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See table of contents

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Article abstract

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THE SPATIAL DIMENSION OF MARITIME CONNECTIVITY: THE CASE OF NORTHERN EUROPE AND THE MEDITERRANEAN

Rania Tassadit Dial, Gabriel Figueiredo de Oliveira, Alexandra Schaffar

Rania Tassadit Dial
(LEAD, University of Toulon)
Faculté de Sciences économiques et de Gestion, Campus Porte d'Italie, 70 avenue Roger Decouvoux 83000 Toulon, France.
rdial.univ@gmail.co

Gabriel Figueiredo de Oliveira
(LEAD, University of Toulon)

Alexandra Schaffar
(LEAD, University of Toulon)
schaffar@univ-tln.fr

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Abstract: The aim of this study is to understand how spatial effects influence maritime connectivity. We use a spatial econometric model on panel data for a sample of 114 countries over the period 2004-2017. The results show that there are positive interaction effects that describe a center-periphery relation. We focus specifically on two regions: Northern Europe and the Mediterranean. The results for these two regions indicate substantial differences. In Northern Europe, there is a significant positive spatial dependence with positive spillover effects. Conversely, the Mediterranean region is characterized by a negative spatial dependence, leading to strong competition between countries.

Key words: maritime connectivity, spatial dependence, regional analysis.

INTRODUCTION

Maritime transportation is a major issue in international trade. Efficient supply chains relying on maritime transportation ensure easier and faster market access for producers and boost international exchange. Seaport organization appears to be a key factor in improving maritime transportation performance, that is, higher shipping connectivity and sea traffic growth (Limao & Venables, 2001; Kummar & Hoffmann, 2002; Fink et al., 2002; Sanchez et al., 2003; Clark et al., 2004; Wilmsmeier et al, 2006; Hoffmann and Wilmsmeier, 2008). Moreover, the development of port and maritime activities enhances regional growth and job creation on a local scale (Ng et al., 2016; Sakalayen et al., 2017).

The UNCTAD report (2015) indicates that liner shipping connectivity plays a crucial role in determining the trade performance of coastal countries as well as of landlocked countries. The report measures and compares the liner shipping connectivity of different countries by estimating a liner shipping connectivity index (LSCI). This index has the advantage of being easily applicable and consistent across countries and time[1]. It can be considered as a good proxy for a country's position in the global container shipping network.

Some studies reach interesting conclusions on the importance of maritime connectivity and its role in reducing trade costs, and more particularly transport costs (Martinez-Zarzoso & Wilmsmeier, 2010; Fugazza & Hoffmann, 2017). Other studies aim in quantifying the connectivity level of different ports (Tang et al., 2011; Low et al., 2009; Bartholdi et al, 2016). Recent literature delivers evidence on the importance of portal activity on the prosperity of coastal cities and regions and on the influence of ports on urban economic development (Ng et al, 2016). However, several questions remain unanswered: what are the main determinants of maritime connectivity? Does geographical proximity between countries affect the level of maritime connectivity?

The shipping connectivity of countries could be spatially related, since ports may develop in neighboring regions, closely linked by sea roads. This means that the shipping services in a country could influence the shipping services deployed in neighboring countries. The work carried out in this paper provides empirical evidence on the importance of spatial interactions within portal regions. By focusing on the existence of spatial spillover effects, these results are decisive for policy-makers.

Spatial autocorrelation may affect the effectiveness of public policies and strategic decisions aiming to improve the level of a port's connectivity. Two alternatives exist: first, the spatial interaction effects between countries imply a positive dependence, i.e. the change in the level of connectivity for a given country leads to a similar change in the level of connectivity for its neighbors; second, the improvement/decrease in maritime connectivity of a country leads to an opposite effect for its neighbors (negative interaction effects).

To test these hypotheses, a Spatial Durbin Model (SDM) is applied to a sample of 114 countries over the period 2004-2017. The results show the existence of significant positive spatial autocorrelation effects. This analysis is then extended to a macroregional scale, in order to investigate if such effects also affect the European and the Mediterranean region on one hand, and the Northern and the Baltic region on the other, since they're both competing to serve the same hinterland (Fremont & Sopé, 2005; Acciaro et al., 2017). The results show substantial differences between these two regions. Northern Europe features a significant positive spatial dependence effect, while the Mediterranean region is characterized by a negative spatial dependence with increased competition between countries.

This paper is organized as follows: the next section provides a literature review. Section 3 presents the model specification, the databases and delivers a descriptive analysis on collected data. Section 4 introduces some methodological issues concerning spatial autocorrelation. Section 5 presents and discusses the results. The final section concludes by examining actual and future port policies.

LITERATURE REVIEW

The connectivity concept has been discussed often in maritime transportation literature. Several definitions exist. According to Wilmsmeier et al. (2006), transport connectivity can be defined as the access to regular and frequent transport services combined to a high/low level of competition in the provision of these services. Jiang et al. (2014) define connectivity as the difference between the sum of the minimum time required for transportation along the shortest path between all origins and destinations in a network and the sum of the maximum capacity flows along the shortest path between all origins and destinations. Rodrigue (2017) also examines connectivity from a network perspective and defines it as the configuration of transport services and physical infrastructure between nodes with attributes such as capacity, reliability and resilience. Finally, according to Arvis et al. (2018), maritime connectivity is a network that refers to the structure and performance of maritime transport outside the port.

The initial studies on connectivity focus on the criteria for port selection. When studying the determinants of port efficiency and performance, Tongzon (1995) highlights the importance of port services and their frequency. Tiwari et al. (2003) consider that the size of the maritime fleet, that is, the number of vessels, is a valuable measure of the performance of a port. They show that an increase of 1% in the number of shipping companies leads to an increase of 5 to 6% in the size of the market of a port. According to Ugboma et al. (2006), shipping companies and shippers attach great importance to efficiency in terms of the frequency of ship visits and the existence of adequate port infrastructure. This assumption is confirmed by empirical work from Chang et al (2008) and Tongzon (2009). The latter shows that seaport efficiency, adequate infrastructure, location, transshipment volumes and the frequency of maritime services are the main factors that guide shipping companies in their seaport selection process.

