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The relationship between port-level maritime connectivity and efficiency

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ABSTRACT

This paper examines the empirical relationship between maritime connectivity and port efficiency. To do so, a stochastic output distance function is employed which permits the effect of connectivity on port technical efficiency to be estimated for a sample of Spanish ports. Previous studies analysing the relationship between efficiency and connectivity have used country-level connectivity indices. In the present study, port-level connectivity indices are used for the first time for this type of analysis. A novel panel dataset of 16 Spanish ports observed over the period 2006–2016 is constructed by crossing port-level connectivity information from UNCTAD's Port Liner Shipping Connectivity Index (PLSCI) with port-level production data from Spanish port authorities. The results from our estimation show a positive relationship between connectivity and port efficiency. It is found that relatively modest improvements in observed connectivity are associated with large differences in expected output.

1. Introduction

In broad terms, maritime connectivity[1] refers to the performance of shipping transport networks and comprises facets such as, among others, the number of destinations served, frequency of services, and logistics costs (Parola et al., 2017). As such, maritime connectivity can be thought of in terms of how well a country or a port is connected to the global shipping network. Better connectivity implies greater access to physical resources and paves the way for economies of scale and specialization by permitting producers to better exploit possibilities in domestic and foreign markets (Trace et al., 2009). In an increasingly globalized world, therefore, improved connectivity plays an essential role in international trade and economic development. The extent of this is underscored by Hoffmann et al. (2017) who note that “connectivity”, defined at country level and bilaterally, is becoming synonymous with national trade competitiveness. In turn, poor connectivity, manifested through inefficiencies in logistics and transport, will negatively affect trade and development due to increased voyage times and increased handling and delivery costs of goods (Lun and Hoffmann, 2016).[2]

The relationship between connectivity and costs has been highlighted by UNCTAD (2019), which emphasizes that the key role played by efficient and well-connected ports in minimizing transport costs, linking supply chains and supporting international trade.[3] As pointed out by Ducruet (2020) in a recent review of maritime network studies, the role of ports as crucial nodes between sea and land has long been recognised and intermodal and supply chain issues are becoming increasingly important. In this context, port performance is fundamental for competitiveness, with port efficiency translating into savings for ports, carriers and shippers. Indeed, the relevance of maritime connectivity for port choice decision to and from specific hinterland locations has been recently assessed by Caballé et al. (2020). Hoffmann et al. (2017) note that modernized port operations and efficient and modern seaports are important for reducing delays and emphasize the role of physical infrastructure in accommodating increased numbers of vessels. Indeed, the importance of port performance measurement is such that UNCTAD developed the Liner Shipping Connectivity Index (LSCI) in 2004 as an indicator of countries' positions within global liner shipping networks.

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[1] Aside from maritime connectivity, land connectivity with the hinterland is also an important link in the logistics chain. In this paper, however, we focus only on maritime connectivity. For a critical review of research related to port-hinterland connectivity, see Sdoukopoulos and Boile (2020).

[2] For a recent study analysing the correlations among connectivity, production and trade, see Hoffmann et al. (2020), which contains a useful literature review on this issue.

[3] See https://unctad.org/en/pages/newsdetails.aspx?OriginalVersionID=2162.

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Our aim in this paper is to investigate the relationship between maritime connectivity and efficiency at port level for a specific country, Spain. The maritime connectivity variables used in port efficiency studies to date have been country-level indices, such as the LSCI (e.g., Figueiredo De Oliveira and Cariou, 2015; Serebrisky et al., 2016), which until recently were the only connectivity indices available. A drawback of using a country-level index such as the LSCI for measuring the efficiency of individual ports, however, is that the index will attribute the same connectivity value to ports in a given country that will be very different in terms of connectivity. A more refined measure when analysing individual port performance is the Port Liner Shipping Connectivity Index (PLSCI) introduced by UNCTAD in 2019 which follows the methodology applied to the country-level LSCI and covers more than 900 ports over the period 2006–2019.[4] We propose to use this index to determine the relationship between connectivity and port efficiency for a sample of Spanish ports. A novel panel dataset is constructed combining the UNCTAD data with port-level production data obtained from Spanish port authorities. The relationship between connectivity and technical efficiency is analyzed using a stochastic output distance function where we control for time-invariant unobserved heterogeneity and a series of characteristics of ports that may affect efficiency, such as degrees of output specialization. As far as we are aware, this is the first paper to use the PLSCI in a study of port efficiency. We use the parameters of the estimated model to quantify the relationship between connectivity and port technical efficiency.

