Regional Trade and Logistics Infrastructure: A Spatial Approach[*]

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Abstract

This paper aims to analyze whether the existing logistics platforms network in Spain affects Spanish transport demand by using a spatial framework. In particular, we use demand for transport to export goods to other Spanish provinces as a proxy for logistics infrastructure demand in Spain. Then, we obtain data for trade flows between provinces (NUTS3) in the year 2007. We also obtain data about the number and area of logistics platforms existing in each Spanish province to proxy for the transportation network structure in Spain. In a first step, we construct weight matrixes considering first-order contiguity and we obtain that spatial dependence is significant in a spatial econometric model of commodity flows (LeSage and Polasek, 2008). Secondly, we incorporate logistics network structure dependence into the model so that the spatial lags measure the impact and significance on trade flows from all origins to all destinations by considering the importance of logistics performance in the neighboring provinces. Finally, we perform the analysis for different economic activities. The results obtained provide evidence about the role of the location of logistics platforms for satisfying existing demand for transport structure in the Spanish provinces.

Keywords: Spanish regions, inter-regional trade, logistics platforms.

JEL classification: R12, R23, R48

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1. Introduction

This paper uses a gravity model as a basis to explain trade flows between Spanish regions in spatial approach terms, incorporating, in addition to the characteristics of each region, information on transport connectivity. Transport connectivity has only recently been considered in gravity studies of trade. In this sense, we can distinguish two ways of defining connectivity. On the one hand, connectivity in a narrow sense is limited to the physical properties of the transport network. On the other hand, connectivity in a broad sense includes those factors related to the features of the services and cooperation of transport operators, which are essential for the efficiency and effectiveness of the transport network. Márquez-Ramos et al (2010), as well as other authors who have considered connectivity, address the concept in a narrow sense (Limao and Venables, 2001; Sanchez et al, 2003; Clark et al, 2004; Micco and Serebrisky, 2004; Wilson et al, 2004), finding that connectivity increases trade flows between trading partners. Nonetheless, these studies do not consider the existence of spatial dependence among regions, which is introduced in this paper to analyse the effect of transport connectivity in the broad sense.

Using a spatial autoregressive model, we consider spatial dependence between Spanish regions at NUTS-3 level. In this sense, we use a connectivity concept by considering the presence of logistics platforms, i.e. the regions adjacent to a particular region that also has logistics platforms. In order to do so, this paper extends the procedure followed by LeSage and Polasek (2008), including weight matrices based on logistics performance in neighbouring regions. One advantage of using this framework is that it allows nearby regions to enter into the determination of spatial lags, with the weight assigned increasing directly with neighbours' logistics performance.

Previous research has shown that spatial correlation exists in heavily broken down geographical data (LeSage and Polasek 2008). LeSage and Llano (2006) already accounted for spatial dependence by using Spanish regions in a gravity framework, involving origin-destination flows. Alamá-Sabater et al (2010) took the analysis of different sectors a step further by following a spatial pattern in accordance with the structure of territory and the type of economic sector. Although both LeSage and Llano (2006) and Alamá-Sabater et al (2010) focused on Spanish regions and their results revealed a spatial pattern, they also revealed the limitations of the level of territorial breakdown chosen; Autonomous Communities (NUTS-2), which are a too large basic unit and too heterogeneous to be treated as a whole. It is therefore necessary to reduce the spatial level and consider a smaller basic unit area. In this paper, we reduce the geographical scale to provincial level (NUTS-3), and we do not only provide evidence regarding the convenience of introducing spatial dependence in gravity models of trade when analysing the role of transport connectivity in regional and sectorial competitiveness, but we also obtain unbiased sectorial elasticities which capture the magnitude of the impact of connectivity understood in a broad sense on Spanish interregional trade flows.

The rest of the paper is organised as follows. Section two describes the model. Section three outlines the data and variables used in the study. The empirical analysis is performed in section four and finally, section five contains the conclusions.

2. The spatial econometric flow model

The purpose of flow models is to explain variation in the magnitude of flows between each origin destination (O-D) pair. The model introduced by LeSage and Pace (2008) is based on the type of spatial auto-regressive models appearing in equation (1):

(1)

As in gravity models (Bergstrand, 1985 and 1989; Deardorff, 1995), ***X***'s matrix captures the characteristics of origin and destination regions that could influence bilateral trade, as well as the distance between the main city in origin-destination regions. Each variable produces an n^2 by 1 vector with the associated parameters at 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 represent origins. As in LeSage and Pace (2008), the model matrices are defined as , and .

