-run from public capital formation.

From these estimates, the direct substitution effects prevail for the peripheral regions. Thus, more precise indications for policy-making can come from further research on the underlying reasons as to why these effects happen. The findings in this paper suggest that regional policy makers would have to implement regional measures where the increases of public capital do not imply negative effects on private capital.

Finally, this paper considers that there exists cross-sectional independence, which probably is not the case. Further analysis on this issue could be conducted in the future using extended versions of the class of VAR models applied in the present work. The natural extension would be to formulate a «Global VAR» model for the Spanish regional system. This would combine all the S-VAR models in a global specification in which the state variables of each region would be related to the state variables of the rest of the regions (see Pesaran *et al.,* 2004, and Dees *et al.,* 2007). Related to this, if there exists spatial dependence in the data, it would be more appropriate to use a «Second Generation» approach in the unit-roots and cointegration analysis of section 3, which assumes the existence of cross-sectional dependence (Breitung and Pesaran, 2008).

Also, as stated by a referee, another extension for the future could be to split public capital into its two main components: i) transport infrastructure and ii) the rest.

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Section EMPIRICAL CONTRIBUTIONS

A revisited gravity equation in trade flow analysis: an application to the case of Tunisian olive oil exports

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ABSTRACT: This study revisits the utility of gravity models in the analysis of the principal determinants of exports. Traditional cross-sectional models are improved by considering the effect of omitted variables and/or the dynamic of trade flows through the use of spatial econometric techniques and panel data specification. This proposal is applied to the Tunisian olive oil exports during the period 2001-2009. The results provide evidence of the inertia found in export volumes, with trade relations anchored in the past likely to continue in the future. Also, we obtain evidence on the existence of a clear similarity in flows between neighbouring importing countries. On the other hand, the results show a positive, significant relationship between the importing country's income level and imported olive oil volume. The effect of importers' human development index is positive. The distance between countries has a negative impact on trade flow. On the contrary, sharing a common language increases olive oil trade flows. Finally, trade figures and results reflect a strong dependence of Tunisian olive oil production on precipitations.

JEL Classification: F10, R15, C23.

Keywords: Gravity model, spatial econometrics, panel data, tunisian olive oil exports.

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Una ecuación de gravedad revisada en el análisis de flujos de comercio: una aplicación al caso de las exportaciones de aceite de oliva tunecino

RESUMEN: Este trabajo revisa la utilidad del modelo de gravedad para el análisis de los principales determinantes de la exportación. Se mejoran los modelos tradicionales de corte transversal mediante la consideración de los efectos de las variables omitidas y/o la dinámica de los flujos de comercio, a través del uso de las técnicas de econometría espacial y de especificaciones para datos de panel. Esta propuesta se aplica a las exportaciones de aceite de oliva tunecino durante el periodo 2001-2009. Los resultados muestran evidencia acerca de la inercia encontrada en los volúmenes de exportación, dado que es probable que las relaciones de comercio afianzadas en el pasado continúen en el futuro. También se obtiene evidencia acerca de la existencia de claras similitudes entre los flujos de los países importadores vecinos. Por otra parte, los resultados muestran una relación positiva y significativa entre el nivel de renta del país importador y el volumen de aceite de oliva importado. El efecto del índice de desarrollo humano de los países importadores es positivo. La distancia entre países tiene un efecto negativo sobre el volumen de comercio. Por el contrario, compartir el mismo idioma aumenta el flujo de comercio de aceite de oliva. Finalmente, las cifras de comercio y los resultados reflejan una fuerte dependencia de la producción de aceite de oliva tunecino de las precipitaciones.

Clasificación JEL: F10, R15, C23.

Palabras claves: Modelo de gravedad, econometría espacial, datos de panel, exportaciones de aceite de oliva tunecinas.

1. Introduction

The gravity model has often been used to explain Origin-Destination (OD) flows such as international or regional trade, transportation flows, population migration, commodity flows, information flows along a network, patients' flows to hospitals, etc. Reasons for the prosperity of this model are the simplicity of its mathematical form and the intuitive nature of its underlying assumptions, as Sen and Smith (1995) noted in their monograph.