Another series of studies incorporates maritime connectivity in the analysis of maritime transport costs. Wilmsmeier et al. (2006) study Caribbean countries and build a series of indicators of port characteristics in order to test their impact on maritime transport costs. They show that an increase of 1% in connectivity, measured by the number of direct links between two countries, decreases freight and transport costs by 0.11%. Moreover, an increase of 1% in customs clearance procedures leads to an increase of 0.05% in transport costs. In this study, liner shipping services are broken down into different indicators that capture the market structure of maritime transport, such as the number of transshipments between two partners or the number of direct lines between two ports. Martinez-Zarzoso & Wilmsmeier (2010) use a proxy for the liner services network structure by considering the same components as the LSCI. They conclude that being excluded from the main international liner-shipping networks has a higher effect on the increase of maritime transport cost than the geographical distance. Wilmsmeier and Hoffmann (2008) introduce different variables measuring the quality of port infrastructures, the level of portal services and the connectivity to the liner-shipping networks. They show that these factors explain nearly 60% of the freight rate variance. Arvis et al. (2016) also highlight the fact that logistics performance (LPI) and maritime connectivity (LSCI) feature

1 The LSCI is calculated for 178 countries and shows maritime connectivity trends from 2004 to 2019.

a more importance source of variation in trade cost than the geographical distance. Fugazza & Hoffmann (2017) use a gravity model to estimate the impact of the bilateral maritime connectivity index LSBCI[2] on exports. They show that improving transport connectivity is an important element of bilateral trade facilitation.

Some studies focus on the level of port connectivity. The number of origin and destination connections is a good proxy for port connectivity (Tang et al., 2011; Low et al., 2009; Bartholdi et al., 2016). Shipping networks are usually studied according to the coverage of the global world network. This leads in the establishment of a hierarchy of primary and secondary networks connecting different hubs and feeder ports (Notteboom et al., 2010; Ducruet & Notteboom, 2012). Some studies focus on a specific range of ports and identify the emergence of primary and secondary hubs in a general portal hierarchy (Wang & Ng, 2011; Wang and Cullinane, 2014; Ducruet, 2020). These studies deliver two main findings: first, they show that the connectivity of a port or a country is integrated into a large-scale network designed by shipping companies (Ducruet et al., 2010). A container ship deployed by a shipping company on a specific loop may call in two or more countries belonging to the same region or, in only one of them. Hence, the maritime networks can be considered as a form of spatial interaction (Ducruet & Notteboom; 2012). Second, they show the first movers' advantage in establishing hub ports which allows them to dominate the global trade network.

Building on these findings, one may assume that the shipping connectivity of a country could be related to its regional environment. This raises the question of whether geographical proximity between countries with important ports plays a role in their access to the global maritime network. By using spatial autocorrelation models, this paper aims to explore the role of spatial proximity between countries in maritime connectivity, by testing two possible neighborhood effects: first, positive spatial interaction between countries, which reveals the presence of spillover effects in terms of maritime connectivity. In this case, countries are complementary in terms of access to the maritime market. Second, a negative spatial interaction, which reflects a competing macroregional environment (Elhorst & Zigova, 2014; Kao & Bera, 2016; Griffith, 2019).

MODEL SPECIFICATION AND DATABASE

3.1. Model Specification

From a theoretical point of view, the definition of the shipping connectivity of a country i, at period t, can be written as follows:

$$C_{it} = F(X_{it}, \mu_i, \delta_t, \eta_{it}) \quad (1)$$

where C_{it} is the maritime connectivity of a country i at period t, which measures the level of integration of the country to the global shipping network, X_{it} is a vector containing the characteristics of country i at period t, μ_i is a country-specific effect and η_{it} represents unobservable variables.

The country characteristics, X_{it} incorporate the market size (D_{it}) and trade facilitations (F_{it}). The market size is a key factor in determining the level of services provided by shipping line companies, since carriers will deploy a higher capacity and the most efficient vessels on routes where the volume of final demand is the highest. The market size depends on the country's GDP (Y_{it}), the country's population (L_{it}) and the number of its effective trade partners (N_{it}). The maritime connectivity may affect some variables related with market size and trade facilities. To reduce endogeneity issues, lagged values of the GDP and the number of trade partners are introduced to the market size equation. We assume that this function has a multiplicative form:

$$D_{it} = \lambda Y_{i,t-1}^{\alpha_1} L_{it}^{\alpha_2} N_{i,t-1}^{\alpha_3} \quad (2)$$

The trade facilitation (F_{it}) depends on restrictive trade policies (T_{it}), administrative procedures ($A_{i,t-1}$) and the quality of port infrastructure (P_{it}). The trade facilitation measure can be expressed as follows:

$$F_{it} = \theta T_{it}^{\alpha_4} A_{i,t-1}^{\alpha_5} P_{it}^{\alpha_6} \quad (3)$$

By replacing the terms in Eq. (1) by the respective expressions in Eqs. (2) and (3), we obtain the following equation:

$$lnC_{it} = \gamma + \alpha_1 lnY_{i,t-1} + \alpha_2 lnL_{it} + \alpha_3 lnN_{i,t-1} + \alpha_4 lnT_{it} + \alpha_5 lnA_{i,t-1} + \alpha_6 lnP_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (4)$$

where α_k (k=1,...,6) are the coefficients of the explanatory variables. γ a constant, μ_i captures the country fixed effects, δ_t is a time fixed effect; the error term ε_{it} is assumed to be i.d.d.

In the presence of spatial interdependence among different countries' connectivity, the use of a-spatial models leads to biased results. Spatial dependence appears when the connectivity of a country is affected by the weighted average of the connectivity of its neighboring countries. To capture spatial interactions, we include spatial effects in the equation 4, which is rewritten as a Spatial Durbin Model (see section 4.1).

3.2. Data sources

In this work, we use a panel dataset of 114 countries covering a 14-year period dating from 2004 to 2017[3], with 1596 observations (114 × 14). The Liner Shipping Connectivity Index (LSCI) is extracted from the UNCTAD database and reflects a country's position in the global container transport network. The index takes into account several factors such as the number of ships, the annual container carrying capacity of these ships, the maximum tonnage of ships, the number of portal services and the number of companies operating container ships to and from a country's ports[4]. The explanatory variables in equation (3) are detailed in table 1 and their a priori expected signs are the following:

- The market size depends on the Gross Domestic Product ($GDP_{i,t-1}$) and on the population size (POP_{it}) of country i. The GDP in nominal values and the population size are obtained from the World Bank Development Indicators data series. The expected sign of these variables, as a determinant of maritime connectivity, is positive, since countries with higher GDP and population meet a larger demand for containerized transport.
- We include two variables to capture the number of a country's effective partners ($N_{i,t-1}$): first, the number of zero flows ($NbrNul_{i,t-1}$), which gives the number of zero trade flows for each country. An increase in this variable would lead in a decrease in shipping connectivity; hence the sign of this variable is expected to be negative. Second, the number of major flows ($NbrMaj_{i,t-1}$), which measures the number of flows to reach 80% of the total trade of a country. The impact of this variable on shipping connectivity is positive, since a country that depends on a small number of partners attracts less liner services. Data is extracted from the COMTRADE database.

2 LSBCI: Liner shipping bilateral connectivity index

3 In order to keep a balanced panel at 14 periods, we collected additional data in 2003 for the time-lagged variables: ($GDP_{i,t-1}$), ($NbrNul_{i,t-1}$), ($NbrMaj_{i,t-1}$), ($TX_{i,t-1}$).