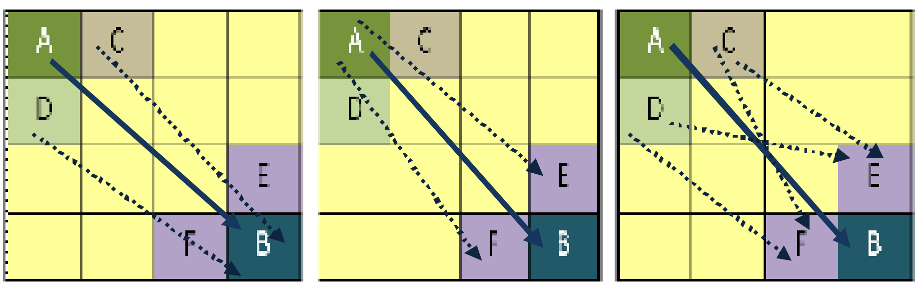
W matrix represents an n by n spatial weight matrix based on a neighbour's criteria as geographical first-order contiguity. Non-zero values for elements i, j denote that zone i is a neighbour to zone j, and zero values denote that zones i, j are not neighbours. The elements on the diagonal are zero to prevent an observation from being defined as a neighbour to itself.

The spatial lag vector 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 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. Finally, the third spatial lag in the model 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.

The model was estimated based on a matrix ***W*** which considers transport connectivity in conjunction with the restriction that only first-order neighbours are included in the formation of the spatial lags.

The three spatial matrices used in the present study are represented in Figure 1. Matrix $\boldsymbol{W_o}$ (origin-based dependence) captures the spatial relationship between trade of regions neighbouring A (C and D) and B, matrix $\boldsymbol{W_d}$ (destination-based dependence) reflects trade between A and regions neighbouring B (E and F), and matrix $\boldsymbol{W_w}$ (O-D-based dependence) considers trade between regions neighbouring A (C and D) and regions neighbouring B (E and F).

Figure 1: Trade flows taken into account ($\boldsymbol{W_o}$, $\boldsymbol{W_d}$, $\boldsymbol{W_w}$, respectively).



In relation to transport connectivity, two opposite effects might arise from Figure 1. On the one hand, a low quality of transport networks in one region compared to its neighbours could be an incentive for firms to locate their activities in a region with better transport connectivity (diversion effect). On the other hand, it seems plausible that forces leading to flows from an origin region to a destination region would create similar flows to neighbouring destinations (creation effect). Therefore, a particular region could benefit from its neighbours' transport networks if the flows of goods from the region of interest have to pass through neighbouring regions to reach consumers. Finally, the higher the level of disaggregation of geographical data, the greater we expect the positive effect to be (the creation effect outweighs the diversion effect), as it is difficult to imagine that a small spatial economic unit could produce many goods without the help of the surrounding areas, as well as the fact that a small economic unit would not benefit from the transport networks of surrounding areas to reach markets if it could not reach without crossing them.

LeSage and Polasek (2008) have already introduced transport connectivity into a spatial econometric model of commodity flows in the case of Austria, modifying the spatial weight matrix by considering geographical criteria together with transport network structure. Nonetheless, the authors only considered the transportation routes that pass through these regions, but did not consider sectorial disaggregation. In this paper, we have modified the spatial matrix to consider the availability of logistics infrastructures at regional level to fully account for the role of transport connectivity, understood in the broad sense, on interregional Spanish trade flows.

3. Data and variables

We generate a dataset with total commodity flows transported between 47 Spanish regions (provinces)[1] during the year 2007. As we are considering the interregional trade in the mainland and the effect of trade with bordering regions, the Canary Islands and the Balearic Islands, Ceuta and Melilla are not taken into account. The regions were based on the NUTS-3 and the interregional trade flow matrices (considering road, rail and air transport) were supplied by C-Interreg. We used 16 origin-destination matrices; one with total trade flows in tonnes, while the others correspond to 15 branches of activity.[2] We focus on extending gravity equations and then consider a number of the characteristics of the origin and destination regions. In order to construct the matrices $\boldsymbol{X_o}$ (origin) and $\boldsymbol{X_d}$ (destination) we used the log of the area, the log of population, the log of GDP per capita and the log of unemployment in each region[3] as explanatory variables. A vector of (logged) distances (km) between the capitals of each O-D region was also included as an explanatory variable, along with an intercept vector. We would expect area, population and GDP per capita to display a positive sign, leading to higher levels of commodity flows (weights) in both the origin and destination regions. The coefficient of unemployment is expected to present an ambiguous sign as this variable might be reflecting sector-specific characteristics such as the degree of resources intensity and technological innovation achievement, whereas the coefficient estimate on distance should be negative, indicating a decrease in commodity flows with distance.

