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Spanish exports and logistics needs. 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 regions as a proxy for logistics infrastructure demand in Spain. Then, we obtain data for trade flows between regions (NUTS2) in the year 2007. We also obtain data about the number and area of logistics platforms existing in each Spanish region 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 regions. 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 regions.

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

JEL classification: R12, R23, R48

1. Introduction

The aim of this study is to define a regression-model-based gravity model to explain trade flows between Spanish regions, incorporating, in addition to the characteristics of each region, information on transport infrastructure and logistics. Using a spatial autoregressive model, we considered the spatial connection between each of the regions, taking into account the spatial dependence between the origin and destination flows. This paper extends the procedure followed by LeSage and Polasek (2008), including weight matrixes based on the logistics performance in neighboring regions. This framework allows nearby regions to enter into the determination of the spatial lags, with the weight assigned increasing directly with the neighbors' logistics performance.

According to LeSage and Pace (2008) the magnitude of trade flows will be assessed according to three types of spatial weight matrixes between origin and destination regions. These spatial weights can be used in the family of spatial econometric models popularized by Anselin (1988) to estimate the relative strength of these three types of spatial connectivity relations between origin regions, such as A, and destination regions (Z). First, origin-based dependence (when trade flows between region A (origin) and Z (destination) must be accompanied by similar flows between A's neighboring regions Z). Second, destination-based dependence (when trade flows between region A and Z must be accompanied by similar flows between region A and Z's neighboring regions and, third, origin-destination dependence (when trade flows between region A and Z must be accompanied by similar flows in A's neighboring regions and Z's neighboring regions).

Our focus is on extending gravity equations and considering some of the characteristics of the origin and destination regions, such as GDP, employment and size and the effects of trade flows between neighboring regions. In this sense, and following the literature on spatial autoregressive models, we use two different geographical continuity concepts. On the one hand, we consider only geographical criteria, thus being contiguous regions. On the second hand, we also consider the presence of logistics platforms, i.e. the regions adjacent to A that also have logistics platforms.

Previous research has shown that there is spatial correlation in heavily broken down geographical data (LeSage and Polasek 2008). LeSage and Llano (2006) find that accounting for heterogeneity across regions produce efficient parameter estimation for the characteristics parameters in a gravity framework which accounts for spatial dependence by using 18 Spanish regions (NUTS2). In the present paper, we estimate spatial autoregressive models and we go further in analyzing different sectors. We expect to obtain a pattern in commodity trade flows making it possible to determine the needs of transport and logistics infrastructure improvements, by following a spatial pattern in accordance with the structure of territory and the type of economic sector.

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

2. The spatial econometric flow model

The model introduced by LeSage and Pace 2008 is based on spatial auto-regressive models of the form appearing in equation (1):

$$y = \rho_1 W_o y + \rho_2 W_d y + \rho_3 W_w y + \alpha + \beta_d X_d + \beta_o X_o + \gamma D + \varepsilon \quad (1)$$

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. In order to explain the model and the dependent variable, y , 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.

Table 1: Elements of the trade flow matrix

y11	y12	y13	y14
y21	y22	y23	y24
y31	y32	y33	y34
y41	y42	y43	y44

Table 2: Data organization

Dyad label	ID origin	ID destination		Origin explanation variables			Destination explanation variables			Distances
			Y							
				1	2	3	1	2	3	
1	1	1	y11	a11	a12	a13	b11	b12	b13	d11
2	2	1	y21	a21	a22	a23	b11	b12	b13	d21
3	3	1	y31	a31	a32	a33	b11	b12	b13	d31
4	4	1	y41	a41	a42	a43	b11	b12	b13	d41
5	1	2	y12	a11	a12	a13	b21	b22	b23	d12
6	2	2	y22	a21	a22	a23	b21	b22	b23	d22
7	3	2	y32	a31	a32	a33	b21	b22	b23	d32
8	4	2	y42	a41	a42	a43	b21	b22	b23	d42
9	1	3	y13	a11	a12	a13	b31	b32	b33	d13
10	2	3	y23	a21	a22	a23	b31	b32	b33	d23
11	3	3	y33	a31	a32	a33	b31	b32	b33	d33
12	4	3	y43	a41	a42	a43	b31	b32	b33	d43
13	1	4	y14	a11	a12	a13	b41	b42	b43	d14
14	2	4	y24	a21	a22	a23	b41	b42	b43	d24
15	3	4	y34	a31	a32	a33	b41	b42	b43	d34
16	4	4	y44	a41	a42	a43	b41	b42	b43	d44

The purpose of flow models is to explain variation in the magnitude of flows between each origin-destination pair. In this model we introduce three continuity spatial matrixes reflecting

the three types of spatial connectivity. Taking into account the trade flows between A and B, matrix W_o (origin-based) captures the spatial relationship between the trade of regions neighboring A and B. Matrix W_d reflects the trade between A and regions neighboring B, and W_w considers the trade between regions neighboring A and regions neighboring B.