In relation to international trade, there exists a large literature on theoretical foundations for these models (Anderson, 1979; Anderson and Wincoop 2004). In the regional science literature the gravity model has been labelled a spatial interaction model (Sen and Smith, 1995), because the regional interaction is directly proportional to regional size measures. The model relies on a function of the distance between origin and destination as well as explanatory variables pertaining to characteristics of both, origin and destination countries. The principal explanatory variables used to explain trade flows are as follows. The variables with a positive effect include size of importing economy, per capita income differential of the two countries involved, their degree of openness, the existence of general trade agreements, the existence of a common official language and/or currency, a shared colonial past or the existence of a favourable exchange rate. The factors with a negative impact on trade volumes include cost of transport, which usually depends on the distance between the countries involved.

Most previous empirical studies analyse cross-sectional data using mean flow data and the respective explanatory variables for several years as the model's variables. However, literature has been developed towards an appropriate treatment of two important issues: i) the consideration of the effect of possible omitted variables that could be correlated with the included ones; and ii) the introduction of dynamics. The solution to these problems can be found within two disciplines. On one hand, within the regional science literature, some solution comes with the use of spatial econometric models; on the other hand, the use of panel data econometrics can also overcome those problems. In this paper, we will compare both possible solutions.

Regarding spatial econometric techniques, the main issue deals with the concept of spatial dependence among the sample of OD flows, since as noted by Griffith and Jones (1980): i) flows from and origin are «enhanced or diminished in accordance with the propensity of emissiveness of its neighboring origin locations» and flows to a destination are «enhanced or diminished in accordance with the propensity of attractiveness of its neighboring destination locations». The usefulness of distance functions as the way of capturing spatial dependence has been deeply analysed in literature (see Griffith, 2007). However, many empirical works still rely on the assumption of independence among OD flows (LeSage and Pace, 2008). Recently, Porojan (2001), for the case of international trade flows, and Lee and Pace (2005), for retail sales, pointed out that residuals from conventional models were founded to exhibit spatial dependence. Within this argument, LeSage and Pace (2008) overcome the problem by using spatial models which, in fact, are solving a possible problem of omitted variables or a lack of capturing dynamics.

The main advantage of panel data econometric is that it prevents the so-called heterogeneity bias in the estimations, which is generated when a relevant variable is missing from the model. Panel models prevent such bias by considering the individual effects related to cross-sectional, generally the countries involved in trade, and/or time units (Matyas, 1997, 1998). Within this line, many studies have been conducted. For example, Wall (2000) applied the technique to trade figures between Canadian provinces and individual US states; Rose (2002) estimated the effect of multilateral trade agreements —World Trade Organisation (WTO), the General Agreement on Tariffs and Trade (GATT) and the Generalised System of Preferences (GSP)— on international trade, using figures from 175 countries for more than 50 years; Rahman (2004) analysed the trade flows of Bangladesh; finally, Abu Hatab *et al.* (2010) analysed Egyptian agricultural exports to its principal trade partners in the 1994-2008 period.

In this context, we proposed to compare the performance of both methodological alternatives. As an application, we offer results for the determinants of Tunisian olive oil exports which is one of the most important agricultural products exported from

Tunisia. The second section of the paper analyses the importance of the country's olive oil sector, analysing the main exporting countries in detail. We then present the estimated econometric model based on a gravity model using spatial and panel econometric framework. The fourth section describes the data and their sources and the fifth analyses the results obtained. The last section contains our conclusions and describes some future lines of research.

2. Tunisian olive oil sector and exports

Olive orchards in Tunisia occupy 1.7 million ha, the equivalent of 30% of the total arable land, and represent about 19% of the world olive orchards (second largest olive land after Spain which counts 3 million ha). Sixty-six million olive trees are widespread all-over the country: North, Centre and South. The olive oil sector employs directly or indirectly over one million persons and 269,000 farmers are dedicated to this growing.

Olive oil production in Tunisia is highly dependent on precipitations. For the last three years olive oil production was stabilized around 170,000 tons/year. Tunisian government is encouraging the use of irrigation (intensive or hyper-intensive growing) to increase the proportion of irrigated olive orchards (2% actually) in order to decrease production fluctuation mainly due to climatic change.

The Tunisian olive oil manufacturing system is composed by three triturating systems that coexist actually: the traditional one called «classic», the Super-Press, and the modern one. The red accounts for 1,734 olive oil mills (MAHR, 2010) decomposed as follows: 628 classic units, 388 Super-Press, 718 continuous chains. Some olive oil mills have more than one type of processing units. They are called mixed units. In addition to this processing structure, the sector counts with 40 industrial units for olive oil packaging, or for pomace olive oil extraction. Actually the overall trend is to increase the number of modern olive oil mills (continuous chains).