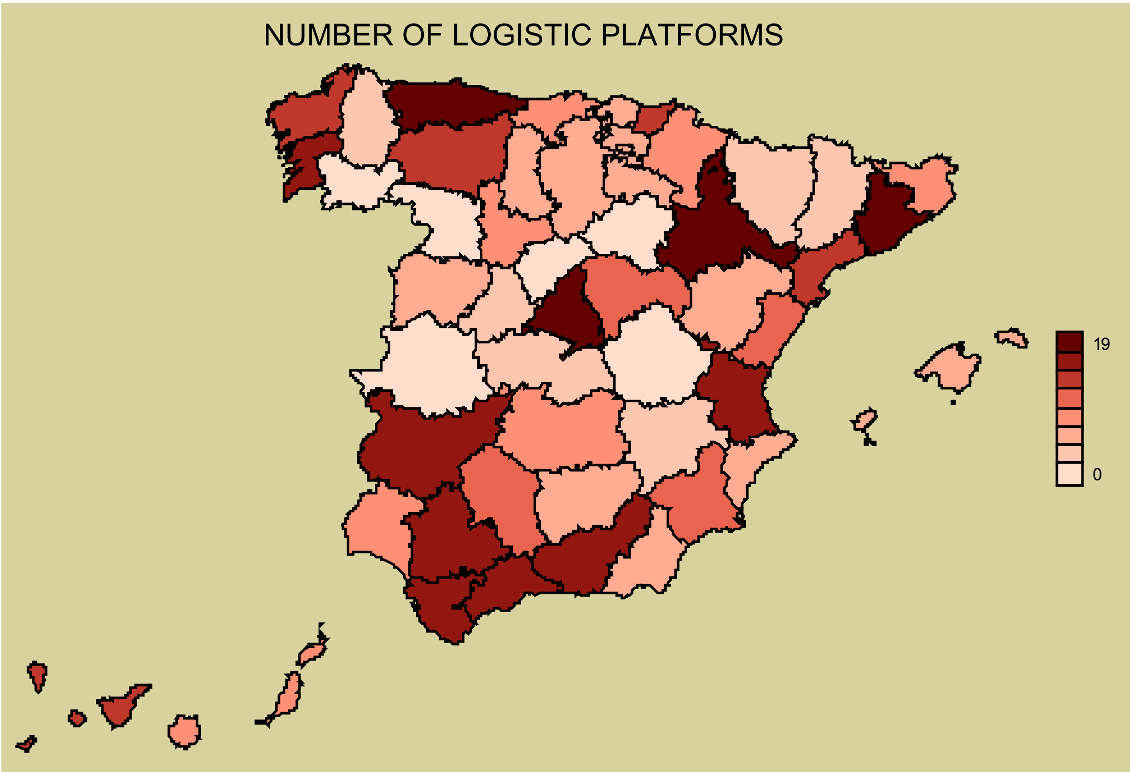
[1] See Figure A.1, in Appendix.

[2] See Table A.1 in the Appendix.

[3] The Spanish Statistical Institute (INE) has been the source of information and, regarding the dependent variables, dates refer to 2007.

Weight matrices have been constructed using a geographical criterion and introducing logistics characteristics,[4] and then we consider the presence of logistics platforms, i.e. the regions adjacent to A (origin) or B (destination) that also have logistics platforms. In order to proxy the quality and level of logistics factors between O-D regions, a connectivity index is calculated as a simple average of two dimension indices, these being the number and size of logistics platforms. Figures 2 and 3 show the number of logistics platforms and the logistics surface area by Spanish region, respectively. Madrid, Barcelona, Zaragoza and Huelva, have the largest 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 the region of Aragon, the Madrid Barajas centre in the Madrid region and the Port of Huelva in Andalusia), which increase the average size of platforms. Provinces such as Valence, in the Valencian Community, and a number of provinces in Andalusia (Seville, Cadiz, Malaga and Granada) also present a large number of logistics platforms. In contrast, provinces in Extremadura, Castile La Mancha and Castile and Leon show a real shortage of square metres devoted to logistics activities. The Balearic and Canary Islands are also home to only a small number of large platforms linked to their ports.