As in LeSage and Pace 2008, the model's matrixes are defined as 1) $W_o = I_n * W$, where W (Anselin, 1988) represents an n by n spatial weight matrix based on a neighbor's criteria as a geographical continuity. Non-zero values for elements i, j denote that zone i is a neighbor to zone j , and zero values denote that zones i, j are not neighbors. The elements on the diagonal are zero to prevent an observation from being defined as a neighbor to itself. The W_o matrix forms an N by 1 vector containing a linear combination of flows that explain origin-based spatial dependence. Similarly, 2) $W_d = W * I_n$ captures destination-based spatial dependence and 3) $W_w = W_o * W_d$ reflects the interaction of both origin-based and destination-based spatial dependence.

The spatial lag vector $W_o y$ would be constructed by averaging flows from neighbors to the origin region, and the parameter ρ_1 would capture the magnitude of impact from this type of neighboring observation on the dependent variable vector y . The spatial lag vector $W_d y$ would be constructed by averaging flows from neighbors to the destination region and parameter ρ_2 would measure the impact and significance on flows from origin to all neighbors to the destination region. It seems plausible that forces leading to flows from an origin region to a destination region would create similar flows to neighboring destination. Finally, the third spatial lag in the model $W_w y$ is constructed using an average over all neighbors to both the origin and destination regions.

Estimating parameters ρ_1 , ρ_2 and ρ_3 provides an inference of relative importance of the three types of spatial dependence between the origin and destination regions. LeSage and Pace (2004) argue that the model can give a rise to a family of other models by establishing a number of restrictions. They defined nine different models derived by placing various restrictions on the parameters ρ_i . In this paper we have estimated the models with the following restrictions: $\rho_2 = \rho_3 = 0$, $\rho_1 = \rho_3 = 0$ and $\rho_1 = \rho_2 = 0$. As LeSage and Pace (2008) point out, the specifications are based on single weight matrixes and allow the use of existing algorithms for maximum likelihood (Pace and Barry, 1997), Bayesian (LeSage, 1997) or a generalized moment estimation moment (Prucha and Kelejian 1999).

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

distance between the main city of origin-destination regions. Each variable produces an $n^2 \times 1$ vector with the associated parameters in origin, β_i , and destination, β_j .

LeSage and Polasek (2006) introduce an additional point of view into this model, modifying the spatial weight matrix considering the geographical criteria together with accessibility. In this sense, the authors consider the transportation routes that pass into these regions. In the present paper, and following the accessibility criteria, we have modified the spatial matrix, adding logistics platforms. We consider that the magnitude of trade flows depends on the facilities to transport commodities, so in order to modify the W matrix we have considered two criteria - geographical continuity and the presence of logistics platforms in regions.

We have information about both the number and size of logistics platforms in every Spanish region. Considering these variables, we have constructed an indicator that measures connectivity, i.e. importance logistics infrastructures in terms of number and area, between the origin and destination regions. In this case, if regions i, j have a good logistics infrastructure and share a border, the matrix element is near 1; 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.

3. Data, sources and variables

In order to apply equation (1), we generate a dataset with total commodity flows transported between 15 Spanish regions, during the year 2007. The regions were based on the NUTS-2 and the interregional trade flow matrixes (considering road, rail and air transport) have been supplied by C-Interreg.¹ We used 18 origin-destination matrixes (origin in rows, destinations in columns); two with total trade flows in value and in tonnes and the others correspond to the activity branches shown in table (3).

As explanatory variables used to construct the matrixes X_0 (origin) and X_d (destination) we used the log of area in each region, the log of GDPpc² in each region and the log of employment in each region. To measure the distance between origin and destination we have used the distance between regional capitals in km. The Spanish Statistical Institute (INE) has been the source of information and, as for the dependent variables, the dates refer to 2007.

¹ We are grateful to Carlos Llano for data availability.

² When regressions for different sectors are run, the GPNpc considered is agricultural or industrial respectively

Table 3: Activity branches.

