A Two-Methodology Comparison Study of a Spatial Gravity Model in the Context of Interregional Trade Flows

Autores y e-mail de la persona de contacto:

Luisa Alamá-Sabater[*]

Laura Márquez-Ramos[*]

Email:lmarquez@uji.es

José Miguel Navarro-Azorín[**]

Celestino Suárez-Burguet[*]

Departamento:

Departamento de Economía

Universidad:

[*]*Universitat Jaume I, Castellón, Spain*

[**] *Universidad Politécnica de Cartagena, Spain*

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This paper argues that the introduction of spatial interactions to model the determinants of origin-destination (OD) flows can potentially result in *excessive* contiguity. To explain flows between OD regions, it is not only what happens in the origin and destination that is relevant, but also what happens in their neighbouring regions. However, what happens if there is a high degree of overlap between origin neighbouring areas and destination neighbouring areas? The paper presents an empirical illustration to re-examine the evidence presented in previous research (Alamá-Sabater *et al.*, 2013) and more closely analyses the territorial level, focusing on the case of interregional trade of goods at the NUTS3 level (Spanish provinces). We then use two different methodologies within the framework of a spatial gravity equation for interregional trade modelling. The findings confirm the importance of spatial dependence on trade flows and in particular that logistics decisions within a province affect shipments from contiguous provinces.

Palabras Clave: *(máximo 6 palabras)*
gravity, spatial dependence, connectivity, interregional trade, Spanish provinces

Clasificación JEL: F14, R12

1. Introduction

The link between spatial dependence and trade flows stems from contributions made by LeSage and Pace (2004; 2008). LeSage and Polasek (2008) and LeSage and Thomas-Agnan (2014) introduce spatial effects into the econometric flow model, which can be interpreted as an extension of OD models used in the international trade literature: the gravity equation. In particular, these authors redefine the concept of spatial effects by considering the idea that the relation between OD flows depends not only on the features of origin and destination, as in a traditional gravity equation, but also on the characteristics of neighbouring regions. These characteristics can be measured by the flows between the neighbouring regions and the origin or destination regions.

This paper contributes to the existing literature in two ways. First, it explores the empirical performance of the gravity model to explain trade flows between regions using a spatial approach. To do so, it employs two different methodologies. The first methodology extends the gravity model controlling for the so-called multilateral resistance (MR) and introducing spatial lags, while the second methodology is based on the spatial econometric flow model introduced by LeSage and Pace (2008). Second, following the latest research in spatial econometrics, we control for the role of connectivity at a highly disaggregated territorial level. Specifically, we focus on level NUTS3[1] in Spain (i.e. provinces).

Recent research has shown that spatial correlation exists in heavily broken down geographical data in Spain (LeSage and Llano, 2013) and it has already analysed the role of transport connectivity across regions on interregional trade in goods using a spatial econometric model approach (Alamá-Sabater *et al.*, 2013). Although LeSage and Llano (2013) and Alamá-Sabater *et al.* (2013) focused on Spanish regions at the NUTS2 level and their results revealed a spatial pattern, Alamá-Sabater *et al.* (2013) show the

[1] Nomenclature of Territorial Units for Statistics.

limitations of the level of territorial breakdown chosen. In particular, they show evidence of problems associated with the excessive size of some of the regions, which leads to distortions, for example, in terms of shared neighbours across origin and destination regions. Certainly, consideration of smaller spatial units, such as provinces should substantially improve the results in terms of positive externalities from transport connectivity.

We acknowledge that a problem of *excessive* contiguity might arise when analysing the determinants of OD flows by taking into account spatial interactions, which cover a wide variety of movements such as journeys to work, migrations, tourism, usage of public facilities, the transmission of information or capital, the market areas of retailing activities, international trade and freight distribution (Rodrigue *et al*., 2013). In fact, economic activities both generate and attract flows. Nonetheless, if regions are too large, depending on their location and the structure of the territory, there might be an *excessive* overlapping between neighbouring regions. A smaller basic unit area should therefore be considered.

The rest of the paper is organized as follows. Section two describes the two methodological approaches used. Section three outlines data and variables used for the present study. The regression analysis is performed in section four. Section five contains the conclusions.

2. The two methodologies

Weighting matrices measure the degree of potential interaction between neighbouring locations. Spatial interactions have been included in gravity equations to model OD flows in a number of empirical applications such as tourism (De la Mata and Llano-Verduras, 2012), migration (LeSage and Pace, 2008) and commodity flows (LeSage and Polasek, 2008). LeSage and Pace (2008) question *traditional* gravity models to explain the flow of goods between origin and destination due to the potential failure of a spatial component that can lead to model parameters being biased and consequently distort statistical inference. Similarly, Corrado and Fingleton (2012) argue that failing to acknowledge network dependence and spatial externalities leads to biased inference and to an incorrect understanding of true causal processes. However, the economic foundation of many spatial econometric models is weak. In order to overcome this shortcoming, we extend the theoretically justified gravity approach using spatial lags.

2.1. Spatial lags

The spatial dependence of the model is captured by the parameters ρ_i. The spatial econometrics literature (Anselin, 1988) measured relations with neighbouring regions by using weighting matrices. The structure of spatial dependence incorporated in weighting matrices preconditions any estimate obtained. With regards to how a neighbouring relation is defined in gravity-type models, the most common definition describes regions with the same border (Porojan, 2001), but there are studies that consider additional criteria, such as Behrens *et al.* (2012),[2] LeSage and Polasek (2008) or Alamá-Sabater *et al.* (2011 and 2013).[3]

In a gravity framework that uses symmetrical spatial interaction data,[4] we have to amplify the weighting matrix and build an $n^2 * n^2$ matrix to take into account all trade flows between all regions. For example, the model matrices might be defined as $\boldsymbol{W_k^*} = \boldsymbol{I_n} \otimes \boldsymbol{W}$, if **W** is n*n, then $\boldsymbol{W_k^*}$ is $n^2 * n^2$. Note that in this type of model the spatial effect is amplified because of the dimension of the flow model, as each region has a relationship with the other regions.