4 The index assigns the value of 100 to the country with the highest average index (China) in 2004.

Table 1. Descriptive statistics of dependent and explanatory variables (2017)

Dependent variable		Source	Obs	Mean	Std. Dev.	Min	Max
LSCI	Liner Shipping Connectivity Index	UNCTAD	114	34.87	31.15	4.04	169.56
Market size		**Source**		**Mean**	**Std. Dev.**	**Min**	**Max**
GDP	Nominal GDP (Current USD)	World Bank	114	6.75e+11	2.23e+12	1.49e+09	1.95e+13
POP	Country population	World Bank	114	5.92e+07	5.92e+07	95843	1.39e+09
NbrNull	The number of zero flows	Comtrade	114	37.59	39.83	6	114
NbrMaj	The number of major flows	Comtrade	114	26.88	39.40	1	114
Trade facilitations		**Source**		**Mean**	**Std. Dev.**	**Min**	**Max**
Tar	The average (weighted) tariff applied to imports	World Bank	114	4.75	4.34	0.03	18.4
TX	Average time to export (days)	World Bank	114	16.29	8.13	6	56
Buss	Ease of Doing Business score	World Bank	114	63.31	13.39	31.67	86.73
Port-Infra	Port Infrastructures quality	World Economic Forum	114	1.68	17.25	0	214.6

Elaborated by the authors.

- We also control for factors the affect trade facilitations. Trade tariffs (Tar_{it}) are measured as the weighted average tariff on imports. They're expected to have a negative effect on maritime connectivity, since a decrease in trade barriers increases trade and the demand of transport services. The time needed to process documents for export ($TX_{i,t-1}$) is used as proxy for administrative procedures that tend to slowdown trade. This variable is expected to negatively affect the demand for maritime transport. Finally, the ease of doing business ($Buss_{it}$), which measures the country's distance to the best regulatory practice, positively impacts the volume of transport demand.
- Port performance is a key element of the strategy of shipping companies. The quality of port infrastructure ($PortInfra_{it}$) plays an important role in determining maritime connectivity. The number of connections usually increases if ports are well equipped and efficient. This variable is aggregated at the country level and its sign is expected to be positive, since the capacity deployed by shipping lines is higher for countries with efficient and well-equipped ports.

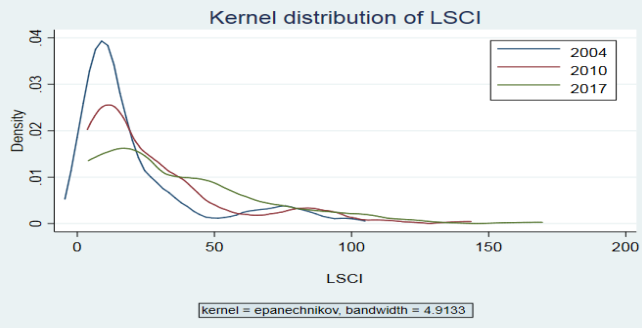
3.3 A descriptive analysis

The definition of the LSCI, as the key maritime connectivity index in 2004, allows to observe constant shifts in the global hierarchy of maritime connectivity, during the last fifteen years. This index features each country's position in the maritime shipping network. Table 1 shows the ranking of 20 countries according to their degree of maritime connectivity in 2004, 2010 and 2017. China ranks first in each year followed by Hong Kong in 2004 and 2010; in 2017, Singapore takes the second place.

With 1,996 container ships scheduled on liner services to and from Chinese ports, 463 maritime services and an annual capacity of over 85 million TEU, China is the world leader of maritime transport and maritime connectivity (LSCI 169.56). With 15 ships, 7 maritime services and a global annual capacity of 173,000 TEU, the Democratic Republic of Congo (LSCI 4.04) appears at the end of the list.

Over the past fifteen years, some countries have considerably improved their connectivity level, such as South Korea, which moved from the tenth place in the global maritime market in 2004 to the third place in 2017, just behind China and Singapore. This improvement is associated with a 55.41% increase in the country's export values over this twelve-year period. Malaysia also climbed the ladder of the global maritime transport network hierarchy by moving from the twelfth place in 2004 to the fifth place in 2017. Of note, the five highest-ranked countries in 2017 are all Asian, with the United States in the sixth place. Except for the United Arab Emirates, all other countries lost their relative position in the maritime hierarchy and fell behind the Asian leaders over this period. Canada fell eighteen places, not because of the deterioration of its trade[5], but because other countries surpassed it in terms of connectivity. Small island states such as Iceland and some developing countries face low levels of connectivity. The bottom of the list features West African countries (Mauritania, Gambia, Cape Verde, Guinea, Sierra Leone, Liberia and the Democratic Republic of Congo) and some Central and South America countries (Belize, Suriname, Nicaragua and Guyana) with an index lower than 10.

Figure 1. Maritime connectivity distribution (kernel density)



Source: authors - UNCTAD data

Figure 1 displays the kernel density function across 114 countries. The horizontal axis represents the maritime connectivity given by the LSCI, while the vertical axis represents the density of countries. The results are provided for 2004, 2010 and 2017.

In 2004, the distribution of the LSCI shows a significant peak which reaches a density of 0.04. It is centered on countries with low levels of connectivity, i.e., below 25. This pattern is consistent with a hub and spoke structure where countries with a higher connectivity level act as global trade hubs and other countries function as peripheral spokes.