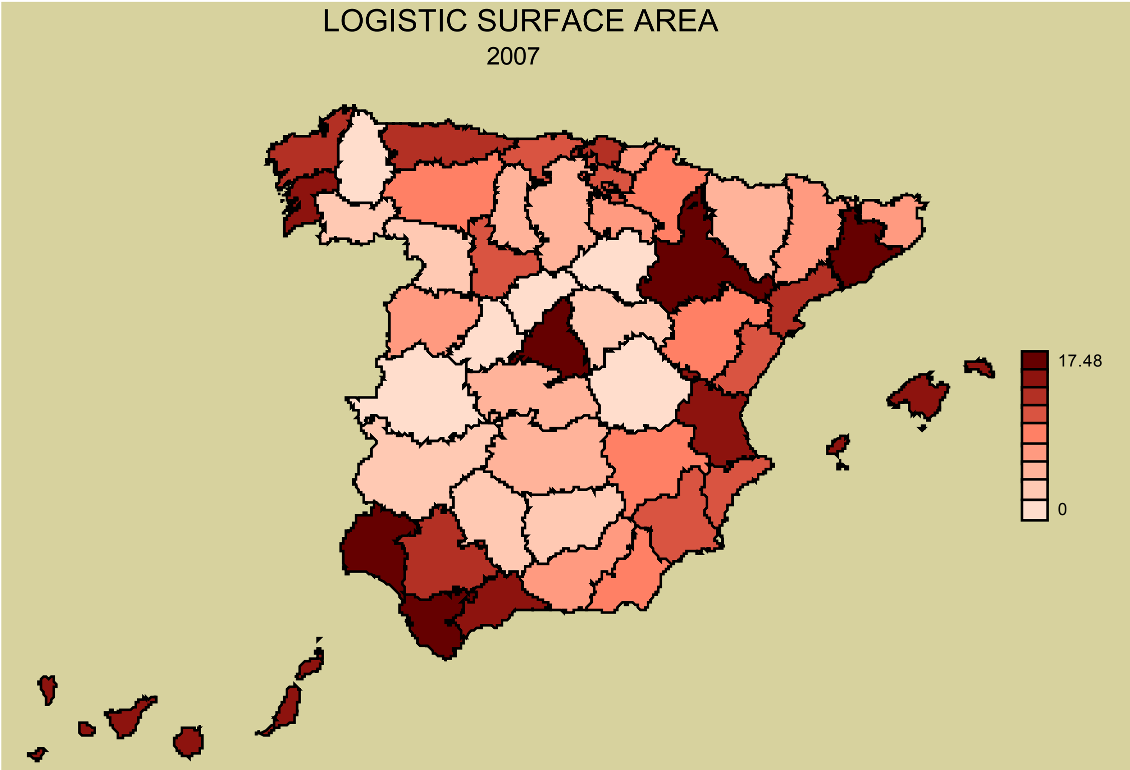
Figure 2: Number of logistics platforms (by Spanish region in 2009).



Source: The RELOG project.

Figure 3: Logistics surface area (by Spanish region in 2009) as a percentage of total logistics surface area in Spain.

[4] The RELOG project ('Red Logística Española') has for the first time compiled comprehensive data on the Spanish network of logistics platforms. Professor Celestino Suárez leads this project.



Source: The RELOG project.

In order to introduce logistics characteristics, the connectivity index 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 O-D. The performance of the connectivity index takes a value between 0 and 1 calculated according to equation (2):

$$CI = \frac{(actual value - observed \min value)}{(observed \max value - observed \min value)} \qquad (2)$$

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

In order to explain the model and the dependent variable in equation (1), we generate an n^2 by 1 vector by stacking the columns of the matrix. If we consider a model with 4 regions, the flow matrix would be represented 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) and ***X***'s the explanatory variables (area, population, GDP per capita and employment, together with geographical distance). Only four regions (Seville, Zaragoza, Barcelona and Madrid) are considered in Table 1 for simplicity. One of the main problems with this kind of models is the dimension of the matrix, as in this paper we have worked at NUTS-3.[5] Nonetheless, when considering logistics platforms, it seems plausible for the trade creation effect to be higher than the

[5] We have worked with 47 regions, so the weight matrix is 2209 rows and 2209 columns (47x47).

trade diversion effect the higher the level of disaggregation as, for example, Gerona (NUTS-3) benefits from transport infrastructures in Barcelona and Zaragoza to reach the market in Madrid.

Table 1: Data organisation

Dyad label	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
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

4. Empirical analysis

4.1. Descriptive analysis

First of all, we present a map of Spain showing regions containing the total trade flows, as export-trade (Figure 4) and as import-trade (Figure 5). The areas where the most important trade flows are concentrated are identified with darker colours (darker red colours reflect higher levels of flows, while lighter red colours indicate lower flow 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 greatest outward and inward intensity are Barcelona, Madrid, Seville and Valencia.