Olive oil consumption in Tunisia ranges between 35,000 to 50,000 tons per year (25% to 30% of total production). Trend consumption is showing a decreasing pattern during the last decade essentially due to price increment, but also to culinary and habit changes in the Tunisian population. Compared to other traditional producing countries, olive oil per capita consumption in Tunisia is very low (around 4 kg/capita/year). Olive oil consumption is mainly in bulk. Tunisian consumers are used to purchase olive oil directly from the manufacture. Bottled olive oil purchase still very limited (3% of total consumption) and concentrated in large cities like Tunis Capital.

Olive oil exports account for 120,000 tons per year representing 70% of total production. They also represent 10% of total exports in values and about 45% of agro-food exports (first ranked product). Tunisia occupies the fourth position as olive oil exporter preceded by Spain, Italy and Greece. These exports are mainly directed to the European Union (Italy, Spain, France), USA, Morocco and Switzerland

(Figure 1). These countries receive from 88% (2002) to 98% (2005 or 2006) of total Tunisian olive oil exports (Table 1). In general, this ranking has remained unaltered over time. These figures show that exports are highly concentrated, which could be seen as a weakness and a threat for future Tunisian olive oil sales abroad.

Figure 1. Value of Tunisian olive oil exports to leading importers (thousands of dollars)

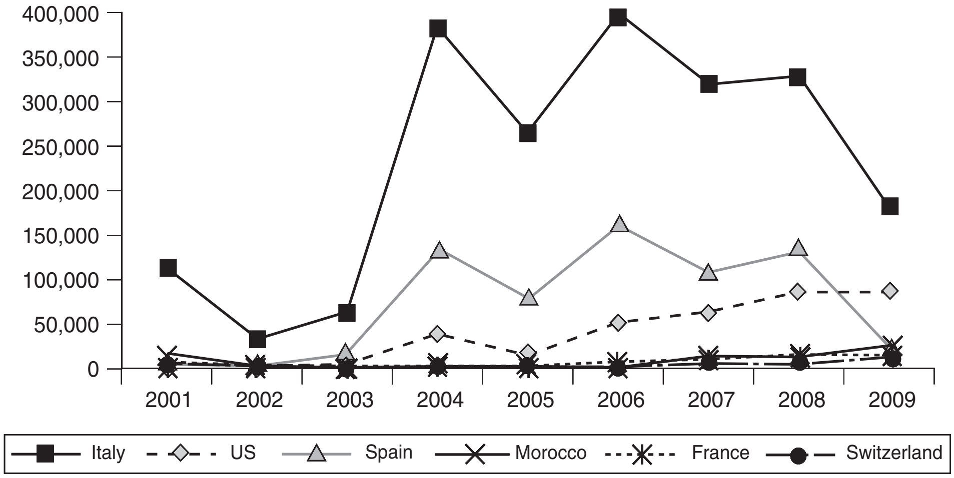

Table 1. Evolution of the market share of leading Tunisian olive oil importers (2001-2009) (%)

	2001	*2002*	*2003*	*2004*	*2005*	*2006*	*2007*	*2008*	*2009*
Italy	80.4	81.0	69.8	66.6	71.5	62.7	58.9	52.9	46.2
US	5.5	6.4	4.1	6.8	4.5	8.3	11.4	14.1	21.7
Spain	5.8	0.0	20.5	23.6	22.0	25.7	20.1	21.3	6.5
Morocco	0.9	0.2	0.0	0.4	0.0	0.2	1.9	2.3	6.1
France	0.7	0.5	0.3	0.2	0.2	1.3	1.8	3.2	3.7
Switzerland	1.3	0.1	0.9	0.5	0.0	0.0	1.5	0.6	3.3
Total	**94.5**	**88.1**	**95.7**	**98.1**	**98.2**	**98.2**	**95.5**	**94.5**	**87.7**

During the last decade (2000 to 2009), around 190 olive oil companies have exported Tunisian olive oil with no continuous frequency. Only 9 companies exported olive oil continuously each year. They regrouped on average 65% of total Tunisian olive oil exports value.