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[2] This application does not contain any form of geographic connectivity as they use a similarity measure based on the relative size of regions.
[3] They construct a measure of transport connectivity to include in the weighting matrices.
[4] Recently, Márquez-Ramos (2014) uses a spatial approach with asymmetrical spatial interaction data (i.e. the number of origins is different from the number of destinations. Moreover, origins cannot also be destinations).

By using "destination-centric ordering", we consider three types of indirect effects in this paper: 1) $W_o = I_n \otimes W$, 2) $W_d = W \otimes I_n$ and 3) $W_w = W_o \cdot W_d$. Where **W** matrix represents an n by n spatial weight matrix based on a neighbour's criteria of geographical first-order contiguity. Non-zero values for elements i and j denote that zone i neighbours zone j, whereas zero values denote that zones i and j are not neighbours. The elements on the diagonal are zero to prevent an observation from being defined as being its own neighbour.

It is important to highlight that when working with autoregressive specifications, as is the case with this paper, the structure of the model implies that the influence of the "neighbours of neighbours" is taken into account. Consequently, with an autoregressive type model in a territorially highly-disaggregated trade dataset, we are taking into account "second order" neighbour relations that generate the abovementioned problem of *excessive* contiguity.

2.2. A theoretically justified gravity approach with spatial lags

According to the traditional gravity model of trade (Anderson, 1979), the volume of aggregate exports between pairs of regions and/or countries, depends on their income, geographical distance and a series of dichotomous variables. Trade is expected to be positively related to income and negatively related to distance. Gravity models applied to the study of trade flows among countries normally include dichotomous variables such as whether or not the trading partners share the same language or have a common border, as well as variables for free trade agreements in order to assess the effects of regional integration. Distance is also included in most empirical studies that employ gravity equations as a proxy for transport costs.

The concept of transport connectivity has already been considered in gravity studies of trade by means of analysing transport–cost reducing measures (Limao and Venables, 2001; Sanchez *et al*., 2003; Clark *et al*., 2004; Micco and Serebrisky, 2004; Márquez-Ramos *et al*., 2011). However, this branch of the literature only considers the spatial effects of the neighbouring regions as additional traditional regressors to be included in gravity equations, not defining weighting matrices. In this sense, ignoring a spatially lagged dependent variable can lead to biased parameter estimates, implying inaccurate estimates of infrastructure impacts (Cohen, 2010).

It is important to highlight that when inherent spatial effects are explicitly taken into account in gravity models, the magnitude of the estimated parameter changes (Porojan, 2001). Porojan (2001) also stressed that with the presence of spatial autocorrelation, the estimated parameter on the distance variable might capture a spatial pattern that reflects the structure of territory. In a more recent study, Behrens et *al.* (2012) estimate a gravity equation using spatial econometrics for Canada-US trade to control for cross-sectional interdependence and find that not a single Ordinary Least Squares (OLS) specification passes Moran's I test. Even after controlling for MR (Anderson and Van Wincoop, 2003), a significant amount of cross-sectional correlation in the OLS residuals still remains.

We then estimate a linear version of a gravity model of trade to explain trade flows between intra-national regions in a spatial approach that incorporates information on transport connectivity measures, in addition to the characteristics of each region:

$$\begin{aligned}\ln X_{ij} &= \gamma_0 + \gamma_1 \ln Y_i + \gamma_2 \ln Yh_i + \gamma_3 \ln Y_j + \gamma_4 \ln Yh_j + \gamma_5 \ln D_{ij} + \gamma_6 CI_i + \gamma_7 CI_j + \\ &+ \gamma_8 \ln area_i + \gamma_9 \ln area_j + \rho_1 \mathrm{W_o} \ln X_{ij} + \rho_2 \mathrm{W_d} \ln X_{ij} + \rho_3\ \mathrm{W_w} \ln X_{ij} + \varepsilon_{ij}\end{aligned} \tag{1}$$

where lnX_{ij} denotes the logarithm of exports from a Spanish region *i* to an importing Spanish region *j*; lnY_i (lnY_j) is the logarithm of the GDP for exporter *i* (importer *j*); Yh_i (Yh_j) is GDP per capita in the exporting region (importing region); $Dist_{ij}$ measures the distance between capital cities or the economic centres of the two regions; CI_i (CI_j) is the connectivity index that measures transportation networks in each exporter (importer), which has been calculated using information on the number of logistics facilities and the number of square kilometres of logistics zones at the NUTS3 level (Suárez-Burguet, 2012); following LeSage and Polasek (2008), we also include $area_i$ ($area_j$) to control for the area of the origin and destination regions. The spatial lag vector $W_o \ln X_{ij}$ would be constructed by averaging flows from neighbours to the origin region and parameter ρ_1 would capture the magnitude of the impact of this type of neighbouring observation on the dependent variable. The spatial lag vector $W_d \ln X_{ij}$ would be constructed by averaging flows from neighbours to the destination region and parameter ρ_2 would measure the impact and significance of flows from origin to all neighbours of the destination region. The third spatial lag in the model $W_w \ln X_{ij}$ is constructed using an average of all neighbours to both the origin and destination regions. Estimating parameters ρ_1, ρ_2 and ρ_3 provides an inference of the relative importance of the three types of spatial dependence between the origin and destination regions. Then, ρ_1, ρ_2 and ρ_3 are the spatial autocorrelation coefficients and the null hypotheses test that $\rho_1=0$; $\rho_2=0$ and $\rho_3=0$. Rejecting these null hypotheses implies that trade flows from/in one region are directly affected by the importance of trade flows from /in neighbouring regions. Finally, ε is a random disturbance.