Figure 4: Spanish regions (NUTS-3) by export intensity.[6]

[6] These maps are constructed by setting flows within regions to zero to emphasize interregional flows.

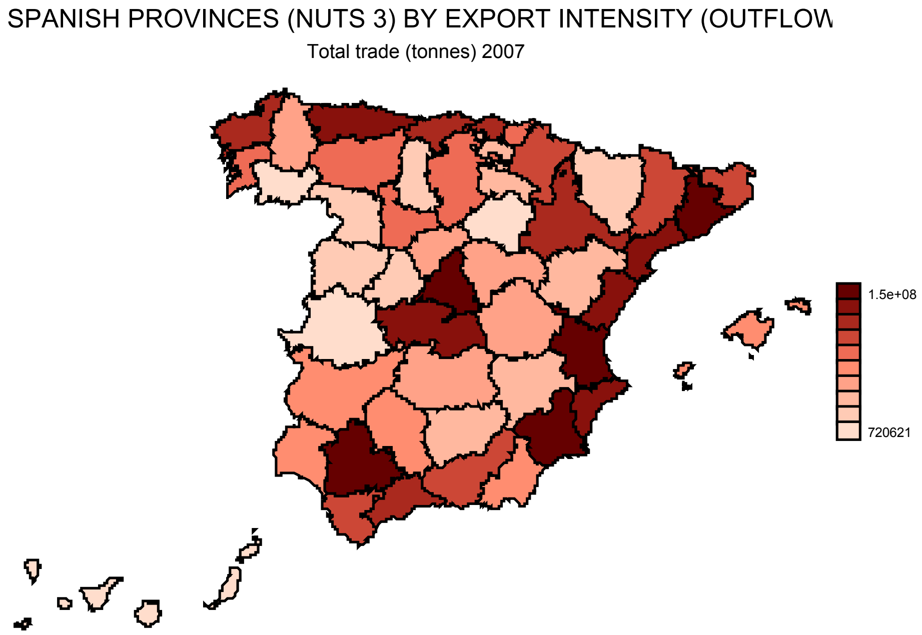
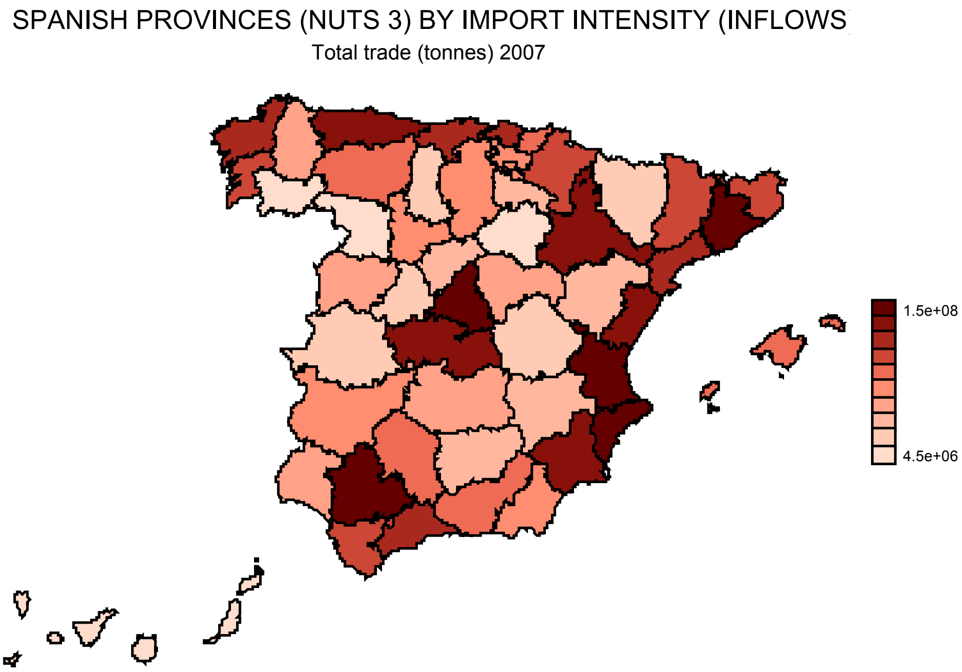