3. Methodology

The traditional econometric formulation of the gravity model applied to the trade between two countries, *i* and *j,* is given by the following expression:

$$\ln\left(F_{ij}\right) = \beta_0 + \beta_1 \ln\left(Xo_i\right) + \beta_2 \ln\left(Xd_j\right) + \beta_3 \ln\left(D_{ij}\right) + u_{ij} \qquad (1)$$

where F_{ij} is the volume of trade between country *i* and country *j*; Xo_i represents the emission capacity of the country of origin (exporter); Xd_j represents the power of attraction of the country of destination (importer); D_{ij} denotes the distance between them; and u_{ij} is the error term under ideal condition.

Traditionally, equation (1) has been applied to cross-sectional data using mean flow data and the respective explanatory variables for several years as the model's variables. However, if a panel data set is available, the corresponding pool gravity model can be expressed as:

$$\ln\left(F_{ijt}\right) = \beta_0 + \beta_1 \ln\left(Xo_{it}\right) + \beta_2 \ln\left(Xd_{jt}\right) + \beta_3 \ln\left(D_{ijt}\right) + u_{ijt} \qquad t = 1,\ldots T \qquad (2)$$

As explained in the introduction section, several authors pointed out that previous specification should be improved in order to consider the effect of possible omitted relevant variables and/or to consider the dynamics of trade. Next, we show how spatial econometrics and panel data econometrics overcome those problems.

3.1. Spatial econometric literature

3.1.1. Treatment of omitted variables

As shown in LeSage and Pace (2008), the use of traditional least-squares regression to estimate gravity models ignores possible spatial dependence in the sample data of flows. As a consequence, the estimated parameter could be biased and inconsistent (LeSage and Pace, 2004). In our case, the origin country (*i*) is Tunisia, while we have *N* the destination countries (*j* = 1..., *N*). Therefore, we analyse what it is called in literature a Local Origin-Destination flow model. For each year, our model involves *N* observations, providing a situation similar to traditional spatial econometric applications. In these circumstances, the spatial weight matrix labelled *W*, represents as a *N* by *N* nonnegative, sparse matrix, would contain positive elements for neighbors to each of the regions treated as destinations. Besides continuities, various measures of proximity such as cardinal distances (e. g. kilometres), and ordinal distance (e. g., the *s* closest neighbors) can be used.

LeSage and Pace (2008) motivate the presence of spatial lags in flows on an omitted variables argument. For instance, we assume that a single omitted variable *z*, for instance, the political situation in countries involved in trade, is an important determinant of trade, but we don't have data on that. Beside, such omitted variable could exhibit spatial dependence, which we represent using a spatial autoregressive process consisting of a scalar spatial dependence parameter ρ and the spatial weight matrix W, as follows:

$$\begin{aligned} \ln\left(F_{ijt}\right) &= \beta_0 + \beta_1 \ln\left(Xo_{it}\right) + \beta_2 \ln\left(Xd_{jt}\right) + \beta_3 \ln\left(D_{ijt}\right) + z_{ijt} \\ z_{ijt} &= \rho W z_{ijt} + \varepsilon_{ijt} \\ \varepsilon_{ijt} &= \gamma_0 + \gamma_1 \ln\left(Xo_{it}\right) + \gamma_2 \ln\left(Xd_{jt}\right) + \gamma_3 \ln\left(D_{ijt}\right) + u_{ijt} \end{aligned} \tag{3}$$

Expression (3) indicates that the omitted and included variables are correlated with the scalar parameter $\gamma \neq 0$, which is the typical assumption made in the omitted variable literature.

From equation (3), we can arrive at the so-called Spatial Durbin Model (SDM) as protection against bias arising from possible omitted variables, with independent, identically distributed (*iid*) disturbances, which in matrix notation can be expressed as:

$$\begin{aligned} &\ln\left(F\right) = \rho W \ln\left(F\right) + X\left(\beta + \gamma\right) + WX(-\rho\beta) + u \\ &\text{with } \beta' = \left[\beta_0\, \beta_1\, \beta_2\, \beta_3\right];\ \gamma' = \left[\gamma_0\, \gamma_1\, \gamma_2\, \gamma_3\right];\ X = \left[\iota \ln\left(Xo_{it}\right) \ln\left(Xd_{jt}\right) \ln\left(D_{ijt}\right)\right] \end{aligned} \tag{4}$$

with ι, we denote a vector of ones. Including the notation $\theta = \beta + \gamma$ and $\phi = -\rho\beta$, previous model can be expressed as:

$$\ln\left(F\right) = \rho W \ln\left(F\right) + X\theta + WX\phi + u \tag{5}$$

From estimated parameter in (5), we can recover estimates for the individual parameters in model (3).