We estimate two additional specifications derived from equation (1). First, we take into account a remoteness factor in our gravity analysis by incorporating proxy variables and also using spatial lags, in line with Márquez-Ramos (2014). Then, we estimate equation (2):

$$\ln X_{ij} = \gamma_0 + \gamma_1 \ln Y_i + \gamma_2 \ln Yh_i + \gamma_3 \ln Y_j + \gamma_4 \ln Yh_j + \gamma_5 \ln Dist_{ij} + \gamma_6 CI_i + \gamma_7 CI_j + \gamma_8 \ln area_i + \\ + \gamma_9 \ln area_j + \gamma_{10} \ln rem_i + \gamma_{11} \ln rem_j + \rho_1 \mathrm{W_o} \ln X_{ij} + \rho_2 \mathrm{W_d} \ln X_{ij} + \rho_3 \mathrm{W_w} \ln X_{ij} + \varepsilon_{ij} \quad (2)$$

Where rem_i (rem_j) is the variable exporter (importer) remoteness based on equation 2a (2b). That is, for a given origin-destination pair i and j, the degree of remoteness of region i is defined as:

$$rem_i = \sum_j \left(\frac{Y_j \cdot Dist_{ij}}{Y^w} \right) \tag{2a}$$

where Y^w is the sum of the income of the importing regions of region *i* considered in this study (total GDP in the Spanish peninsula). Similarly, the variable remoteness is also calculated for the importer:

$$rem_j = \sum_i \left(\frac{Y_i \cdot Dist_{ij}}{Y^w} \right) \tag{2b}$$

In order to control MR factors, dummies for exporters and importers can be added to the empirical model instead of remoteness variables. However, since income, surface and transport connectivity variables are region specific, we estimate an additional version of equation (1) that includes country dummies for importers (δ_j) and for exporters (η_i), and assumes that the effect of the transport connectivity variables is of equal magnitude for both exporters and importers (i.e. $CI_{ij}=CI_i*CI_j$):

$$\ln X_{ij} = \gamma_0 + \eta_i + \delta_j + \gamma_1 \ln Dist_{ij} + \gamma_2 CI_{ij} + \rho_1 \mathrm{W_o} \ln X_{ij} + \rho_2 \mathrm{W_d} \ln X_{ij} + \rho_3 \mathrm{W_w} \ln X_{ij} + \varepsilon_{ij} \tag{3}$$

We estimate equations 1, 2 and 3 using instrumental variables (IV) (Gibbons and Overman, 2012) and, as the dependent variable is for year 2007, we use the (7-year) lagged dependent variable to construct the spatial lags, namely trade flows in 2000. Consequently, the excluded instruments are $\mathrm{W_o} \ln X_{ij,2000}$, $\mathrm{W_d} \ln X_{ij,2000}$ and $\mathrm{W_w} \ln X_{ij,2000}$. One way of validating the results is to observe whether they are robust for the different specifications (i.e. equations 1, 2 and 3).

2.3. The spatial econometric modelling of OD flows

LeSage and Pace (2009) and Behrens *et al*. (2012) suggest using spatial econometrics to control for MR. Therefore, our second methodology is the spatial econometric flow model (LeSage and Pace, 2008). Its purpose is to explain variation in the magnitude of flows between each OD pair and it is based on the type of spatial autoregressive models appearing in equation (4):

$$\ln X_{ij} = \alpha + \beta_o X_o + \beta_d X_d + \gamma \ln Dist_{ij} + \rho_1 \mathrm{W_o} \ln X_{ij} + \rho_2 \mathrm{W_d} \ln X_{ij} + \rho_3 \mathrm{W_w} \ln X_{ij} + \varepsilon_{ij} \quad (4)$$

As in gravity models, X's matrix captures the characteristics of origin and destination regions that could influence bilateral trade. Each variable produces an n^2 by 1 vector with the associated parameters in origin i, β_o, and destination j, β_d. The dependent variable represents an n by n square matrix of interregional flows from each of the n origin regions to each of the n destination regions, where each of the n columns of the flow matrix represents a different destination and the n rows reflect origins.

Our focus is on extending gravity equations and then, we consider a number of characteristics of the origin and destination regions. As per LeSage and Polasek (2008), the explanatory variables used to construct the matrices X_o (origin) and X_d (destination) are the (logged) area, the (logged) population, the (logged) GDP per capita and the (logged) employment in each region. In keeping with the existing literature (LeSage and Polasek, 2008; Alamá-Sabater *et al*., 2011 and 2013), we estimate the variant of equation (4) using maximum likelihood.

In a preliminary analysis and in order to compare results obtained when the model is estimated with and without spatial lags, we rely on the maximum likelihood method to test for spatial dependence. As the null hypothesis of absence of spatial dependence is rejected, the gravity model that includes the spatial lags appears to be a better alternative. In addition, lower values are produced for the Akaike Information Criterion

(AIC) and Root Mean Squared Error (RMSE), indicating that the spatial model is preferred. Therefore, the empirical illustration relies on regressions that include the spatial lags.

3. Data and variables

We generate a dataset containing total commodity flows transported between 47 of the Spanish provinces during the year 2007 (see Figure A.1, Appendix).[5] As we are considering the interregional trade in the peninsula and the effect of trade with bordering regions, neither the Canary and Balearic Islands, nor Ceuta and Melilla are included in the regressions.