Branch	Description
R1-	AA,BB- Agriculture, forestry and fishing
R2-	CA,CB- Mining and quarrying
R3-	DA- Food Industry
R4-	DB- -Textile and clothing
R5-	DC- Leather and Footwear Industry
R6-	DD- Manufacture of wood and cork
R7-	DE- Paper, printing and graphic arts
R8-	DG- Chemical Industry
R9-	DH- manufacture of rubber and plastic products
10-	DI- industry, non-metallic mineral products
R11-	DJ- Basic metals and fabricated metal products
R12-	DK- Manufacture of machinery and mechanical equipment
R13-	DL- electrical equipment, electronic and optical
R14-	DM- Manufacture of transport equipment
R15-	DN- Diverse industries
R16-	DF, EE- energy industry, power distribution, gas and water

Source: INE (2010)

As LeSage and Polasek (2008) note, one of the main problems with this kind of models is the dimension of the matrix. We have worked with 15 regions, so the weight matrix is 225 rows and 225 columns, but the W_o , W_d and W_w matrixes dimension are considerably higher, thus being 50,625 rows and 50,625 columns. It is important to note that the increased level of disaggregation creates a problem with the size of the database; according to LeSage and Pace (2004) that problem is minimized by replacing the determinant of matrixes W_o , W_d , W_w with the determinant of matrix W .

We have modified the weighting matrixes (W) by introducing infrastructure and logistics characteristics. In particular, we have considered the number and the size of logistics platforms in each region to proxy for the quality and level of logistics factors between the origin region and destination region. Therefore, we have constructed a connectivity index as expressed in equation (2):

$$Iconect_{ij} = \frac{1}{2} \left(\frac{\frac{size_i - minsize}{maxsize - minsize} + \frac{platf_i - minplatf}{maxplatf - minplatf}}{2} + \frac{\frac{size_j - minsize}{maxsize - minsize} + \frac{platf_j - minplatf}{maxplatf - minplatf}}{2} \right) \quad (2)$$

We have applied two different weight matrixes, thus being the W matrix (constructed by using a geographical criterion based on a first-order contiguity) and W^m matrix (constructed by using both the geographical and the connectivity index criteria), so we substitute the non-

zero values from the W matrix for the values of connectivity index, thus considering the spatial distribution of logistics infrastructures in trade flows.

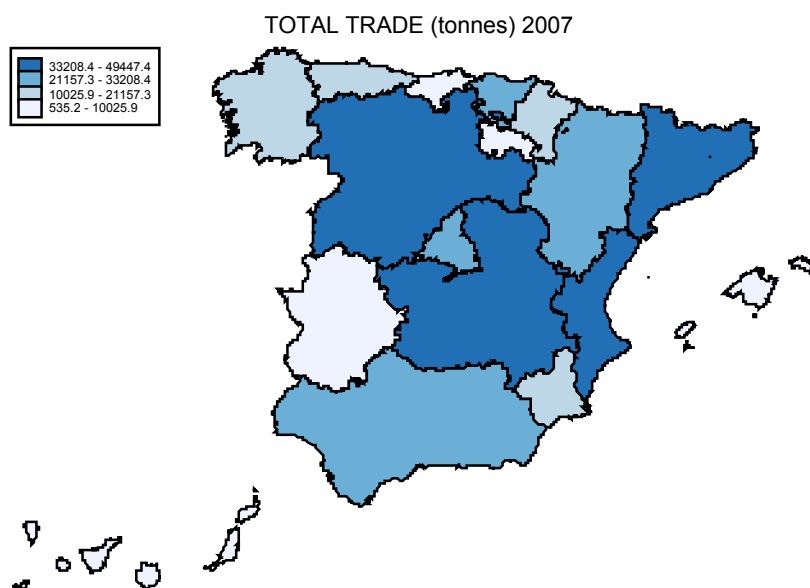
The modified spatial matrix (W^m) has been constructed taking into account two elements, as in the W matrix, the first-order geographical continuity and second is the index connectivity between the origin and destination (Iconectij), so we substitute the non-zero values from W matrix form the connectivity index in the W^m matrix, thus considering the logistics performance in trade flows.