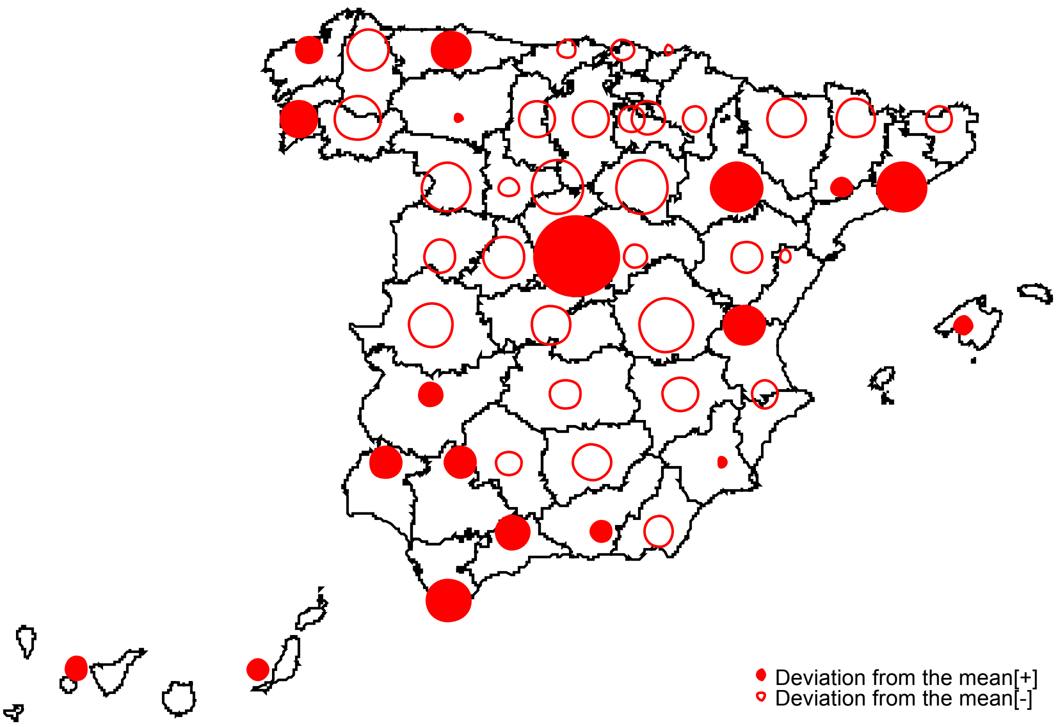
Figure 5: Spanish regions (NUTS-3) by import intensity.



Finally, Figure 6 shows the map of the connectivity index from equation (2) which has been used in the weighting matrix. In Figure 6, the regions containing the highest logistics performance index values are dark red. This example illustrates a case where a clear differentiation can be made between regions in terms of logistics performance. This should provide a good test of whether explicitly incorporating such prior information into the spatial connectivity structure of the model results in substantial differences in the estimates and inferences.

Figure 6: Spanish regions (NUTS-3) - Connectivity index

CONNECTIVITY INDEX



Examining the maps in Figures 4 and 5 in conjunction with that of the logistics network in Figure 6, there appear to be more flows in origin and destination regions in the regions where logistics networks are more extensive than in regions with less developed logistics networks.

4.2. Main results

In order to analyse the spatial dependence of interregional Spanish trade flows, we estimate equation (1) by maximising the log-likelihood function concentrated with respect to the parameters ρ1, ρ2 and ρ3, and the parameters β_i.

Our model reflects the logistics performance in Spanish regions discussed in Section 3, 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. 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.

Different columns in Table 2 present the results obtained when estimating Equation (1) for total trade and different activity branches (R1-R15). Column (1) shows that area, population and income display the expected positive sign and are significant. The bigger surface, population and income are in a region the higher export and import flows. Unemployment is found to be not significant, whereas distance is positive signed and significant. The positive sign found in the variables of area, population and income, in conjunction with the positive sign found in distance variable might be pointing towards the idea that provinces trade more with the largest economic centres, which are not necessarily the nearest ones when a much disaggregated territorial level is taken into account. The negative sign for distance variable found in sectors R4 (Textile and Clothing), R5 (Leather and Footwear Industry), R9 (Manufactures of Rubber and Plastic Products) and R12 (Manufactures of Machinery and Mechanical Equipment) seems to indicate a higher importance of interregional road transportation costs in these sectors, as the higher the geographical distance, the lower trade, and as a consequence they might be tending to locate nearer to the most important economic and geographical Spanish centres. The variable of unemployment is found to be positive and significant in sectors R1 (Agriculture, Forestry and Fishing), R2 (Mining and Quarrying), R11 (Basic Metals and Fabricated Metal Products) and R14 (Manufactures of Transport Equipment). This result might be reflecting that these industries are intensive in labour, as a lower number of workers engaged in these industries (higher unemployment), the lower production and trade.