If the parameter $\gamma = 0$, it means that the included and excluded variables are not correlated, and the restriction $\phi = -\rho\theta$ holds. In this case, a Spatial Error Model (SEM) emerges:

$$\left(\ln\left(F\right) - \rho W \ln\left(F\right)\right) = \left(X - \rho WX\right)\beta + u \quad \text{or} \quad \begin{cases} \ln\left(F\right) = X\beta + z \\ z = \rho W z + u \end{cases} \tag{6}$$

Note that, both, SDM and SEM models rely on a model that includes spatial lags of the dependent and explanatory variables.

A likelihood-ratio (LR) test based on log-likelihood values from SDM and the SEM models tests the restriction $\phi = -\rho\theta$ for the coefficient on WX and X. Obviously, this restriction can only hold when the parameter $\gamma = 0$, indicating no omitted variables exist that are correlated with those included in the model.

3.1.2. How to introduce dynamic into the model

As shown in LeSage and Pace (2008), the Spatial Autoregressive model (SAR) can be behind a purpose of considering a time-lag relationship describing a diffusion process over space. In other words, they view the spatial dependence as a long-run equilibrium of an underlying spatiotemporal process. That is, starting with a time-lag relationship as the following:

$$\ln\left(F_{ijt}\right)=\rho W\ln\left(F_{ijt-1}\right)+\beta_0+\beta_1\ln\left(Xo_i\right)+\beta_2\ln\left(Xd_j\right)+\beta_3\ln\left(D_{ij}\right)+u_{ijt} \qquad (7)$$

where they omit the time subscript on the explicative variables to reflect a situation where they reflect regional characteristics that describe regional variation flow changes slowly over time, relative to the change in flows. As shown in LeSage and Pace (2008), using the recursive relation: $\ln(F_{ijt-1}) = \rho W \ln(F_{ijt-2}) + \beta_0 + \beta_1 \ln(Xo_i) + \beta_2 \ln(Xd_j) + \beta_3 \ln(D_{ij}) + u_{ijt-1}$, implies in model (7), we can reach as the steady-state equilibrium model the Spatial Autoregressive (SAR) model, commonly used in the context of spatial econometric techniques:

$$\ln\left(F_{ijt}\right)=\rho W\ln\left(F_{ijt}\right)+\beta_0+\beta_1\ln\left(Xo_{it}\right)+\beta_2\ln\left(Xd_{jt}\right)+\beta_3\ln\left(D_{ijt}\right)+u_{ijt} \qquad (8)$$

3.2. Panel data econometric literature

3.2.1. Treatment of omitted variables

The use of the gravity model with panel data has the advantage that it prevents bias from omission of relevant variables by considering what is known as unobservable heterogeneity. If we have panel data, instead of considering the model's estimation for all the data, or the pool model, expressed in (2), we can estimate the following model:

$$\ln\left(F_{ijt}\right)=\beta_0+\beta_1\ln\left(Xo_{it}\right)+\beta_2\ln\left(Xd_{jt}\right)+\beta_3\ln\left(D_{ij}\right)+\beta_{ij}+u_{ijt} \qquad (9)$$

in order to take into account the unobserved heterogeneity thought the term β_{ij}.

3.2.2. How to introduce dynamic into the model

In the context of panel data set, previous model can be dynamised, considering the strong inertia in trade relations between countries. This would lead us to specify the following dynamic model:

$$\ln\left(F_{ijt}\right)=\beta_0+\beta_1\ln\left(Xo_{it}\right)+\beta_2\ln\left(Xd_{jt}\right)+\beta_3\ln\left(D_{ij}\right)+\beta_{ij}+\sum_{\tau=1}^{n}\rho_\tau\ln\left(F_{ij,t-\tau}\right)+u_{ijt} \qquad (10)$$

The traditional estimation of equation (10) consisted of applying the Generalised Method of Moments, using appropriate tools, to the model's first difference equations (Arellano and Bond, 1991) or the System Generalised Method of Moments («system GMM») proposed by Blundell and Bond (1998), which combines the moments conditions for the first difference model with the moments conditions for the level model.