4. Empirical analysis

4.1. Descriptive analysis

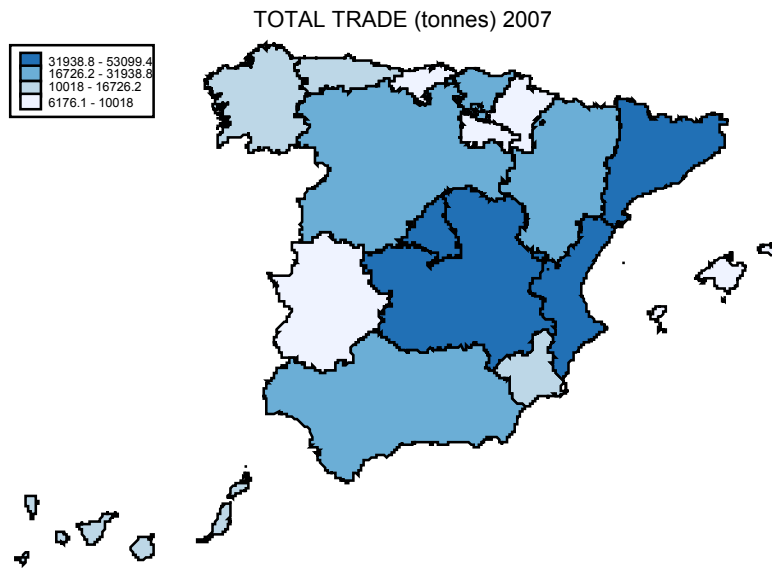
First of all, we represent a map of Spain showing regions containing the total trade flows, as export-trade and (figure 1) as import-trade (figure 2). The areas where the most important trade flows are concentrated are identified with dark color (Darker blue colors reflect lower levels of flows while lighter blue colors indicate higher flow levels). These maps represent total trade flows, so the analysis should be carried out from a general point of view.

Figure 1—Spanish regions (NUTS 2) by export intensity.³



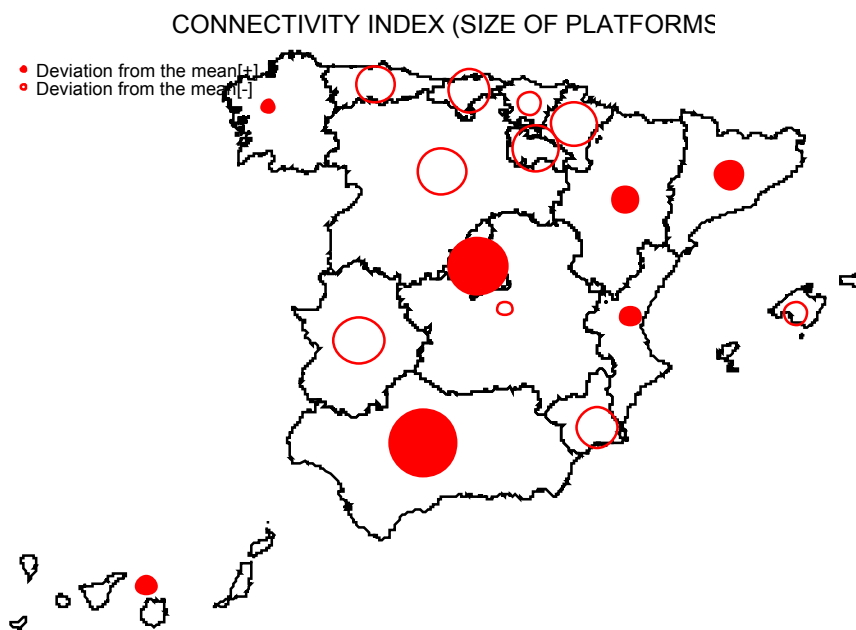
³ These maps are constructed by setting flows within regions to zero values to emphasize interregional flows.

Figure 2—Spanish regions (NUTS 2) by import intensity



The maps (figure 1 and 2) are quite similar. The Spanish regions with the greatest export intensity are Castile la Mancha, Castile León, Catalonia and Valencia and regions with the greatest import intensity are Madrid, Castile La Mancha, Catalonia and Valencia.

Figure 3—Spanish regions (NUTS 2) size of logistics platforms



Figures 3 and 4 show the connectivity index but taking into account only one component, size and number of platforms, respectively. Finally, figure 5 shows the map of the connectivity index from equation (2) and which has been used in matrix the modified matrix (W^m).