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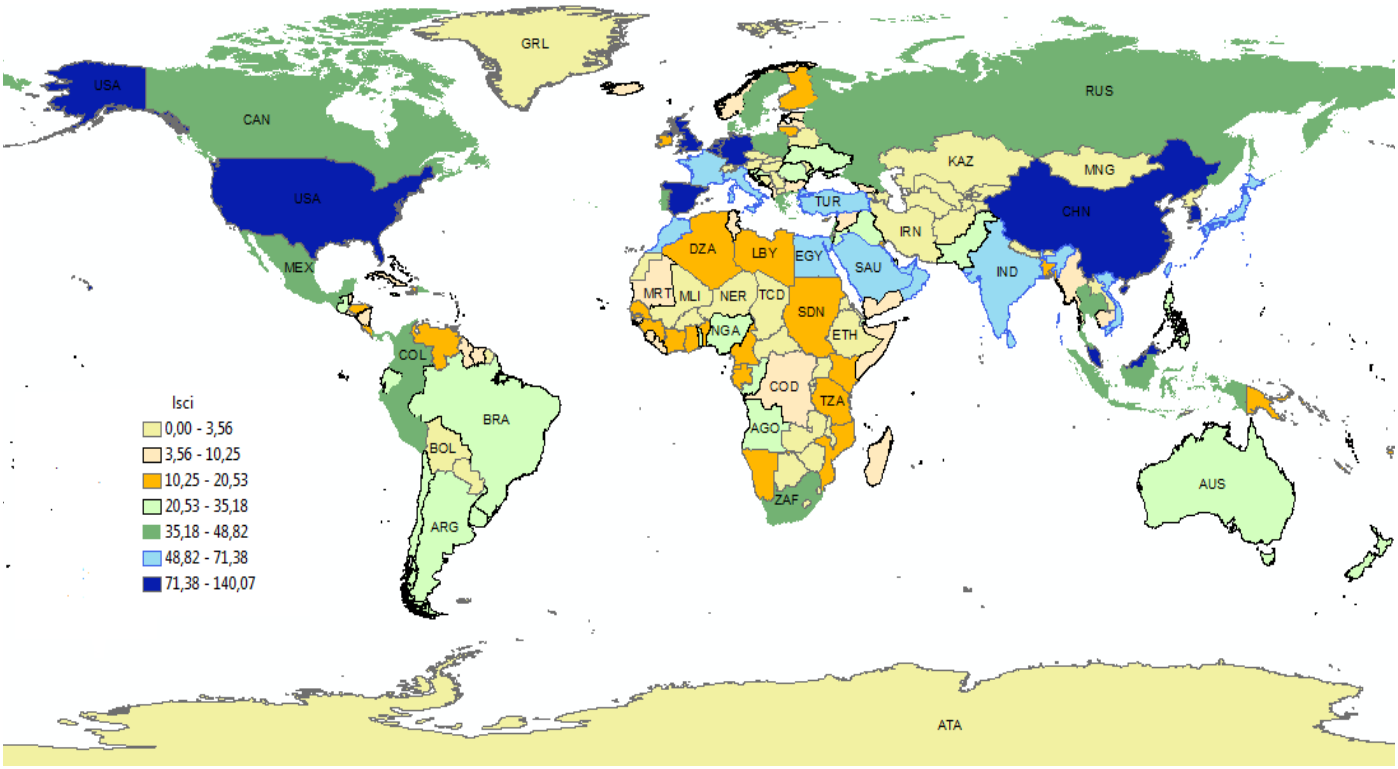
5 According to UNCTAD data, Canadian exports have increased by 15% in the last 15 years.

Figure 2. Spatial distribution of the Liner Shipping Connectivity Index



Source: authors – UNCTAD data

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In 2010 and 2017, the density levels decrease (0.025 and 0.018 respectively), and the peaks move slightly to the right. These two peaks correspond to connectivity values around 16 for 2010 and 20 for 2017. Overall, the level of connectivity improved for 83% of the countries between 2004 and 2010 and decreased for the remaining 17%. Connectivity for most countries stagnated during the 2008 financial crisis period and only experienced growth after 2010. 88% of the countries increased in maritime connectivity from 2010 to 2017.

Figure 2 shows the spatial distribution of the maritime connectivity values in 2017 for each country. Values for landlocked countries are not available in the UNCTAD database; thus, their LSCI is equal to zero.

The most connected countries are located in the northern hemisphere and belong to the three dominant economic poles (except for Southeast and South Asian countries such as India and Vietnam). In addition, spatial clustering appears at a regional level, since the connectivity levels are very close for countries belonging to the same region (e.g. Northern Europe, East Asia, South American countries and sub-Saharan Africa).

This raises the question of whether the level of maritime connectivity can be explained by the geographical proximity of countries. In other words, is there a form of spatial interaction between countries in terms of maritime connectivity and if so, which type of interaction exist within these different groups when they are examined separately?

METHODOLOGICAL ISSUES

4.1 Econometrics

Spatial autocorrelation models are the most appropriate tools for estimating the impacts of neighboring countries' performances on the maritime connectivity of a country. Ignoring spatial interaction effects can produce misleading conclusions about the determinants of maritime connectivity. The existence of spatial autocorrelation means that the observed values of a country's LSCI are related to the values of the neighboring countries' LSCI. This relationship is positive when the observed LSCI values of a country and its neighbors are similar, and it is negative when these values differ.

Three types of spatial interactions exist: an endogenous interaction in which an economic decision or policy in a territory depends on the decisions or policies of its neighbors, an exogenous interaction in which the economic decision or policy in a territory depends on the observable characteristics of its neighbors, and finally a spatial interaction, where the characteristics and the decisions in a territory are linked to the unobservable characteristics of its neighbors (Elhorst, 2010).

These different interactions measure the degree of spatial proximity of a given set of N spatial elements represented by a neighborhood matrix W. W is a square matrix of size $N*N$ whose diagonal elements are zero. Each element of this matrix is designated by (i,j) where Wij expresses the degree of spatial proximity between the pair of elements i.

A Spatial Durbin Model (SDM) is set up as a starting point. The weight matrix is associated with the vector of explanatory variables and with the endogenous variable. When the matrix is associated with the vector of endogenous variables and with the error terms, the result is the Kelejian-Prucha[6] model. Both the SDM and the SAC

6 This model is also called Spatial Auto-regressive Confused (SAC).

models include special cases of the Spatial Autoregressive Model (SAR) and the Spatial Error Model (SEM)[7].

The following model is both a general specification and a test for various other spatial panel models such as the Spatial Error Model (SEM) and the Spatial Autoregressive Model (SAR) (Elhorst, 2010; Belotti et al.2016):

$$Y_{it} = \rho(\sum_{j=1}^{n} W_{ij} Y_{jt}) + X_{it}\beta + (\sum_{j=1}^{n} W_{ij} X_{jt})\theta + \mu_i + \delta_t + \varepsilon_{it} \quad (5)$$

where i,j =1...114, n=114 and t=2004.....2014

Y_{it} indicates the dependent variable to be estimated (LSCI) for country i in year t. X_{it} is a vector of explanatory variables for country i in year t. β is a parameter vector to be estimated for the explanatory variables. The expression $\sum_{j=1}^{n} W_{ij} Y_{jt}$ defines the spatial lag of the dependent variable, which can be interpreted as a proximity-weighted value of the maritime connectivity in year t of country i with its neighboring countries, where the parameter ρ is the estimated coefficient of spatial dependence. $\sum_{j=1}^{n} W_{ij} X_{jt}$ is the lag of explanatory variables vector and θ is the parameter that measures the interaction forces of the explanatory variables of the observations of neighboring countries. μi denotes specific spatial effects and δt captures the time-period specific effects. The omission of these parameters could bias the estimation results.