The paper proceeds as follows. A brief review of the empirical literature on the relationship between connectivity and port efficiency is provided in Section 2. In Section 3 we present the output distance function approach used to model the relationship between connectivity and port efficiency. Section 4 presents the data used. Estimation results are presented in Section 5, which includes an analysis based on the estimated parameters to quantify the relationship between port output and connectivity. Section 6 contains a discussion and conclusions.

2. Connectivity and port efficiency: a brief review of the literature

The literature on the relationship between port efficiency and connectivity is relatively recent, and efficiency studies initially focused on the role of land-based (rail and road) connectivity or hinterland connectivity. For example, Turner et al. (2004) identified a significant positive effect of railroad connectivity on port efficiency for North American ports. Wanke et al. (2011) used the connectivity of the terminal to railroad lines as an explanatory variable in the explanation of efficiency in Brazilian port terminals and Wanke (2013) incorporated a measure of highway connectivity as a possible determinant of efficiency in Brazilian ports. Wan et al. (2014) analyzed the relationship between port efficiency and rail and road connectivity for a panel of 12 U.S. container ports. Finally, Wanke and Barros (2015, 2016) included highway access, river access and rail access as determinants of port efficiency in studies of 27 major Brazilian ports. It should be noted that all these studies relating port efficiency to connectivity with the hinterland through rail and road access use two-stage DEA-based methodologies where DEA is used to estimate efficiency scores and then second-stage regressions are used to relate estimated port efficiency to connectivity variables. These studies have generally found positive relationships between hinterland connectivity and port efficiency.

Turning to studies analysing the impact on port efficiency of maritime connectivity, which is our concern in this work, we find that previous studies incorporating maritime connectivity into analyses of port efficiency have generally used country-specific connectivity indices. Of these, the Liner Shipping Connectivity Index (LSCI) number produced by the United Nations Commission for Trade and Development (UNCTAD), which measures the degree to which countries are connected to the global maritime shipping network, has been the most popular choice. Figueiredo De Oliveira and Cariou (2015) used a two-stage process including a bootstrapped truncated regression to explain efficiency scores for 200 container ports observed in 2007 and 2010. The LSCI was used as an explanatory variable of efficiency and a positive relationship was found. Serebrisky et al. (2016) included the LSCI of country-level connectivity as a control variable in an analysis of performance in 63 container ports in Latin America and the Caribbean using a stochastic frontier approach. In that study the connectivity index was included as a control variable in the deterministic frontier and was found to be positively related to throughput. The LSCI connectivity measure was also included as a control variable in the deterministic frontier by Suárez-Alemán et al. (2016). They analyzed container port performance using both stochastic frontier and DEA approaches for a sample of 203 ports from 70 developing countries and found that ports with higher liner connectivity have higher levels of predicted output. An alternative measure of connectivity, again at country level, is the Logistic Performance Index (LPI) constructed by the World Bank Group. This index was used by Schøyen et al. (2018) to investigate the efficiency of 26 container ports located in six North Sea/Baltic Area countries. Efficiency scores were calculated using Data Envelopment Analysis and then the sensitivities of port efficiency scores to country-specific logistics service delivery outcomes were tested.[5]

As is clear, the literature relating maritime connectivity to port efficiency is relatively recent, with only a handful of papers having appeared to date. Moreover, these papers have all used country-level indices of connectivity. To measure the effect on port efficiency, ideally port-level measures should be used and it is this gap in the literature that we propose to fill. It should be noted that several papers exist that have estimated port–level connectivity measures based on the LSCI methodology (e.g., Bartholdi et al., 2016; Jia et al., 2017) and the Annualised Slot Capacity (ASC) methodology (e.g., Lam and Yap, 2011; Wang et al., 2016). A recent critical discussion of these methodologies and review of the corresponding literature is provided by Martínez-Moya and Feo-Valero (2020). The literature using port-level connectivity indices does not, however, study port efficiency.