Figure 4—Spanish regions (NUTS 2)

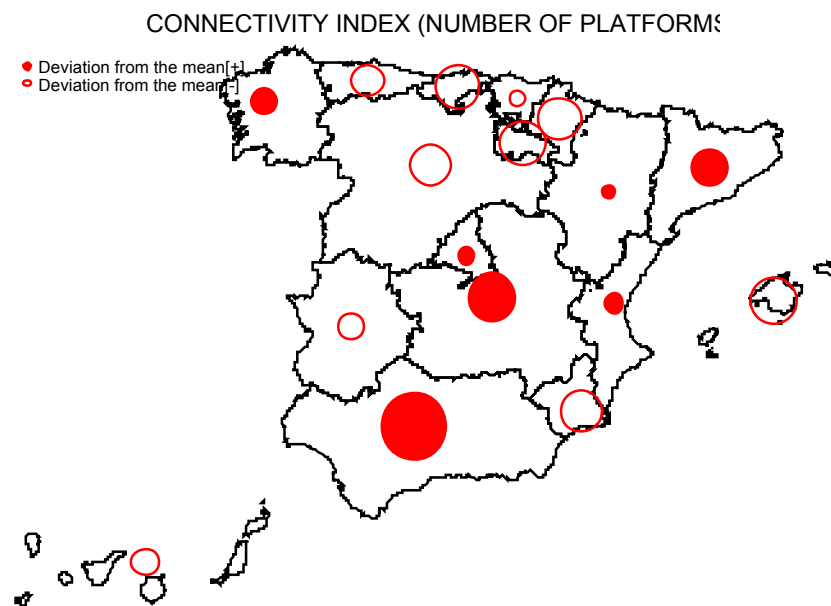
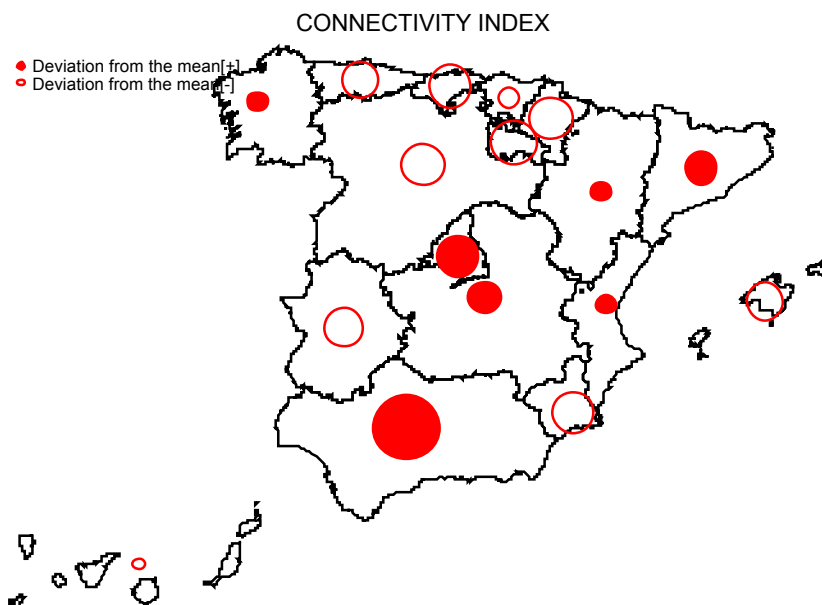


Figure 5—Spanish regions (NUTS 2) - Connectivity index



In Figure 5, the regions containing the highest logistics performance index values are dark orange. As already noted, 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.

Examining the maps in Figures 1 and 2 in conjunction with that of the logistics network in Figure 5, it is clear that the level of flows in origin and destination regions that have more developed logistics networks is higher than for regions with less developed logistics networks.

Second, to analyze whether the inter-regional trade values are based on the locations where they are measured, we use Moran's I measure of spatial autocorrelation. In order to do so, we use the *spatwmat* command in STATA to generate the three weight matrixes based on the locations in our data (first-order contiguity: *Wo*, *Wd*, *Ww*) and the *spatgsa* command in STATA to calculate Moran's I measure. Our results show that we can reject the null hypothesis that there is zero spatial autocorrelation present in the trade variable, both when it is measured in values as well as in tonnes.

Table 4. Moran's I measure of spatial autocorrelation. First-order contiguity.

	<i>Trade values</i>	<i>Trade weights/tonnes</i>
<i>Wo</i>	0.345*** (7.107)	0.432*** (8.890)
<i>Wd</i>	0.478*** (9.822)	0.411*** (8.460)
<i>Ww</i>	0.041** (1.823)	0.150*** (6.151)

Notes: ***, **, * indicate significance at 1%, 5% and 10%, respectively. Z- statistics are given in brackets. Moran's I measure of spatial autocorrelation is calculated for the natural logarithm of exports in value (millions euros) from region i (origin) to j (destination) – Column 1 - as well as for the natural logarithm of exports in (thousands of tonnes) – Column 2. Data is for the year 2007.