When including the endogenous spatially lagged dependent variable in equation (4), we obtain the final estimation equation:

$$\begin{aligned} lnLsci_{it} = {} & \rho(\sum_{j=1}^{n} W_{ij} lnLsci_{it}) + \beta_1 lnpop_{it} + \beta_2 lngdp_{i,t-1} + \\ & \beta_3 lnPortInfra_{it} + \beta_4 lnTar_{it} + \beta_5 lnBuss_{it} + \beta_6 lnTX_{i,t-1} + \\ & \beta_7 lnNbrMaj_{i,t-1} + \beta_8 lnNbrNul_{i,t-1} + \sum_{j=1}^{n} W_{ij}(\beta_9 lnpop_{jt} + \\ & \beta_{10} lngdp_{j,t-1} + \beta_{11} lnPortInfra_{jt} + \beta_{12} lnTar_{jt} + \\ & \beta_{13} lnBuss_{jt} + \beta_{14} lnTX_{j,t-1} + \beta_{15} lnNbrMaj_{j,t-1} + \\ & \beta_{16} lnNbrNull_{j,t-1})\theta + \mu_i + \delta_t + \varepsilon_{it} \end{aligned} \quad (6)$$

Some recent work in the spatial econometrics literature points out the sensitivity of the results of the econometric models as being linked to the choice of the weighted matrix. Opinions on this subject are, however, controversial. LeSage & Pace (2014) consider the idea that the effects of explanatory variables and inferences are sensitive to the use of a matrix of particular weight to be probably "the biggest myth" about spatial regression models.

To determine the correct specification[8], we consider various weight matrices based on the SDM estimation in equation 4. First is the binary contiguity matrix in which W_{ij} is dichotomous, equal to 1 if country i shares borders with country j and 0 otherwise. Then we consider Euclidian distance matrices where W_{ij} is a continuous function. Finally, we consider the inverse distance matrix: this is an exponential distance weight matrix, based on an inverse distance function. The latter specification allows us to consider that the weight of more distant countries decreases with distance.

Table 2. Spatial interaction tests (Moran Index)

H0: Spatial Lagged Dependent Variable has No Spatial Auto-Correlation
H1: Spatial Lagged Dependent Variable has Spatial Auto-Correlation

	Statistics(I)	P-value
LSCI	0.071	0.000

H0: Spatial Lagged explanatory Variable has No Spatial Auto-Correlation
H1: Spatial Lagged explanatory Variable has Spatial Auto-Correlation

	Statistics (I)	P-value
GDP	0.120	0.000
POP	0.043	0.003
PortInfra	0.111	0.000
Tar	0.123	0.000
Buss	0.169	0.000

Source: authors

In order to distinguish between local and global spillover effects, we introduce a threshold (the influence is decreasing from a certain distance)[9] in the inverse distance matrix: the countries j are no longer considered as neighbors of i and therefore no longer appear in the local specification. according to LeSage (2014) the use of a weighting matrix based on distance (without a cut-off threshold) scrambles the distinction between these two specifications. LeSage & Pace (2014), show that a weighting matrix specification based on an inverse distance with a decrease in influence beyond a certain distance or number of closest neighbors (zero weight), is likely to produce estimates and inferences on effects that are robust to weighting matrices based on alternative choices of decrease or threshold.

The row-normalized, inverse-distance matrix seems to perform best. Its size $N*N$ (i.e., 114*114) gives a total of 12,998 elements. This matrix assumes that the relationships between countries i and j decrease as the distance between i and j increases. In this situation dij[10] *is the distance based on the longitude and latitude of the centroid of each country* i and j, with $i \neq j$.

4.2. Spatial interaction tests

The results from the Moran, testing for spatial autocorrelation, are presented in Table 2. Since the Moran index is significant, the null hypothesis of an absence of spatial autocorrelation both on dependent and explanatory variables is rejected with a probability of 1%. The coefficient of the Moran index is higher than the expected value I =0.071> E(I)= -0.009 and suggests the presence of positive spatial interaction. The LISA diagram in Figure 3 represents spatial interaction regarding maritime connectivity at the regional level.

Most of the observations are characterized by a positive spatial association (32% in quadrant HH and 29% in quadrant LL), while the other countries are characterized by a negative spatial association (23% in quadrant HL and 16% in quadrant LH). The first quadrant HH (High High) includes countries with a high connectivity index located in a regional environment which features a high degree of

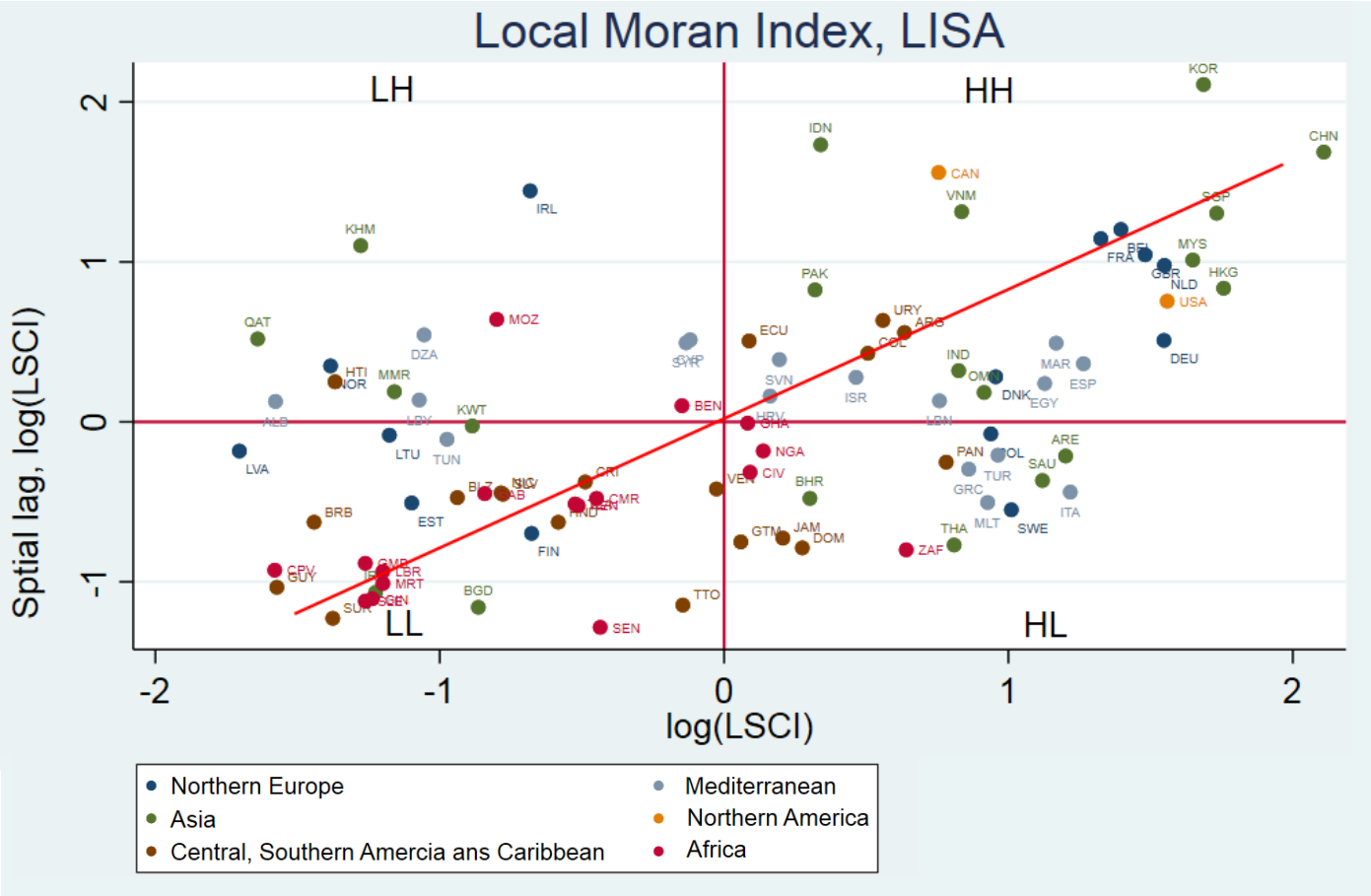
7 In the SAR model the weighted matrix is associated with the endogenous variable. In the SEM model it is associated with the error term.