With regard to the sectorial parameters which capture the magnitude of the impact of connectivity on Spanish interregional trade flows ($\rho 1$, $\rho 2$ and ρ_3), we find a positive and significant effect of connectivity, understood in its broad sense, on total trade flows. This should not be surprising, as the spatial lags for the origin and destination (associated with parameters $\rho 1$ and $\rho 2$) average of neighbouring regions on the logistics network should be positively associated with the level of commodity flows.

Table 2: Estimates from the transport connectivity spatial model

	Total trade	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15
Origin Area	0.73***	1.18***	0.32	0.42*	0.09	0.23***	0.42**	0.26	0.66***	0.33**	0.62***	0.84***	0.17	0.47***	0.26	0.57***
	(4.16)	(5.70)	(1.52)	(1.91)	(0.94)	(2.58)	(2.33)	(1.55)	(3.32)	(2.12)	(2.94)	(4.18)	(1.46)	(2.76)	(1.50)	(3.83)
Origin Population	1.25***	1.12***	1.05***	0.98***	0.49***	0.52***	0.87***	1.32***	1.25***	1.17***	1.39***	1.59***	0.21***	1.15***	0.93***	1.01***
	(11.34)	(9.16)	(8.40)	(7.37)	(8.59)	(10.13)	(8.14)	(11.94)	(10.27)	(12.76)	(10.68)	(12.47)	(3.27)	(11.00)	(8.80)	(11.47)
Origin GDPpc	2.42***	4.20***	2.32***	2.02***	0.26	0.23	1.34**	2.39***	2.55***	1.35**	2.81***	4.97***	0.39	1.82***	2.16***	2.17***
	(3.93)	(5.72)	(3.13)	(2.62)	(0.73)	(0.70)	(2.12)	(4.01)	(3.67)	(2.45)	(3.77)	(6.91)	(0.95)	(3.03)	(3.50)	(4.14)
Origin Unemployment	0.04	0.13**	0.11*	0.01	-0.02	-0.03	-0.007	-0.02	0.06	-0.05	0.06	0.26***	0.02	0.03	0.09*	0.10**
	(0.74)	(2.21)	(1.81)	(0.21)	(-0.61)	(-1.12)	(-0.13)	(-0.45)	(0.97)	(-1.19)	(0.99)	(4.24)	(0.48)	(0.57)	(1.68)	(2.38)
Destination Area	0.62***	1.22***	0.28	0.94***	0.11	0.12	0.44**	0.21	0.65***	0.31**	0.74***	0.40*	0.17	0.71***	0.22	0.32**
	(3.52)	(5.75)	(1.32)	(4.36)	(1.10)	(1.33)	(2.40)	(1.22)	(3.22)	(2.00)	(3.50)	(1.93)	(1.50)	(4.22)	(1.24)	(2.16)
Destination Population	0.76***	0.69***	0.66***	1.02***	0.47***	0.35***	0.43***	1.22***	1.16***	1.06***	0.95***	1.18***	0.37***	1.11***	0.96***	0.85***
	(7.33)	(5.95)	(5.49)	(7.94)	(8.25)	(7.12)	(4.31)	(11.23)	(9.32)	(10.88)	(7.20)	(9.24)	(5.78)	(10.87)	(8.98)	(9.17)
Destination GDPpc	1.76***	3.98***	1.66**	2.39***	0.13	0.23	0.47	2.78***	2.18***	1.49***	1.65**	4.30***	1.32***	3.34***	2.87***	-0.002
	(2.90)	(5.49)	(2.22)	(3.20)	(0.38)	(0.72)	(0.75)	(4.64)	(3.07)	(2.71)	(2.24)	(5.98)	(3.20)	(5.62	(4.62)	(-0.005)
Destination Unemployment	0.01	0.20***	0.06	0.04	-0.05*	-0.004	-0.07	-0.05	-0.02	-0.15***	-0.01	0.19***	0.06*	0.13***	0.07	-0.15***
	(0.20)	(3.35)	(0.99)	(0.69)	(-1.67)	(-0.16)	(-1.40)	(-1.01)	(-0.31)	(-2.90)	(-0.12)	(3.22)	(1.68)	(2.62)	(1.32)	(-3.06)
Distance	0.88***	0.60***	0.64***	0.63***	-0.13***	-0.08**	1.13	-0.03	0.22**	-0.17**	0.56***	0.19*	-0.17***	-0.12	0.009	-0.08
	(10.52)	(5.78)	(5.53)	(5.94)	(-2.94)	(-2.03)	(1.46)	(-0.39)	(2.36)	(-2.44)	(5.03)	(1.96)	(-2.99)	(-1.35)	(0.11)	(-1.14)
Constant term	-30.07***	-21.65***	-18.90***	-25.99***	-11.51***	-12.13***	-18.33***	-16.38***	-27.14***	-21.09***	-30.80***	-16.54***	-3.52	-21.15***	-10:86***	-23.07***
	(-8.12)	(-5.17)	(-4.36)	(-5.88)	(-5.49)	(-6.40)	(-4.88)	(-4.76)	(-6-64)	(-6.67)	(-7.00)	(-3.92)	(-1.49)	(-6.16)	(-2.94)	(-7.43)
ρ1	0.22***	0.31***	0.26***	0.49***	-0.02	-0.02	0.24***	0.23***	0.18***	-0.08**	0.22***	0.09**	0.08**	0.16***	0.27***	-0.07*
	(5.75)	(8.42)	(7.17)	(14.51)	(-0.54)	(-0.73)	(6.41)	(6.91)	(4.87)	(-2.30)	(5.69)	(2.45)	(2.47)	(4.68)	(8.46)	(-1.89)
ρ 2	0.41***	0.41***	0.30***	0.42***	0.10***	0.12***	0.26***	0.22***	0.36***	0.22***	0.51***	0.41***	0.05	0.18***	0.31***	0.37***
	(11.45)	(12.13)	(8.61)	(11.56)	(3.39)	(4.16)	(7.96)	(6.62)	(10.98)	(6.70)	(15.33)	(12.64)	(1.35)	(5.60)	(9.98)	(12.25)
ρ 3	0.46***	0.33***	0.54***	-0.03	0.05	0.18***	0.33***	-0.06	0.19***	0.12***	0.23***	0.22***	0.25***	0.23***	-0.04	0.16***
	(8.61)	(6.91)	(11.19)	(-0.71)	(1.23)	(4.30)	(6.73)	(-1.43)	(4.05)	(2.65)	(4.88)	(4.96)	(4.72)	(5.27)	(-1.00)	(3.54)