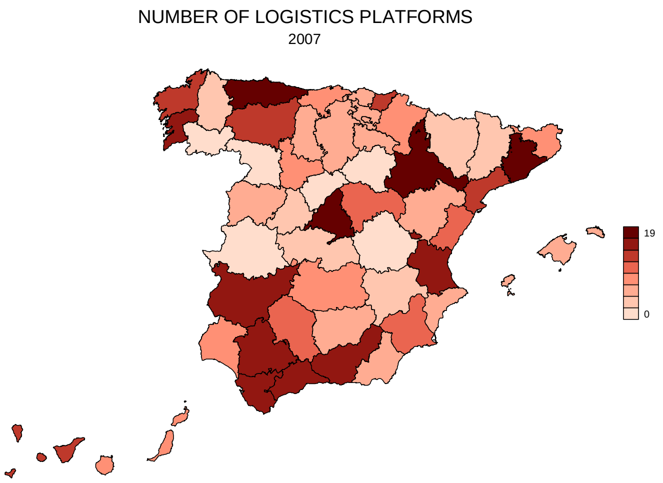
Weighting matrices have been constructed using a geographical criterion and introducing logistics characteristics. The geographical criterion controls for contiguity across regions (contiguity model) and we also consider the presence of logistics platforms (connectivity model), i.e. the regions adjacent to A (origin) or B (destination) that also have logistics platforms. To proxy for the quality and level of logistics factors between OD regions, a transport connectivity index is calculated as a simple average of two dimension indices, the number and the size of the logistics platforms.

Figures 1 and 2 show the number of logistics platforms and the logistics surface area as a percentage of the total logistics surface area in Spain (by province), respectively. Madrid, Barcelona, Zaragoza and Cadiz have the largest relative surface area of logistics platforms, mainly due to the presence of very large logistics platforms in these regions (such as the Zaragoza Logistics Centre in Aragon, the Madrid Barajas centre in the Madrid region and the Port of Algeciras in Andalusia). Provinces such as Valencia, in the Valencian Community, and a number of provinces in Andalusia-Extremadura

[5] The Spanish Statistical Institute has been the source of information for explanatory variables and, as for the dependent variable, the data refer to 2007. Interregional trade data has been supplied by C-Intereg (Llano et al., 2009 and 2010) for the Relog Project (Suárez-Burguet, 2012). Note that trade data is available for two years: 2007 and 2000.

(Seville, Malaga, Granada and Badajoz[6]) also have a large number of logistics platforms. In contrast, the provinces in Extremadura, Castile-La-Mancha and Castile-and-Leon display a real shortage of square metres dedicated to logistics activities. The Balearic and Canary Islands are also home to only a small number of large platforms linked to their ports. This transport connectivity picture is in line with the international or supra-regional intermodal nodes identified in PEIT (2005), which are located in the areas of Madrid, Barcelona/Catalonia, the Basque Country and Valencia, Zaragoza, Algeciras and Seville, as well as with the main national combined traffic corridors located along the Mediterranean Axis, the Central Corridor (Asturias-Madrid, Basque Country-Madrid and from there to Andalusia) and the Ebro Axis. Traffic levels are also significant in the Madrid-Levante[7] Corridor.

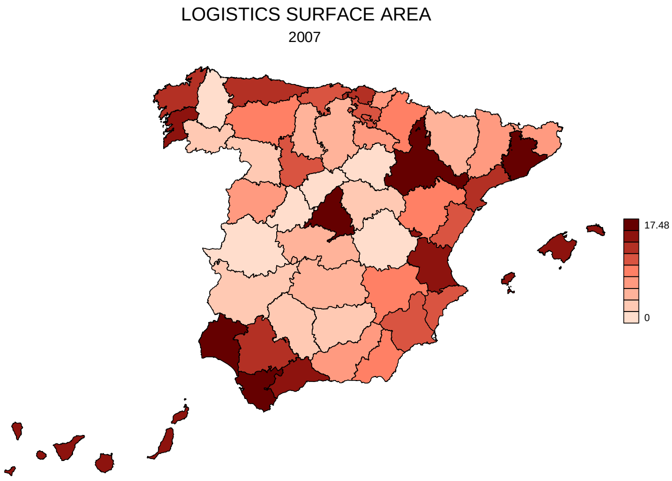
Figure 1:



Source: Own elaboration and Suárez-Burguet (2012).

[6] Note that the Madrid-Badajoz-Portugal axis is also a very important corridor.
[7] The term ‘Levante’ refers to the eastern region of the Iberian Peninsula, on the Spanish Mediterranean coast.

Figure 2:



Source: Own elaboration and Suárez-Burguet (2012).

In order to introduce logistics characteristics, the (transport) connectivity index (CI) is calculated as a simple average of the number and size of logistics platforms. Scores of every dimension are derived as an index relative to the maximum and minimum achieved by both origin and destination regions, based on the assumption that logistics play a comparable role in OD. The performance of the CI takes a value between 0 and 1 calculated according to equation (5):

$$CI = \frac{(actual\,value - observed\ \min value)}{(observed \max\ value - observed \min value)} \qquad (5)$$

According to this index, if regions i and j have a good logistics performance and share a border, the matrix element is close to 1; if however they border one another but the logistics infrastructure is poor, the matrix element is close to zero, and if they do not border one another the matrix element is zero.

Figure A.2 in the Appendix presents an example to illustrate the accuracy difference regarding transport connectivity in interregional trade flows between both the first-order contiguity and the connectivity model. In the example, Zaragoza has eight neighbours (Huesca, Lleida, Tarragona, Teruel, Guadalajara, Soria, La Rioja and Navarra) and, whereas in the contiguity model the eight regions are assigned equal weights (the geographical criteria are the same for all regions), in the connectivity model the imposed filter weights the eight regions with the connectivity index defined above, resulting in three regions being allocated the highest weightings (Tarragona, Guadalajara and Navarra).