8 As suggested by Elhorst (2010), we choose the appropriate matrix by comparing the log-likelihood values.

9 We have introduced several 200, 500, 800 cut-offs and retain the 500km threshold.

10 Latitude and longitude location data were collected on the CEPII website.

Figure 3. Spatial interactions (Local Indicator of Spatial Association)



Source: authors based on UNCTAD data

connectivity. This is particularly the case for countries in East Asia[11], Northern Europe[12], and North America.

The opposite quadrant LL (Low Low), includes countries with low connectivity located in global regional environments which feature low connectivity. This is the case for countries in Central America, South America, the Caribbean, and Africa.

The HL (High Low) quadrant contains countries with high connectivity located in environments of low connectivity. These countries are well connected not for being part of a regional cluster; but because of either their size (e.g. Italy, Turkey) or a geographical position near main maritime routes (e.g. Panama, Malta).

The fourth LH (Low High) quadrant includes countries that have a low connectivity index (neither large in size nor positioned on main shipping routes) but are surrounded by countries that are well connected. This fragmentation is often carried out by cabotage lines[13] operated by smaller shipping companies. This is particularly the case for some Northern European countries, such as Ireland or Norway, that have a low connectivity score (less than 10), but are located in the Northern Range port region that features a high maritime connectivity.

4.3 A spatial model specification

To choose the appropriate model, Elhorst (2010) starts from a general regression model (General Nesting Spatial Model) incorporating all interaction effects. A first series of LM Robust tests is applied to this model under the null hypotheses: $H0: \rho = 0, \theta = 0, \lambda = 0$. These tests allow to choose between the following models: SDEM, SAC, SDM. Depending on the model selected, a second series of LR (Likelihood Robust) tests is applied, which does not limit the choice between the SAR and SEM models, but also proposes the particular case of the SLX model (Vega & Elhorst, 2015).

Instead of following the more standard econometric model selection path, Vega & Elhorst (2015) recommend taking the SLX model as the starting point for studies seeking to analyze interaction effects, since it is the simplest model with flexible spillovers. We follow Belotti et al. (2017) by assuming that the SEM and SAR models are nested in the SDM model. A model is considered to be nested in another if the first model can be generated by imposing restrictions on the parameters of the second model. The Likelihood Ratio test (LR test) is often used to evaluate the difference between nested models. It raises the question of whether constraining the parameters to zero (i.e., excluding them from the estimation) reduces the model fit. Applying the LR test requires the comparison of two models: the first with one set of parameters (e.g. the SAR model), and the second with the parameters of the first model plus additional variables (e.g. the SDM model).

The first LR test compares the SDM model to the SAR model with $H0: \theta=0$. The results show that the addition of the constrained variables leads to a statistically significant improvement of the model

11 China, Hong Kong, Singapore, and Japan

12 Netherlands, France, Germany, Great Britain, and Belgium

13 Cabotage refers to the transport of goods over short distances, it mainly refers to transport by sea hence the term "short sea shipping" but is also used for road and air transport.

fit. The null hypothesis is rejected and the SDM is the selected model. The second LR test consists in comparing the SDM to the SEM model with $H0: \theta+\beta\rho=0$. Once more, the results lead to reject the null hypothesis and the SDM is selected. The last test controls the SDM versus the SAC model. Since these are not nested models and the two previous tests selected the SDM model, Akaike's (AIC) and Schwarz's Bayesian Information Criteria (BIC) are used to check whether the SAC is the appropriate model instead of the SDM (Belotti et al., 2017). The best model is the one with the weakest criteria. The results of the model selection tests are presented in Appendix 1. The SDM model is selected based on the results of the comparison of the models

In the second stage, we estimate the model at a regional level, with a special focus on two groups, Northern Europe[14] and the Mediterranean region[15]. Reverse distance weight matrices were built for each group and tests were carried out for different model choices. The SAR model is used to estimate the spatial impact on maritime connectivity for Northern Europe, and the SDM model is used for the Mediterranean region.

RESULTS AND DISCUSSION

The interpretation of the results in spatial econometric models differs from the one in linear models. In the case of a spatial model with fixed effects, the introduction of a spatially shifted variable ρWY implies the presence of global effects which are both direct (impacts of a change in X_i in country i) and indirect (impacts of a change in X_i in neighboring countries), regardless of neighborhood ties (Vega & Elhorst, 2015). These models also have a multidirectional dimension: a change in country i impacts a neighboring country j which in turn impacts i through a feedback effect.

The introduction of spatially shifted explanatory variables WX induces not global but local spillover effects: the variation of an explanatory variable directly affects the dependent variable for the country i and indirectly the dependent variable of its neighbors, but does not affect the neighboring countries of the latter, that is, the neighbors' neighbors.

Table 3 delivers the results for the maritime connectivity determinants. In the a-spatial model, GDP, population and the ease of doing business in a country have a positive effect on maritime connectivity. The weighted tariff applied to imports of manufactured goods has a negative impact on connectivity.

When running the spatial Durbin model, it is noteworthy that the spatial autocorrelation parameter ρ is statistically significant at the 5% level, indicating the existence of a positive spatial dependence. This implies that a change in a country's maritime connectivity impacts, in the same way, the maritime connectivity of neighboring countries.

In the spatial model, a 1% increase in port infrastructure leads to a 0.5% increase in maritime connectivity. Similarly, a 1% improvement in the business climate leads to a 0.17% improvement in maritime connectivity. Tariff restrictions have a moderate impact on connectivity: a 1% increase in tariff barriers leads to an improvement of 0.07% in maritime connectivity.