4. Data analysis

Table 2 describes the data used in this analysis, its measurement unit and the sources used. The model's dependent variable refers to olive oil exports from Tunisia (country *i*) to the leading importers (countries *j* = Italy, US, Spain, Morocco, France and Switzerland). This information comes from the International Trade Centre (ITC). With regards to the explanatory variables, we use the variables commonly used in this type of model, such as importers' GDP [1], distance, together with a variable indicating a language shared by exporter and importers. To this last respect, we consider that France and Morocco are sharing the same language with Tunisia. All information refers to the period 2001 to 2009; therefore, we have a total number of 54 observations for each variable.

Table 2. Description of variables and data sources

Variable	*Description*	*Source*
F_{ij}: Exports from *i* to *j*	Thousands of dollars	International Trade Centre, calculations based on COMTRADE statistics [a]
GDP_d_j: *GDP* of importer *j*	GDP, PPP (current international $)	World Bank [b]
HDI_d_j: *HDI* of importer *j*	Standard of living in importing country	UN Development Programme [c]
D_{ij}: Distance from *i* to *j*	Distances between country capitals (km)	Distances between cities [d]
$Lang_{ij}$: Dummy variable related to language of countries.	1 if the importer and exporter have the same official language, 0 otherwise.	

[a] *http://www.trademap.org/Index.aspx*.
[b] *http://data.worldbank.org/country*.
[c] *http://hdr.undp.org/en/*.
[d] *http://www.marinewaypoints.com/learn/greatcircle.shtml*.

[1] As we are analysing unidirectional flows from Tunisia (what it is called in literature a Local Origin-Destination flow model), the characteristics of destination countries are the main determinants of flows.

Finally, particularly interesting is the variable related to the standard of living in both the importing and exporting country, known as the Human Development Index (HDI), which was edited by the United Nations Development Programme. This index measures a country's status in relation to three dimensions: health, education and living standards. The health dimension refers to life expectancy at birth, the education dimension to mean years and level of education and the living standards dimension to per capita income. Figure 2 shows this variable for Tunisia, the exporter, and the different importing countries.

Figure 2. Evolution of the Human Development Index (HDI) in Tunisia and importing countries

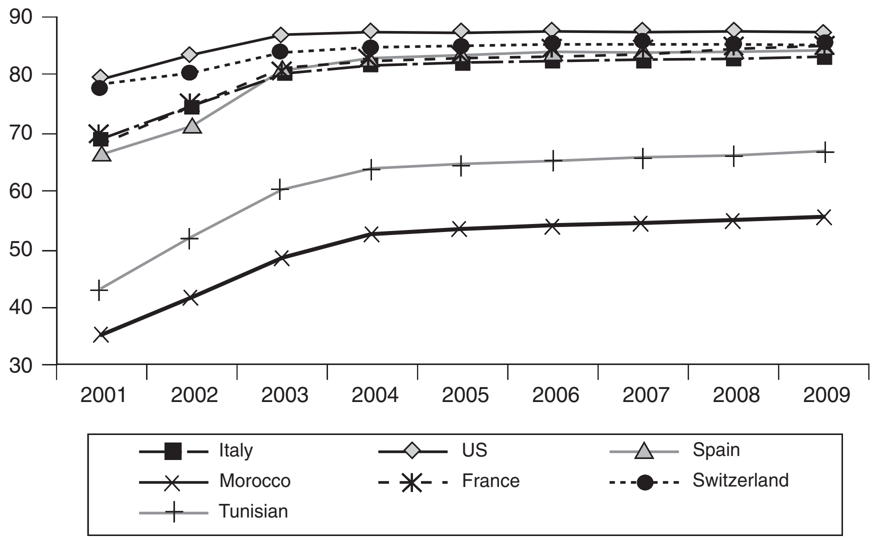

Figure 2 clearly leads us to several conclusions. On the one hand, the index has grown more since 2004, since which it has remain practically constant. On the other, the country with the lowest index is Morocco, followed closely by Tunisia. Finally, the ranking of the other countries is similar and stable over time, in the following order: Spain, Italy, France, Switzerland and the US.

Finally, in order to capture spillover and estimate the models, we must specify a W matrix to reflect the network of cross-sectional relationships in the system of importing countries. The weight matrix, W, is obtained after row-standardizing the matrix which weights are the inverse of the square distance between any pair of importers:

$$w_{ij} = \frac{1}{D_{ij}^2} \tag{11}$$

This specification captures the fact that distance between countries negatively affects interactions.