In order to explain the model and the dependent variable, we generate an n^2 by 1 vector by stacking the columns of the matrix. If we consider a model with four regions, the flow matrix would appear as in Table 1. Columns show the dyad label (4 origin regions x 4 destination regions = 16), identifier (ID) of the origin region and ID of the destination region. Y denotes the dependent variable (exports)[8] and Xs the explanatory variables (for example, in the second methodology, area, population, GDP per capita and employment, together with geographical distance). For simplicity, only four regions (Seville, Zaragoza, Barcelona and Madrid) are considered in Table 1.

Table 1: Data organization

Dyad labels	Region origin	ID origin	Region destination	ID destination		Origin explanation variables			Destination explanation variables			Distances
					Y	X1	X2	X3	X1	X2	X3	
1	Seville	1	Seville	1	y11	a11	a12	a13	b11	b12	b13	d11
2	Zaragoza	2	Seville	1	y21	a21	a22	a23	b11	b12	b13	d21
3	Barcelona	3	Seville	1	y31	a31	a32	a33	b11	b12	b13	d31
4	Madrid	4	Seville	1	y41	a41	a42	a43	b11	b12	b13	d41
5	Seville	1	Zaragoza	2	y12	a11	a12	a13	b21	b22	b23	d12
6	Zaragoza	2	Zaragoza	2	y22	a21	a22	a23	b21	b22	b23	d22
7	Barcelona	3	Zaragoza	2	y32	a31	a32	a33	b21	b22	b23	d32
8	Madrid	4	Zaragoza	2	y42	a41	a42	a43	b21	b22	b23	d42
9	Seville	1	Barcelona	3	y13	a11	a12	a13	b31	b32	b33	d13
10	Zaragoza	2	Barcelona	3	y23	a21	a22	a23	b31	b32	b33	d23
11	Barcelona	3	Barcelona	3	y33	a31	a32	a33	b31	b32	b33	d33
12	Madrid	4	Barcelona	3	y43	a41	a42	a43	b31	b32	b33	d43
13	Seville	1	Madrid	4	y14	a11	a12	a13	b41	b42	b43	d14

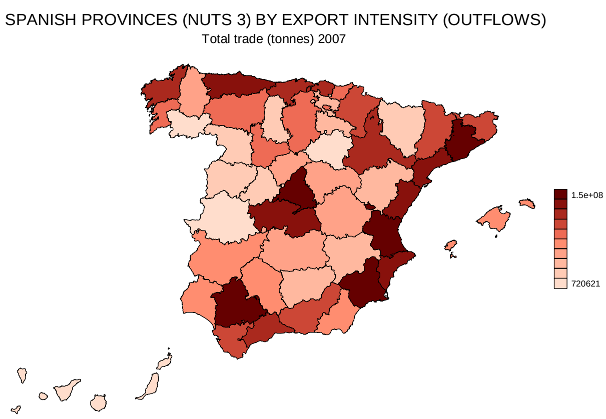
[8] Note that shipments made between regions within the customs territory of the European Union are no longer considered exports but rather intra-community supplies of goods and, more specifically, expeditions (or introductions, when it comes to goods receipts). Therefore, exports denote shipments from the origin to the destination Spanish region.

14	Zaragoza	2	Madrid	4	y24	a21	a22	a23	b41	b42	b43	d24
15	Barcelona	3	Madrid	4	y34	a31	a32	a33	b41	b42	b43	d34
16	Madrid	4	Madrid	4	y44	a41	a42	a43	b41	b42	b43	d44

In the empirical analysis we use the two methodologies described above. A first variant of our models includes only first-order contiguity (contiguity-based model, with a modified matrix $\mathbf{W}_{\mathbf{m\_contiguity}}$), whereas our second variant of the model (transport connectivity model, with a modified matrix $\mathbf{W}_{\mathbf{m\_connectivity}}$) reflects transportation networks in Spanish provinces by using the surface area and size of logistics platforms.

As a descriptive analysis, we present a map of Spain showing regions containing total trade flows, as export-trade (Figure 3) and as import-trade (Figure 4).[9] The areas where the most important trade flows are concentrated are identified with darker colours (a darker shade of red reflects higher levels of flow, while lighter shades of red indicate lower levels). These maps represent total trade flows, so the analysis should be carried out from a general point of view. According to our data, the Spanish regions with the most outward and inward interregional trade flows are Barcelona, Madrid, Seville and Valencia.[10]

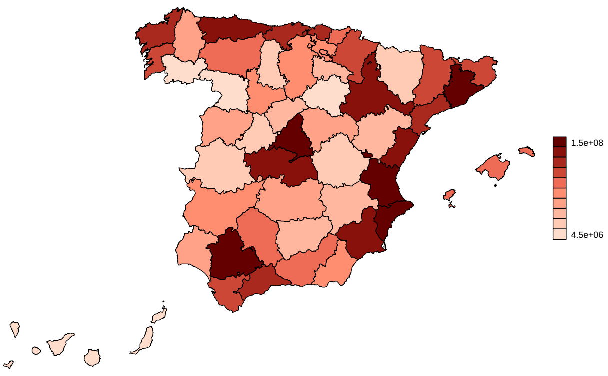
Figure 3:



Source: Own elaboration.

[9] These maps are constructed by setting flows within regions to zero to emphasise interregional flows.
[10] Note that the maps on intensity of trade flows are measured in tonnes. As a result, they do not control for the value/volume relation of flows. Consequently, a number of regions could appear to be very important trading regions, although in reality they are not.