3. Modelling the relationship between connectivity and productive efficiency: the output distance function

Given that port activity is multi-output, distance functions are a natural tool with which to measure technical efficiency. We use an output-oriented distance function, which measures the extent to which outputs can be radially expanded for a given input endowment (Cullinane et al., 2004; Trujillo and Tovar, 2007; Chang and Tovar, 2014a, 2014b; Chang and Tovar, 2017a, 2017b; Chang and Tovar, 2021).[6]

More formally, to measure efficiency in a multi-output setting where there are K inputs and M outputs, define the production set as:

$$\mathscr{P} = \left\{(xy) \in R_{+}^{K+M} \,\middle|\, x \text{ can produce } y\right\} \tag{1}$$

For a firm located at $(x_0, y_0) \in R_{+}{}^{K+M}$ an output-oriented measure of technical efficiency, namely the Shephard (1970) output distance function, can be defined as:

[4] https://unctad.org/news/container-ports-fastest-busiest-and-best-connected#_edn1.

[5] Relative geographical centrality or isolation has also been used as a proxy of connectivity. See, for example, Niavis and Tsekeris (2012), who used distance from Suez as a measure of connectivity in an analysis of the efficiency of container ports in South-Eastern Europe.

[6] An alternative would be an input-oriented distance function measuring the potential radial reduction in inputs for a given level of output. We follow Gonzalez and Trujillo (2008), among others, who justify the output-oriented approach by arguing that port authorities have some control over the production level through the use of commercial policies and concessions.

$$D_0(x, y) = min\{\delta | (x, y/\delta) \in \mathscr{P}, \delta > 0\} \tag{2}$$

For any combination (x_0, y_0), the output distance function is the smallest scalar needed to divide actual output so that it expands to the frontier of $\mathscr{P}$, holding inputs fixed. Note that when $(x_0, y_0) \in \mathscr{P}$, $\delta \leq 1$.

The output distance function should comply with homogeneity of degree one in outputs, which implies that

$$D_0(x, \theta y) = \theta D_0(x, y) \text{ for any } \theta > 0 \tag{3}$$

This can be imposed by normalising the distance function by one of the outputs, say the Mth output, y_M (see, for example, Coelli and Perelman, 2000). Thus, setting $\theta = 1/y_M$ in (3a) we have

$$D_0(x, 1/y_M) = D_0(x, y)/y_M \tag{4}$$

The efficiency scores for each unit i, D_{0i}, are obtained by estimating a parametric stochastic output-oriented distance frontier, for which the flexible translog functional form is most-commonly used.

To get to an estimable econometric model, we write

$$ln(D_{0i}(x_i, y_i)/y_{Mi}) = TL(x_i, y_i/y_{Mi}, \alpha, \beta) \tag{5}$$

where $TL(.)$ denotes the translog functional form and (α, β) are parameters to be estimated. (5a) can be written as

$$lnD_{0i}(x_i, y_i) - lny_{Mi} = TL(x_i, y_i/y_{Mi}, \alpha, \beta) \tag{6}$$

Rearranging:

$$-lny_{Mi} = TL(x_i, y_i/y_{Mi}, \alpha, \beta) - lnD_{0i}(x_i, y_i) \tag{7}$$

To express as this as an estimable stochastic distance frontier, we add error terms:

$$-lny_{Mi} = TL(x_i, y_i/y_{Mi}, \alpha, \beta) + v_i - u_i \tag{8}$$

where v_i is a symmetric random disturbance term, assumed to be distributed as $iid\, N(0, {\sigma_v}^2)$, and we set $u_i = \ln D_{oi}(x, y)$, where $u_i \geq 0$ is the technical inefficiency term.