The coefficients of the SDM model do not directly reflect the marginal effects of the corresponding explanatory variables on the dependent variable (LeSage and Pace, 2009). We thus report, in Table 4, the direct, indirect, and total effects of the independent variables. Since the SDM model contains endogenous interaction effects (ρWY), estimates of direct effects include feedback effects.

Table 3. Spatial regression results for full data model

	A-spatial	Main (SDM)
Ln GDP(L1)	0.037	0.041
	(1.01)	(0.56)
Ln POP	0.177*	-0.07
	(1.75)	(-0.30)
Ln Port_infra	0.461***	0.502**
	(5.87)	(2.55)
Ln Tariff	-0.063**	-0.068*
	(-3.49)	(-1.73)
Ln Nbr_Maj(L1)	0.007	-0.004
	(-0.71)	(-0.27)
Ln NBR_null(L1)	-0.050***	-0.058
	(-2.36)	(-1.45)
Ln Buss	0.164***	0.176**
	(2.32)	(2.05)
Ln TX(L1)	-0.053	-0.034
	(-1.22)	(-0.40)
cons	-2.778	
	(-1.43)	
Spatial lagged Variables		
Ln GDP(L1)		-0.054
		(-0.44)
Ln POP		0.94
		(0.77)
Ln Port_infra		-0.693
		(-1.23)
Ln Tariff		0.080
		(0.65)
Ln Nbr_Maj(L1)		-0.022
		(-0.31)
Ln NBR_null(L1)		0.035
		(0.63)
Ln Buss		-0.092
		(-0.25)
Ln TX (L1)		-1.081
		(-1.57)
Spatial ρ		0.330**
		(2.52)
N	114	114
T	14	14
N*T	1596	1596
R2 within	0.40	0.39
R2 between	0.62	0.24
R2 total	0.59	0.25

Notes: The dependent variable is the LSCI, ρ denotes the global interaction effect.
t statistics in parentheses: * p < 0.10, ** p < 0.05, *** p < 0.01. L1 denotes the time-lagged variables.
Source: authors' calculations.

The three variables mentioned above have a direct effect on connectivity, which means that improvements in port infrastructure and in the business climate, as well as lower tariffs directly impact the level of connectivity in country i. These variables have no indirect effect.

Next, we focus on Northern Europe and on the Mediterranean region. The reasons for focusing on these regions are threefold: first, these two regions feature a high density[16] of ports and a high level of

14 Belgium, Germany, Denmark, Estonia, Finland, France, United Kingdom, Ireland, Iceland, Lithuania, Latvia, Netherlands, Norway, Poland, Sweden, Syria, Tunisia and Turkey.

15 Albania, Cyprus, Algeria, Egypt, Spain, France, Greece, Croatia, Israel, Italy, Lebanon, Libya, Morocco, Malta and Slovenia.

16 According to Frémont and Sopé (2005), there is on average one port every 80 kilometers in the Hamburg-Le Havre range

Table 4. Average direct, indirect, and total effects from fixed-effects SDM estimates

	Direct effects	Indirect effects	Total effects
Ln GDP(L1)	0.041	-0.61	-0.020
	(0.56)	(-0.36)	(-0.12)
Ln POP	-0.061	1.36	1.30
	(-.029)	(0.85)	(0.89)
Ln Port_infra	0.496**	-0.782	-0.028
	(2.55)	(-0.97)	(-0.37)
Ln Tariff	-0.068*	0.086	0.017
	(-1.74)	(0 .49)	(0.11)
Ln Nbr_Maj(L1)	-0.004	-0.036	-0.040
	(-0.28)	(-0.33)	(-0.37)
Ln NBR_null(L1)	-0.058	0.024	-0.033
	(-1.46)	(0.35)	(-0.65)
Ln Buss	0.175**	-0.051	0.124
	(2.05)	(-0.09)	(0.23)
Ln TX(L1)	-0.044	-1.22	-1.26
	(0.51)	(-1.51)	(-1.55)

Notes: The dependent variable is the LSCI, ρ denotes the global interaction effect.
t statistics in parentheses: * p < 0.10, ** p < 0.05, *** p < 0.01. L1 denotes the time-lagged variables
Source: authors' calculations.

Table 5. Spatial regression results per region: Northern Europe and Mediterranean

	Northern Europe (SAR)	Mediterranean (SDM)
Ln GDP(L1)	0.24	-0.053
	(0.87)	(-0.30)
Ln POP	0.021	0.296
	(0.02)	(0.57)
Ln Port_infra	1.00	1.072***
	(0.95)	(4.50)
Ln Tariff	0.030	-0.161**
	(0.29)	(-2.35)
Ln Nbr_Maj(L1)	0.200	0.093*
	(1.05)	(1.76)
Ln NBR_null(L1)	0.081	-0.204**
	(1.29)	(-1.92)
Ln Buss	0.630	0.571
	(1.25)	(1.15)
Ln TX(L1)	0.229	-0.083
	(0.88)	(-0.27)
Spatial Lagged Variables		
Ln GDP(L1)		0.231
		(0.79)
Ln POP		1.312
		(1.01)
Ln Port_infra		0.551
		(0.44)
Ln Tariff		0.430***
		(2.61)
Ln Nbr_Maj(L1)		0.08
		(0.44)
Ln NBR_null(L1)		0.259*
		(1.72)
Ln Buss		0.713
		(0.51)
Ln TX(L1)		-1.120
		(-1.02)
Spatial ρ	0.2718**	-0.129*
	(2.41)	(-1.94)
N	15	18
T	14	14
N*T	210	252
R2 within	0.20	0.49
R2 between	0.78	0.55
R2 total	0.74	0.54

Notes: The dependent variable is the LSCI, ρ denotes the global interaction effect.
t statistics in parentheses: * p < 0.10, ** p < 0.05, *** p < 0.01. L1 denotes the time-lagged variables
Source: authors' calculations.

maritime traffic[17]. In both regions, the structure of maritime networks gives rise to complex regional relations which involve both external (shipping companies) and local actors (port institutions and intermodal transport operators).

Second, the coastal population of the Mediterranean region accounts for more than 250 million inhabitants on both shores, which reflects a very high potential demand. The Northern Europe coastal areas also benefit from a densely populated hinterland with a high concentration of economic activity. These two regions feature high-quality logistics and infrastructure networks linking them to the most flourishing economic activity centers and markets in Europe. In addition of being the gateways to very large regions, the ports of these countries have a relatively similar level of hinterland accessibility and often serve the same inland territories.