Figure 4:



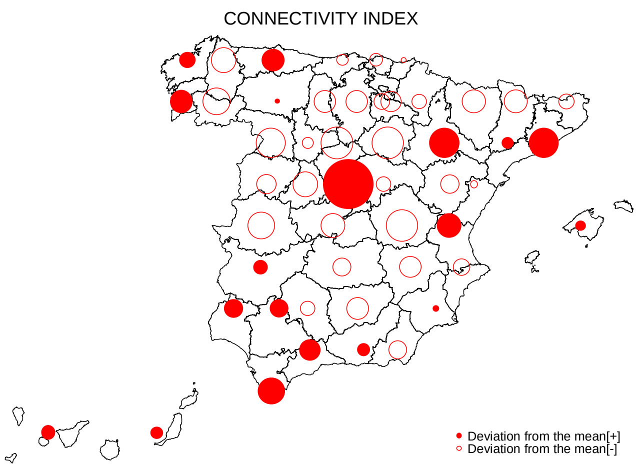
Source: Own elaboration.

Figure 5 shows the map of the connectivity index derived from equation (5).[11] Examining the maps in Figures 3 and 4 in conjunction with that of the logistics network in Figure 5, there appears to be more flows in origin and destination regions in the provinces where logistics networks are more extensive than in provinces with less developed logistics networks. Therefore, in the case of Spain, a clear differentiation can be made between provinces in terms of logistics performance. This descriptive test emphasizes the need to explicitly incorporate such information into the spatial and network dependence structure when analysing trade flows, as it might result in substantial differences in the estimates and inferences. It can also be compared to previous research that uses the spatial econometric flow model at the NUTS2 level in Spain (Alamá-Sabater *et al*., 2011 and 2013). Although their results support the use of an empirical framework where the spatial dependence of interregional trade flows is introduced, they also provide evidence of the limited significance of spatial lags.[12] It is therefore expected that the higher the level of disaggregation of geographical data, the greater the positive effect of the spatial lags. There are three main reasons for this: First, it seems unlikely that a small spatial economic unit could produce many goods without

[11] The regions containing the highest values are in dark red.
[12] The Moran's I statistic is used to analyse the existence of spatial autocorrelation.

the help of the surrounding areas, or that a small economic unit would not benefit from the transport networks of the surrounding areas to reach markets that would otherwise be unreachable without crossing them. Second, the variability of data means that the larger the geographical units, the more heterogeneous they are when treated as a whole. Finally, a problem of *excessive* contiguity might potentially arise due to the structure of the territory.

Figure 5:



Source: Own elaboration and Suárez-Burguet (2012).

4. Regression analysis

4.1. Spatial gravity approach. Main results.

Table 2 shows the results of the spatial lags when estimating the equations (1), (2) and (3). Our first variant of the model includes only first-order contiguity (contiguity), whereas our second variant of the model reflects the logistics performance in Spanish regions discussed in the previous section, as we employ a matrix W which considers logistics performance in conjunction with the restriction that only first-order neighbours are included in the formation of the spatial lags (connectivity). This results in a direct relationship between increased numbers of the nearest neighbours and the performance of the logistics segments that go on to form the spatial lag variables. Findings show that the spatial lags are both positive and significant. Provinces therefore benefit from their neighbours' transportation networks.

With regards to the remaining variables included in the equations:[13] income, income per capita (for the exporter) and area present a positive and significant influence on trade in 2007. The coefficient of distance gives the expected results (negative) and is statistically significant. The variable remoteness (included in equation 2) is significant and positive for the exporter. The variables that proxy for transport connectivity have a non-significant effect on Spanish interregional trade when they are included in equations (1) and (2). Nonetheless, results of estimating equation (3) show that CI_{ij} is both positive and significant.

Table 2: Estimates from the connectivity and the contiguity spatial models by instrumental variables. Methodology 1. Total trade.

	Equation 1	Equation 2	Equation 3
ρ1. Connectivity	0.105*** (5.021)	0.102*** (4.952)	0.057*** (2.687)
ρ2. Connectivity	0.108*** (6.617)	0.109*** (6.742)	0.071*** (3.727)
ρ3. Connectivity	0.079*** (3.559)	0.073*** (3.316)	0.063** (2.107)
ρ1. Contiguity	0.117***(4.761)	0.109*** (4.374)	0.063** (2.467)
ρ2. Contiguity	0.080*** (5.551)	0.083*** (5.813)	0.078*** (3.549)
ρ3. Contiguity	0.059*** (3.513)	0.052*** (3.049)	0.138*** (3.964)

Notes: ***, **, * indicate significance at 1%, 5% and 10%, respectively. Z-statistics are given in brackets. The (logged) dependent variable is measured in Tonnes.

4.2. The spatial econometric flow model. Main results.

In order to analyse the spatial dependence of interregional Spanish trade flows, we estimate equation (4) by maximizing the log-likelihood function with respect to parameters ρ_1, ρ_2 and ρ_3. As before, for simplicity, only the results of the spatial lags are presented as they are the main focus of this paper. First, Table 3 shows the results of the spatial lags for total trade in the contiguity and the connectivity models, and shows that the spatial lags are positive and significant.

[13] These results have been omitted to save space. They are available from the authors upon request.

Table 3: Estimates from the connectivity and the contiguity spatial models. Methodology 2. Total trade.

ρ1. Connectivity	0.22*** (5.75)
ρ2. Connectivity	0.41*** (11.45)
ρ3. Connectivity	0.46*** (8.61)
ρ1. Contiguity	0.27*** (6.62)
ρ2. Contiguity	0.42*** (11.91)
ρ3. Contiguity	0.53*** (9.14)

Notes: ***, **, * indicate significance at 1%, 5% and 10%, respectively. Z-statistics are given in brackets. The (logged) dependent variable is measured in Tonnes.