5. Results

This section shows the results obtained when the gravity model is estimated with both approaches: spatial and panel data econometric. As said before, the nature of the model, as a Local Origin-Destination flow model, makes that destination countries are the main determinants of flows. Analogously, spatial and panel models considers the effect of possible omitted variables referred to importers' countries. Table 3 shows the results obtained for spatial econometric and panel data techniques.

As regards spatial specifications, we follow the following steps. We start by estimating the traditional pool gravity model, expressed in (2), by Ordinary Least squares (OLS) enlarged by considering one dummy variables associated to the first three years of the sample, 2001-2003, which are characterised by a much smaller export volume. Results are displayed in the first column of the table. Next, we test the null hypothesis of no spatial dependence through the Lagrange Multipliers (LM) tests for panel data (Elhorst, 2009). As shown in the table, the null hypothesis of no spatial autocorrelation is rejected and, attending to the robust version of the statistics, the SAR specification is slightly preferred to the SEM model. Nevertheless, next we estimate both specifications, together with the SDM. Since, both, SAR and SEM are nested on the SDM, a selection among them can be carried out through the corresponding Likelihood Ratio (LR) tests. The LR obtained for testing the null hypothesis of preference of the SAR over the SDM model equals 18.72, while the LR obtained for testing the null of preference of the SEM specification over the SDM equals 20.40. Both LR statistics are higher than a critical value of $\chi^2(4)$ and, therefore, the SDM is the preferred specification.

As regards panel econometric techniques, we analyse the dynamic version of the model (equation 10). The results of estimating this model following Blundell and Bond (1998) are shown in the last column of Table 3. In relation to the need to dynamise the model, we see how the parameter associated to the export volume in the previous period variable is significant.

From previous results, we can draw the following conclusions. Initial gravity equations can be benefit from considering the effect of omitted variables and dynamics, both through the consideration of spatial dependence or panel data techniques. However, in order to compare results for SDM and dynamic panel model, we have to take into account that for SDM we have to calculate what it is known the average direct effect with respect to a variable Xd_j, which represent the average effect of flows to such variable over the sample of observations. It can be calculated as follows:

$$\text{Average Direct Effect}_j = N^{-1}\,\text{Trace}\left[\left(I_N - \rho W\right)^{-1}\left(I_N\theta_j + W\phi_j\right)\right] \qquad (12)$$

Table 3. Results obtained for spatial and panel specifications [(a), (b)]

	Ordinary least square	*Spatial models*			*Panel model, dynamic model*
		SEM	SDM	SAR	
Ln (GDP_d)	2.10** (5.69)	1.99** (6.14)	3.68** (3.58)	2.21** (6.22)	1.79** (3.67)
HDI _d	0.01 (0.10)	0.04 (0.44)	0.14 (1.25)	0.01 (0.11)	0.35** (2.64)
Ln (D)	–2.49** (–4.20)	–2.47** (–4.51)	–5.27** (–3.02)	–2.68** (–4.82)	–2.83** (–4.42)
Lang	3.52 (1.12)	3.95 (1.24)	11.49** (2.49)	3.48 (1.21)	14.21** (3.29)
W*Ln (GDP_d)			2.77 (1.49)		
W* HDI _d			–0.26** (–2.04)		
W*Ln (D)			–6.34 (–0.40)		
W* Lang			1.84 (0.26)		
Dyear2001–2003	–2.07** (–2.24)	–1.88* (–1.91)	–1.77* (–1.91)	–1.49* (–1.65)	–0.48 (–0.48)
Constant	–31.67** (–3.03)	–30.89** (–3.07)	–78.04 (–1.20)	–35.24** (–3.55)	–51.99** (–4.35)
ρ		0.17 (1.14)	0.15 (1.00)	0.22 (1.59)	
Ln (export (t-1))					0.24* (1.85)
Log-likelihood	–111.693	–111.14	–100.94	–110.30	
R^2	0.58	0.57	0.72	0.60	
Adjusted R^2	0.53	0.57	0.71	0.59	
σ^2	4.12	3.56	2.40	3.43	
Spatial diagnostics: Testing the null of no spatial dependence on the residuals					
LM test no spatial lag	3.47				
Robust LM test no spatial lag	8.92**				
LM test no spatial error	1.11				
Robust LM test no spatial error	6.56**				
Specification tests for dynamic panel model					
Arellano-Bond test for AR(1) in first difference, z:					–3.00 **
Arellano-Bond test for AR(2) in first difference, z:					–0.64
Sargan test of overidentifying restrictions					43.04

[(a)] In parenthesis are the t-ratios.
[(b)] Two asterisks means that the null hypothesis is rejected at the 5% level of significance; one asterisks means that the null hypothesis is rejected at the 10% level of significance.