Third, the actors involved in these relationships interact within the framework of an "Integrated Maritime Policy" at the regional level, which was set up by the European Parliament in July 2007. One of the fields of action of this European level policy is the setting of "sea basin strategies", based on cooperation between countries sharing the same sea basin in order to address common challenges and seize common opportunities.

Table 5 presents the results of the estimation when considering spatial dependence within each region: in Northern Europe, spatial dependence is significantly positive, which means that this region features positive interaction effects between countries sharing the same maritime network. The countries in this region develop complementary and cooperative relationships rather than competitive ones. The coefficient of the endogenous variable ρ shows that a 1% increase in the maritime connectivity of its neighboring countries leads to a 0.27% increase in the connectivity of country i. Due to the absence of local spillover effects and of an overall indirect effect, this result provides empirical evidence of the existence of potentially cooperative relationships between the countries of this region in accessing maritime networks.

This seems to be the result of the 2007 European Maritime Integration Policy, which improves the coordination of European costal regions' policies when it comes to portal and maritime activities.

On the opposite, in the Mediterranean region, we observe a negative spatial dependence: in an environment of high/low connectivity (H/L), competition rules seem to prevail over any positive spillover effects. Negative spatial dependence appears as the result of regional competition, and more generally describes a general competitive environment within this region, overpowering cooperation policies.[18]

17 Every 10 min three vessels use the Channel Sea Corridor to and from the Northern Range ports.

18 In their initial study on researchers' productivity, Elhorst and Zigova (2014) show that the productivity of one research unit is negatively dependent on that of its neighbors, weighted by inverse distances. This is consistent with competition between researchers but also between universities for discoveries.

Table 6. Average direct, indirect, total effects from fixed-effects SAR model-Northern Europe

Northern Europe			
	Direct effects	Indirect effects	Total effects
Ln GDP(L1)	0.249	0.08	0.339
	(0.87)	(0.77)	(0.86)
Ln POP	0.021	0.007	0.029
	(0.02)	(0.02)	(0.02)
Ln Port_infra	1.012	0.363	1.37
	(0.96)	(1.30)	(1.06)
Ln Tariff	0.030	0.010	0.04
	(0.29)	(0.28)	(0.29)
Ln Nbr_Maj(L1)	0.202	0.072	0.275
	(1.05)	(1.12)	(1.10)
Ln NBR_null(L1)	0.082	0.029	0.112
	(1.30)	(1.39)	(1.39)
Ln Buss	0.636	0.228	0.865
	(1.25)	(1.28)	(1.32)
Ln TX(L1)	0.232	0.083	0.315
	(0.88)	(0.79)	(0.88)

Notes: The dependent variable is the LSCI, ρ denotes the global interaction effect.
t statistics in parentheses: * p < 0.10, ** p < 0.05, *** p < 0.01. L1 denotes the time-lagged variables
Source: authors' calculations.

Table 7. Average direct, indirect, total effects from fixed-effects SDM model (Mediterranean)

Mediterranean			
	Direct effects	Indirect effects	Total effects
Ln GDP(L1)	-0.056	0.214	0.157
	(-0.31)	(0.78)	(0.77)
Ln POP	0.279	1.145	1.42
	(0.54)	(0.99)	(1.22)
Ln Port_infra	1.06***	0.371	1.438
	(4.47)	(0.33)	(1.26)
Ln Tariff	-0.167**	0.405***	0.237
	(-2.42)	(2.79)	(1.48)
Ln Nbr_Maj(L1)	0.092*	0.065	0.157
	(1.71)	(0.37)	(0.96)
Ln NBR_null(L1)	-0.208*	0.256*	0.048
	(-1.91)	(1.75)	(0.79)
Ln Buss	0.563	0.574	1.137
	(1.14)	(0.45)	(0.87)
Ln TX(L1)	-0.68	-0.997	-1.06
	(-0.23)	(-1.02)	(-0.99)

Notes: The dependent variable is the LSCI, ρ denotes the global interaction effect.
t statistics in parentheses: * p < 0.10, ** p < 0.05, *** p < 0.01. L1 denotes the time-lagged variables
Source: authors' calculations.

Port infrastructures have a positive effect on the maritime connectivity of the Mediterranean region's countries. The impact of this variable for the Mediterranean region is twice as important as its impact on the full sample: a 1% improvement in port infrastructure in these countries leads to a 1% improvement in maritime connectivity. In addition, a 1% increase in major flows increases the level of connectivity by 0.09%. This result means that a low trade dependency upon foreign partners has a positive impact on their access to the maritime transport network. Consequently, a decrease in tariff restrictions also leads to an increase in their level of connectivity. These last two variables exert a local positive spillover effect on maritime connectivity.

Finally, an increase in neighboring tariff restrictions or a decrease of the trade partners in a neighboring country *j* leads to an improvement of the connectivity of country *i*. This is a major result that shows a deflection traffic towards the most advantageous country and confirms the existence of a competitive environment within the Mediterranean region. In addition to these local spillover effects, there are global spillover effects due to tariff restrictions and to the number of the null flows (as seen in the indirect effects column in table 7).

CONCLUSION

The general aim of this study is to show how spatial dependence affects the shipping line connectivity. We provide evidence of spatial autocorrelation in maritime connectivity between countries. The Moran's index indicates a positive spatial correlation on the full sample. The spatial autocorrelation model confirms the positive impact of spatial dependence and neighboring effects.

The recommendations from these findings are as follows:

First, policy makers should not only focus on the connectivity *within* each country but also take into consideration the connectivity effects *between* neighboring countries. This implies that the policies and decisions implemented in one country affect also other countries.

Second, the quality of port infrastructure, a rich and diversified business environment, a moderate tariff policy and a limited number of zero flows, that is an extended number of trade partners, all seem to be relevant factors for improving the maritime connectivity.

In addition to this overall analysis, this paper focuses on two regions in particular: Northern Europe and the Mediterranean. Positive spatial dependence characterizes the Northern Europe region. The countries in this area feature cooperation relations. On the opposite, the Mediterranean region features a negative spatial dependence. The Mediterranean countries are characterized by negative spatial interaction effects in terms of maritime connectivity, which implies the existence of a competition among them. This result confirms that, in this region, there is a potential deviation effect to the benefit of the most commercially attractive countries (e.g. low tariffs applied to imports).

Future research should use additional information with data at the port level instead of the country level in order to test more factors affecting line shipping connectivity. This could improve the present analysis with more accurate findings focusing more particularly on port connectivity.

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APPENDICES

Appendix 1. The model choice

Tests	Results
LR Test SDM vs. SAR	34.71***
LR Test SDM vs. SEM	59.77***
LR Test SDM vs. SAC	SDM AIC -128.4537 BIC -31.69907 SAC AIC -110.1183 BIC -50.99052
Haussmann Test	20.28***

* p < 0.10, ** p < 0.05, *** p < 0.01. Source: authors' calculations