If we compare results in Table 3 with those obtained at NUTS2 in previous literature (see Table 1 in Alamá-Sabater *et al.*, 2013), they are in line with the expectation that the higher the level of disaggregation of geographical data, the greater the positive effect of transport connectivity on interregional trade flows. Spatial dependence is relevant in terms of explaining OD interregional trade flows, and if there are good logistics conditions in neighbouring provinces, trade flows increase. The findings are also in line with earlier research and confirm that both destination-based and OD-based dependence are more important than origin-based dependence for interregional Spanish commodity flows.

Turning our attention to specific sectors,[14] Tables 4 and 5 show the results by sector for the connectivity and the contiguity model, respectively. These results can be compared to those obtained at a NUTS2 level in previous literature (see Table A.1 in the Appendix).[15] Table 4 shows that three different patterns emerge. First, those sectors for which origin-based dependence is the most important (R3: Food Industry and R7: Paper, printing and Graphic Arts), where an origin region with a good transportation connection network to surrounding regions benefits the most in terms of interregional

[14] To do so, we follow previous research that introduces spatial lags in the spatial econometric flow model and estimates different regressions by activity branch (Alamá-Sabater *et al.*, 2011 and 2013).

[15] Although the level of significance and the elasticity of X variables changes for regressions in different sectors, overall, our results show that area, population and income per capita are both positive and significant. The larger the area, population and income per capita of a region, the greater the interregional trade flows. Unemployment is found not to be significant in most of the regressions, whereas distance results are ambiguous. Full results are available from the authors upon request.

exports. Second, we determine sectors where destination-based dependence is the most important (R1, R4, R8, R9, R10, R11, R14 and R15), where a destination region with a good transportation connection network to surrounding regions benefits the most in terms of interregional trade. Finally, we also find those sectors where OD dependence is the most important (R2, R5, R6, R12 and R13). Then, destination-based dependence, i.e. that dependence considering trade between an origin region and regions neighbouring the destination, is found to be of greater importance than origin-based dependence in a number of sectors.

Table 4: Estimates from the connectivity model (by sector).

	NUTS3 (connectivity model)	**ρ_1**	**ρ_2**	**ρ_3**
1	R1 - Agriculture, forestry and fishing	0.31***	0.41***	0.33***
		(8.42)	(12.13)	(6.91)
2	R2 – Mining and quarrying	0.26***	0.30***	0.54***
		(7.17)	(8.61)	(11.19)
3	R3 – Food industry	0.49***	0.42***	-0.03
		(14.51)	(11.56)	(-0.71)
4	R4 - Textile and clothing	-0.02	0.10***	0.05
		(-0.54)	(3.39)	(1.23)
5	R5 – Leather and footwear industry	-0.02	0.12***	0.18***
		(-0.73)	(4.16)	(4.30)
6	R6 – Manufacture of wood and cork products	0.24***	0.26***	0.33***
		(6.41)	(7.96)	(6.73)
7	R7 – Paper, printing and graphic arts	0.23***	0.22***	-0.06
		(6.91)	(6.62)	(-1.43)
8	R8 – Chemical industry	0.18***	0.36***	0.19***
		(4.87)	(10.98)	(4.05)
9	R9 – Manufacture of rubber and plastic products	-0.08**	0.22***	0.12***
		(-2.30)	(6.70)	(2.65)
10	R10 – Industry, non-metallic mineral products	0.22***	0.51***	0.23***
		(5.69)	(15.33)	(4.88)
11	R11 – Basic metals and manufactured metal products	0.09**	0.41***	0.22***
		(2.45)	(12.64)	(4.96)
12	R12 – Manufacture of machinery and mechanical equipment	0.08**	0.05	0.25***
		(2.47)	(1.35)	(4.72)
13	R13 – Electrical equipment, electronic and optical	0.16***	0.18***	0.23***
		(4.68)	(5.60)	(5.27)
14	R14 – Manufacture of transport equipment	0.27***	0.31***	-0.04
		(8.46)	(9.98)	(-1.00)
15	R15 – Diverse industries	-0.07*	0.37***	0.16***
		(-1.89)	(12.25)	(3.54)

Notes: ***, **, * indicate significance at 1%, 5% and 10%, respectively. Z-statistics are given in brackets. The (logged) dependent variable is measured in Tonnes.

Finally, Table 5 shows the results by sector for the contiguity model. The sign and significance of ρ_1, ρ_2 and ρ_3 are similar in both the contiguity and the connectivity models, excluding the case of R12 (Manufacture of machinery and mechanical equipment), for which origin dependence seems to be more important than destination dependence in the transport connectivity model, whereas the opposite is true for the first-order contiguity model. It is important to note that there is a consistent pattern of parameter ρ_2 being positive and significant more times than ρ_1 in a number of sectors, suggesting that neighbours of the destination region in both the contiguity and the connectivity model represent a more important determinant of higher levels of industrial commodity flows between OD pairs.

Table 5: Estimates from the contiguity model (by sector).