Thirdly, we also analyze the existence of spatial autocorrelation when we include the transportation network and logistics infrastructure in the weighting matrixes. We find that spatial autocorrelation exists in origin (*Wo*), destination (*Wd*) and in the interaction between origin and destination (*Ww*), as we reject the null hypothesis that there is zero spatial autocorrelation in the three cases.

Table 5. Moran's I measure of spatial autocorrelation. First-order contiguity and logistics platforms.

	<i>Trade values</i>	<i>Trade weights/tonnes</i>
<i>Wo_connect</i>	0.359*** (6.831)	0.468*** (8.889)
<i>Wd_connect</i>	0.493*** (9.431)	0.420*** (8.049)
<i>Ww_connect</i>	0.059** (2.128)	0.205*** (7.059)

Notes: ***, **, * indicate significance at 1%, 5% and 10%, respectively. Z-statistics are given in brackets. Moran's I measure of spatial autocorrelation is calculated for the natural logarithm of exports in value (millions euros) from region i (origin) to j (destination) –Column 1 - as well as for the natural logarithm of exports in thousands of tonnes Column 2-. Data is for the year 2007.

These results point towards the importance of considering a framework where spatial dependence is taken into account. In the next section, we will illustrate this aspect of model specification using our sample data for the 15 Spanish regions.

4.2. Main results

In order to analyze the spatial dependence of inter-regional Spanish trade flows, we estimate equation (1) using commodity flows transported between 15 regions in Spain during the year 2007. The regions were based on the NUTS2 regions.⁴ The flows used represent the value in euros (millions) and tonnes (thousands), with the source of the data being Interreg. As in LeSage and Polasek (2008), the interregional flow magnitudes were transformed using logs.

The algorithms used to produce the estimates were those described in LeSage and Pace (2005) and LeSage and Polasek (2008), which involve maximizing the log-likelihood function concentrated with respect to parameters β and σ in the model. This results in a three-parameter optimization problem involving the parameters ρ_1 ; ρ_2 ; ρ_3 .

Two variants of the model were estimated, one based on the spatial weight structure proposed by LeSage and Pace (2005) and another which reflects the logistics performance in Spanish regions discussed in Section 2. The first approach relied on a matrix W based on the first-order contiguous neighboring regions as the basis for constructing the weight matrixes W_o ; W_d ; W_w used by the model. The second approach relied on a matrix W which considers logistics performance in conjunction with the restriction that only first-order neighbors are included in the formation of the spatial lags. This will result in a direct relationship between increased numbers of the nearest neighbors and the performance of the logistics segments that go to form the spatial lag variables.

As explanatory variables used to form the matrixes X_o and X_d , we use the log of area in each region; the log of employment and the log of GDP per capita. A vector of (logged) distances between the capital of each region was also included as an explanatory variable, along with an intercept vector.

We would expect that employment would show a positive sign, leading to higher levels of commodity flows (values and weights) in both the origin and destination regions. The coefficient estimate on distance should be negative, indicating a decrease of commodity flows with distance, whereas the impact of area and GPD is ambiguous.

Our estimate focuses on comparing the model based on spatial weights constructed from first-order contiguity relationships and the model based on logistics network structure.

On the one hand, the left part of Table 6 (Models 1-6) presents the results obtained when using the spatial weights constructed from first-order contiguity relationships. Models 1, 2 and

⁴ Andalusia, Aragon, Asturias, Cantabria, Castile and León, Castilla-la-Mancha, Catalonia, Valencia, Extremadura, Galicia, Madrid, Murcia, Navarre, Basque Country, La Rioja. The Canary Islands and the Balearic Islands, Ceuta and Melilla are not considered. We are considering the interregional trade in the peninsula and the effect of trade with bordering regions, so in this case the island have not bordering regions.

3 show the obtained results when the dependent variable is trade in value, and they separately include origin (ρ_0), destination (ρ_d) and origin-destination (ρ_w) lags, respectively. Models 4-6 show the results obtained when the dependent variable is trade in weights. On the other hand, the right-hand part of Table 6 (Models 7-12) presents the results obtained when using the spatial weights constructed from both the first-order contiguity relationships and the logistics network structure.⁵

Table 6 shows that the explanatory variables show the expected sign and are significant in all cases. Additionally, Table 6 presents the parameter estimates for both the first-order contiguity-based spatial weight model (left part) and for the modified model (right part). From the two models we see a similar pattern of values when the variable is measured in values: $\rho_1 < 0$, $\rho_2 > 0$ and $\rho_3 < 0$, although ρ_1 is positive signed when running the regressions with the dependent variable in tonnes. Although destination dependence has the expected sign in all cases, it is only significant in the contiguity model since the spatial lags are not significant in the model constructed by considering logistics performance in neighboring regions. For the dependent variable in weight ρ_1 , ρ_2 , ρ_3 are positive signed in all cases, although they are only significant at origin dependence. Otherwise spatial dependence is not significant in the modified model.