Regarding panel data results, we can derive the short and long-run effects. The obtained results are shown in Table 4.

Table 4. Responses of olive oil flows with respect to continuous explicative variables

	SDM	*Dynamic panel model*	
	Average direct effect	*Short-run*	*Long-run*
Ln (*GDP_d*)	3.85**	1.79**	2.36**
HDI *_d*	0.13	0.35**	0.46**
Ln (*D*)	–5.64**	–2.83**	–3.72**
Lang	11.67**	14.21**	18.69**
D year 2001-2003	–1.79*	-0.48	–0.63

For spatial and panel specification, the empirical evidence obtained shows, as expected, a positive and significant relationship between the importer's income level and imported olive oil volume. According to the SDM model the average direct elasticity is 3.85, while from panel specification the short-run and long-run elasticity are 1.79 and 2.36, respectively. The importers' HDI has a positive effect in both cases, although only significant in the case of the panel specification. This result is also logical, since it is expected that an increase in the standard of living of importers' countries will increase the demand of healthy products, such as the Tunisian olive oil. For both selected models, the distance has a significant, negative effect on trade flows. As for the SDM, flows decrease in 5.64% in response to a one-percent increase of the distance between countries. Elasticities derived from the panel specification are a bit lower: –2.83 and –3.72 for the short-run and long-run, respectively. This result implies that Tunisia could try to develop trade relationship with other closest countries, taking also advantage of their current development. Regarding the common language variable, we can conclude that sharing a common language increases olive oil trade flows. In other words, this means that Morocco and France get benefits from sharing the language with Tunisia. This result implies that in order to enlarge trade flows, Tunisia could try to develop other trade relationships with other Arabic countries or French colonies. As regards the time dummy variable introduced into the model, estimation results show that the exported volume during the period 2001-2003 is lower than in the rest of the years. This result reflects the problem concerning the high production fluctuation due to climatic change. As said before, olive oil production in Tunisia is highly dependent on precipitations, and when the harvest is poor, as from 2001 to 2003, exports to the different countries highly decreases. As a consequence, it should be advisable for Tunisia government to support the use of irrigation.

Finally, specific information obtained from SDM or panel results are the following. On one hand, the estimation for the ρ parameter of the SDM model indicates that flows to a destination are enhanced in accordance with the propensity of attractiveness of its neighboring destination locations. In other words, result points to the existence of a clear similarity in flows between neighbouring importing countries. On the other hand, panel data results let measure the inertia affecting trade flows between countries, with a clear time-dependence effect.

6. Conclusions

This study shows the importance of olive oil as one of the leading agrofood products exported from Tunisia. The sector is vulnerable, however, because its exports are heavily concentrated in six countries. We have therefore attempted to identify the principal determinants in Tunisia's trade with the product.

A revisited gravity equation has been estimated by paying attention to the effect of possible omitted variables and the consideration of trade dynamics. Spatial and panel econometric techniques have been applied to a panel sample referring to the 2001-2009 period. The results obtained show a positive, significant relationship between the importer's income level and imported olive oil volume. The effect of importers' human development index is positive. There is a significant, negative effect of the distance between countries, while sharing a common language, such as Morocco and France, increases the volume of trade. This result implies that Tunisia could try to develop trade relationships with other closest Arabic countries, taking also advantage of their current development. Export figures and results reflect the strong dependence of olive oil production on precipitations. As a consequence, it should be advisable for Tunisia government to support the use of irrigation. Furthermore, results show evidence concerning the inertia related to export volumes, as trade relations anchored in the past will probably continue in the future. Finally, results show the existence of a clear similarity in flows between neighbouring importing countries.

Future research will be aimed at investigating whether the evidence obtained for olive oil is applicable to other agrofood products that are important for the Tunisian economy, such as dates and fishery products.

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