Notes: ***, **, * indicate significance at 1%, 5% and 10%, respectively. Z-statistics are given in brackets.

Overall, O-D-based dependence, i.e. that dependence considering trade between regions neighbouring origin and regions neighbouring destination, is found to be of greater importance than origin-based and destination-based dependence. If we compare these results with those obtained in Alamá-Sabater et al (2010), 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.

Furthermore, when different sectors are distinguished, 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 exports. Second, we find sectors for which 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 trade. Finally, we also find those sectors for which O-D dependence is the most important (R2, R5, R6, R12 and R13). As previous research which revealed a spatial pattern when analysing interregional trade flows in Spain (Alamá-Sabater et al, 2010), there is a consistent pattern of parameter $\rho 2$ being of greater importance than $\rho 1$, suggesting that neighbours to the destination region in the analysed logistics model represent the most important determinant of higher levels of industrial commodity flows between O-D pairs.

5. Conclusions

This paper analyses the role of transport connectivity in interregional trade flows using a spatial approach. We find evidence of the importance of transport connectivity, understood in a broad sense, on trade. Additionally, it is confirmed that the gravity equation replays the determinants of interregional trade with a large degree of significance in terms of the use of economic and geographical variables (income, population, area, and distance).

We provide evidence that forces leading to flows from an origin region to a destination region would create similar flows to neighbouring destinations and then, a particular region benefits from its neighbours' transport networks. Finally, we find that the higher the level of territorial breakdown the higher the positive effect of logistics networks on competitiveness, as a smaller territorial unit depend to a higher extend on their neighbours' transport networks.

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Appendix

Figure A.1. Regions in Spain (NUTS-3).

Table A.1: Activity branches.

R1-	Agriculture, forestry and fishing
R2-	Mining and quarrying
R3-	Food Industry
R4-	Textile and clothing
R5-	Leather and Footwear Industry
R6-	Manufacture of wood and cork
R7-	Paper, printing and graphic arts
R8-	Chemical Industry
R9-	Manufacture of rubber and plastic products
R10-	Industry, non-metallic mineral products
R11-	Basic metals and fabricated metal products
R12-	Manufacture of machinery and mechanical equipment
R13-	Electrical equipment, electronic and optical
R14-	Manufacture of transport equipment
R15-	Diverse industries

Source: Spanish Statistical Institute, INE, Spain (2010). www.ine.es