In order to improve our understanding of the results obtained, we go further by running different regressions for exports (in thousands of tonnes) included in different economic activities, as we believe the problem may arise from aggregation bias.

⁵ When estimates are run for different sectors, the effect of both per capita GDP and surface are found to be ambiguous. This is probably due to the fact that the GDP for agriculture and industry is included in the different agriculture and industry branch regressions respectively. These results are available upon request from the authors.

Table 6: Estimates from the contiguity-based spatial model (m1-m6) and the modified logistics model (m7-m12)

Variable	Exports in Value			Exports in Tonnes			Exports in Value			Exports in Tonnes		
	m1	m2	m3	m4	m5	m6	m7	m8	m9	m10	m11	m12
Origin area	0.50***	0.50***	0.51***	0.50***	0.47***	0.48***	0.50***	0.50***	0.51***	0.48***	0.48***	0.47***
Origin GDPpc	(4.93)	(5.03)	(4.99)	(4.80)	(4.60)	(4.66)	(5.00)	(4.94)	(5.07)	(4.638)	(4.62)	(4.60)
	2.56***	2.20***	2.55***	1.57***	1.54***	1.59***	2.59***	2.42***	2.55***	1.51***	1.63***	1.57***
Origin employment	(5.40)	(4.51)	(5.37)	(3.27)	(3.11)	(3.31)	(5.46)	(4.93)	(5.40)	(3.12)	(3.31)	(3.26)
	0.34***	0.29***	0.34***	0.27***	0.28***	0.28***	0.34***	0.33***	0.34***	0.28***	0.29***	0.28***
Destination area	(5.26)	(4.39)	(5.26)	(4.16)	(4.04)	(4.16)	(5.24)	(4.89)	(5.18)	(4.24)	(4.28)	(4.25)
	0.40***	0.43***	0.40***	0.37***	0.36***	0.37***	0.41***	0.40***	0.41***	0.36***	0.36***	0.36***
Destination GDPpc	(3.98)	(4.24)	(3.98)	(3.57)	(3.50)	(3.58)	(4.02)	(3.95)	(4.04)	(3.48)	(3.51)	(3.49)
	1.49***	1.44***	1.46***	0.83*	1.01**	1.06**	1.57***	1.47***	1.32***	0.89*	1.00*	1.00**
Destination employment	(3.00)	(3.03)	(3.02)	(1.66)	(2.06)	(2.16)	(3.15)	(3.06)	(2.70)	(1.76)	(2.03)	(1.99)
	0.40***	0.39***	0.39***	0.37***	0.41***	0.40***	0.41***	0.40***	0.37***	0.39***	0.40***	0.41***
Distance	(5.60)	(6.00)	(6.00)	(5.16)	(6.11)	(6.10)	(5.98)	(6.09)	(5.69)	(5.58)	(6.06)	(6.05)
	-0.78***	-0.87***	-0.80***	-1.21***	-1.14***	-1.10***	-0.75***	-0.82***	-0.80***	-1.18***	-1.12***	-1.13***
Constant term	(-5.30)	(-6.24)	(-5.73)	(-8.21)	(-7.97)	(-7.77)	(-5.08)	(-5.84)	(-5.84)	(-7.98)	(-7.84)	(-8.01)
	-15.38***	-14.31***	-15.11***	-7.17***	-7.53**	-9.02**	-15.82***	-14.86***	-13.98***	-6.94**	-7.67*	-7.46*

	(-4.60)	(-4.33)	(-4.35)	(-2.12)	(-2.22)	(-2.55)	(-4.68)	(-4.43)	(-4.08)	(-2.02)	(-2.26)	(-2.13)
	$\rho 1$	$\rho 2$	$\rho 3$	$\rho 1$	$\rho 2$	$\rho 3$	$\rho 1$	$\rho 2$	$\rho 3$	$\rho 1$	$\rho 2$	$\rho 3$
	-0.02	0.14**	-0.02	0.11*	0.02	0.16	-0.05	0.05	-0.11	0.06	-0.03	-0.01
	(-0.23)	(2.46)	(-0.21)	(1.63)	(0.3)	(1.42)	(-0.83)	(1.03)	(-1.51)	(1.05)	(-0.57)	(-0.11)
Observations	210	210	210	210	210	210	210	210	210	210	210	210
Log likelihood	-299.59	-296.67	-299.6	-302.39	-303.67	-302.71	-299.28	-299.09	-298.49	-303.16	-303.55	-303.71