	NUTS3 (contiguity model)	ρ_1	ρ_2	ρ_3
1	R1 - Agriculture, forestry and fishing	0.32***	0.46***	0.37***
		(8.07)	(12.63)	(7.02)
2	R2 – Mining and quarrying	0.28***	0.32***	0.69***
		(6.73)	(7.94)	(11.92)
3	R3 – Food industry	0.51***	0.48***	0.04
		(14.30)	(12.82)	(0.887)
4	R4 - Textile and clothing	-0.01	0.14***	0.12*
		(-0.17)	(3.52)	(1.83)
5	R5 – Leather and footwear industry	-0.05	0.22***	0.36***
		(-1.19)	(5.71)	(5.04)
6	R6 – Manufacture of wood and cork products	0.26***	0.31***	0.46***
		(6.44)	(8.06)	(7.53)
7	R7 – Paper, printing and graphic arts	0.30***	0.31***	-0.05
		(7.92)	(8.15)	(-1.03)
8	R8 – Chemical industry	0.22***	0.41***	0.22***
		(5.44)	(11.48)	(4.14)
9	R9 – Manufacture of rubber and plastic products	-0.05	0.32***	0.22***
		(-1.24)	(8.66)	(3.86)
10	R10 – Industry, non-metallic mineral products	0.23***	0.61***	0.31***
		(5.52)	(17.30)	(5.62)
11	R11 – Basic metals and manufactured metal products	0.12***	0.47***	0.32***
		(2.82)	(13.86)	(6.05)
12	R12 – Manufacture of machinery and mechanical equipment	0.04	0.11***	0.44***
		(1.01)	(2.71)	(5.85)
13	R13 – Electrical equipment, electronic and optical	0.19***	0.28***	0.36***
		(4.69)	(7.09)	(6.27)
14	R14 – Manufacture of transport equipment	0.36***	0.39***	-0.05
		(9.74)	(10.85)	(-0.85)
15	R15 – Diverse industries	-0.06	0.50***	0.31***
		(-1.55)	(14.75)	(5.02)

Notes: ***, **, * indicate significance at 1%, 5% and 10%, respectively. Z-statistics are given in brackets. The (logged) dependent variable is measured in Tonnes.

5. Conclusions

This paper analyses the role of transport connectivity in interregional trade flows using a spatial approach by using highly-disaggregated regional trade data at a provincial level in Spain. In order to do so, we use a gravity framework and take into account multilateral resistance in a two-methodology comparison. In order to test whether incorporating transport connectivity information into the spatial structure of the model results in substantial differences in the estimates, we have defined different types of neighbour relations. In particular, two different variants of the model were estimated, based on first-order contiguity and transport connectivity criteria in order to construct the weighting matrices.

We find evidence that transport connectivity has a bearing on interregional trade. Moreover, we show that forces leading to flows from an origin province to a destination province would create similar flows to neighbouring destinations. Regions therefore benefit from their neighbours' transport connectivity. These results not only provide evidence about the role of the location of logistics platforms in satisfying the existing demand for transport structures, but also as to the benefit of introducing spatial dependence in gravity models of trade when analysing interregional trade flows, as ignoring spatial lags might lead to biased estimation of the parameters.

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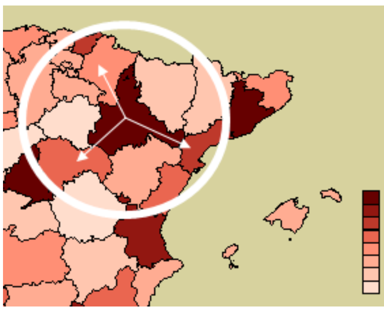
APPENDIX

Figure A.1. Provinces in Spain (NUTS3).

Note: The provinces in the same colour belong to the same Autonomous Community (NUTS2). Source: Hierro and Maza (2010).

Figure A.2. First-order contiguity *versus* transport connectivity model.



Source: Own elaboration

Table A.1: Estimates from the connectivity model at NUTS2 (by sector).

	NUTS3 (connectivity model)	**ρ_1**	**ρ_2**	**ρ_3**
1	R1 - Agriculture, forestry and fishing	0.14**	0.11*	0.04
		(2.09)	(1.81)	(0.41)
2	R2 – Mining and quarrying	0.05	0.04	-0.05
		(0.59)	(0.53)	(-0.36)
3	R3 – Food industry	0.05	0.02	-0.01
		(1.38)	(0.81)	(-0.17)
4	R4 - Textile and clothing	0.05	0.02	-0.03
		(1.58)	(0.65)	(-0.54)
5	R5 – Leather and footwear industry	0.26***	0.26***	0.54***
		(3.43)	(3.36)	(4.54)
6	R6 – Manufacture of wood and cork products	-0.1	0.18**	0.06
		(-0.92)	(2.08)	(0.41)
7	R7 – Paper, printing and graphic arts	0.06	0.11***	-0.03
		(1.02)	(2.7)	(-0.48)
8	R8 – Chemical industry	-0.05	0	0.06
		(-1.05)	(-0.04)	(1.04)
9	R9 – Manufacture of rubber and plastic products	-0.03	0.09	0.18
		(-0.34)	(1.22)	(1.41)
10	R10 – Industry, non-metallic mineral products	-0.1	-0.05	0.04
		(-1.46)	(-0.77)	(0.39)
11	R11 – Basic metals and manufactured metal products	-0.02	-0.03	0.06
		(-0.68)	(-0.99)	(1.36)
12	R12 – Manufacture of machinery and mechanical equipment	0.06	-0.19	-0.11
		(0.45)	(-1.31)	(-0.44)
13	R13 – Electrical equipment, electronic and optical	0.14*	0.14**	0.09
		(1.78)	(2.01)	(0.73)
14	R14 – Manufacture of transport equipment	0.05	0.02	-0.03
		(1.58)	(0.65)	(-0.54)
15	R15 – Diverse industries	0.26***	0.26***	0.54***
		(3.43)	(3.36)	(4.54)

Notes: ***, **, * indicate significance at 1%, 5% and 10%, respectively. Z-statistics are given in brackets. The (logged) dependent variable is measured in Tonnes. Source: Alamá-Sabater *et al.* (2013)