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

4.3 The logistics network neighborhood model for agricultural and industrial sectors

Turning attention to the logistics modified model, we see a pattern of estimates for ρ_1 ; ρ_2 ; ρ_3 where all three parameters are positive. This should not be surprising, since the spatial lags for the origin and destination (associated with parameters ρ_1 and ρ_2) average over neighboring regions on the logistics network which should be positively associated with the level of commodity flows. The significance of the spatial lags varies by sectors, whereas ρ_1 and ρ_2 are positive and significant in sector 1; they are not significant for the other agricultural activities. In addition, the spatial lag for the interaction term averages covering neighbors to the origin and neighbors to the destination that are also on the network is not significant in any of the cases.⁶

Table 7: Estimates from the logistics spatial model. Agriculture sectors (R1, R2, R3)

	ρ_1	ρ_2	ρ_3
R1	0.14**	0.11*	0.04
	(2.09)	(1.81)	(0.41)
R2	0.05	0.04	-0.05
	(0.59)	(0.53)	(-0.36)
R3	0.05	0.02	-0.01
	(1.38)	(0.81)	(-0.17)

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

Table 8 shows that ρ_1 ; ρ_2 ; ρ_3 are positive for most economic activity industrial exports. However, the spatial lag is only significant for the case of the exports included in R5, R6, R7, R13 and R15. There is a consistent pattern of parameter ρ_2 being more times significant than ρ_1 in a number of sectors (R6, R7), suggesting that neighbors of the destination region in the logistics model represent the most important determinant of higher levels of industrial commodity flows between O-D pairs.

Table 8: Estimates from the logistics spatial model. Industrial sector (R4-R15)

	ρ_1	ρ_2	ρ_3
R4	0.05	0.02	-0.03
	(1.58)	(0.65)	(-0.54)
R5	0.26***	0.26***	0.54***
	(3.43)	(3.36)	(4.54)
R6	-0.1	0.18**	0.06
	(-0.92)	(2.08)	(0.41)
R7	0.06	0.11***	-0.03
	(1.02)	(2.7)	(-0.48)
R8	-0.05	0	0.06
	(-1.05)	(-0.04)	(1.04)
R9	-0.03	0.09	0.18

⁶ The results for the other explanatory variables are available upon request from the authors.

	(-0.34)	(1.22)	(1.41)
R10	-0.1	-0.05	0.04
	(-1.46)	(-0.77)	(0.39)
R11	-0.02	-0.03	0.06
	(-0.68)	(-0.99)	(1.36)
R12	0.06	-0.19	-0.11
	(0.45)	(-1.31)	(-0.44)
R13	0.14*	0.14**	0.09
	(1.78)	(2.01)	(0.73)
R14	0.05	0.02	-0.03
	(1.58)	(0.65)	(-0.54)
R15	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.

5. Conclusions

The aim of this study was to focus in the spatial (geographical) model determined by commodity flow interregional trade, highlighting the spatial dynamic synergies generated between neighboring regions to the origin region, and neighboring regions to the destination region. In a spatial model in which the results are related to the regional characteristics, the spatial unit chosen is crucial. This paper has opted for NUTS-2, being aware of the biases to which breakdowns can lead. The analysis was made at sectoral level (15 branches) in order to capture any sectoral differences. There are regions where agriculture is more important, while others are more dedicated to manufacturing activities, specifically the Basque Country or Madrid ahead of Andalusia or Murcia. In this case, analyzing the spatial dependence in different sectors is of great interest.

The results have thus revealed a spatial pattern, but also the limitations of the level of territorial breakdown chosen, Autonomous Communities (NUTS-2) are a basic unit too large and heterogeneous to be treated as a whole, especially in some cases, such as Andalusia, Castile la Mancha or Castile León. It is necessary to reduce the spatial level and consider a smaller basic unit area. In further research, we aim to reduce the geographical scale to provincial level (NUTS-3), as well as improving the connectivity index.

For the Spanish case, our results show that, at total values and tonnes of commodities moved from one region to another, spatial dependence is only significant when the weight matrixes are constructed as first-order continuity. However, spatial dependence is not significant when the weight matrixes are constructed using both contiguity and connectivity measures. These results support the hypothesis that the way in which the weight matrixes are constructed is of great importance. Our results support the idea that sectoral breakdown levels also have to be taken into account in order to capture spatial dependence.

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