To get the actual equation to be estimated, we need to substitute for $TL(x_i, y_i/y_{Mi}, \alpha, \beta) = ln\,(D_{0i}(x_i, y_i)/y_{Mi})$ in Eq. (8). Assume that port i has M outputs and K inputs. The translog specification for each port i without imposing homogeneity of degree 1 in outputs (i.e., without normalising by one of the outputs) can be written as:

$$TL(x_i, y_i, \alpha, \beta) = lnD_{oi}(x, y) = \alpha_0 + \sum_{m=1}^{M} \alpha_m lny_{mi} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \alpha_{mn} lny_{mi} lny_{ni} + \sum_{k=1}^{K} \beta_k lnx_{ki} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} lnx_{ki} lnx_{li} + \sum_{k=1}^{K}\sum_{m=1}^{M} \beta_{kl} lnx_{ki} lny_{mi} \tag{9}$$

Imposing homogeneity of degree one in outputs by normalising the distance function by one of the outputs, y_M gives:

$$\begin{aligned} TL(x_i, y_i/y_{Mi}, \alpha, \beta) &= ln(D_{oi}(x, y)/y_{Mi}) \\ &= \alpha_0 + \sum_{m=1}^{M-1} \alpha_m ln(y_{mi}/y_{Mi}) + \frac{1}{2}\sum_{m=1}^{M-1}\sum_{n=1}^{M-1} \alpha_{mn} ln(y_{mi}/y_{Mi}) ln(y_{mi}/y_{Mi}) + \sum_{k=1}^{K} \beta_k lnx_{ki} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} lnx_{ki} lnx_{li} + \sum_{k=1}^{K}\sum_{m=1}^{M-1} \beta_{kl} lnx_{ki} ln(y_{mi}/y_{Mi}) \end{aligned} \tag{10}$$

Substituting into (8) yields:

$$-lny_{Mi} = \alpha_0 + \sum_{m=1}^{M-1} \alpha_m ln(y_{mi}/y_{Mi}) + \frac{1}{2}\sum_{m=1}^{M-1}\sum_{n=1}^{M-1} \alpha_{mn} ln(y_{mi}/y_{Mi}) ln(y_{mi}/y_{Mi}) + \sum_{k=1}^{K} \beta_k lnx_{ki} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} lnx_{ki} lnx_{li} + \sum_{k=1}^{K}\sum_{m=1}^{M-1} \beta_{kl} lnx_{ki} ln(y_{mi}/y_{Mi}) + v_i - u_i \tag{11}$$

where v_i is the symmetric random disturbance term which we have assumed to be distributed as $iid\, N(0, {\sigma_v}^2)$, and $u_i = \ln D_{oi}(x, y) \geq 0$ is the technical inefficiency term. We make the following distributional assumptions about the inefficiency term:

$$u_i \sim iid\, N^+(0, \sigma_{ui}^2), \sigma_{ui}^2 = g(z_i; \delta) \tag{12}$$

That is, u is assumed to follow a non-negative half-normal distribution and to depend on a series of explanatory variables, z (Caudil et al., 1995), which will include the connectivity index and suitable control variables.

In the next section we present our dataset and describe the variables available to us. Before doing so, we note first that we have panel data available, so that individual port fixed effects (α_i) to capture unobserved heterogeneity as well as a time trend (t) and its square (t^2) can be included in the equation to be estimated. We also note that several ports have zero values for some of the outputs in our dataset. In order not to lose observations when estimating the translog distance function, a slight modification needs to be made to Eq. (11). In particular, we follow the procedure outlined by Battese (1997) where the output variables are replaced with $y_{mit}{}^* = Max\,(y_{mit}, D_{mit})$, and

$$D_{mit} = 1 \text{ if } y_{mit} = 0 \text{ and } D_{mit} = 0 \text{ if } y_{mit} > 0 \tag{13}$$

Making these replacements in Eq. (11), the econometric specification of the output distance function to be estimated is then:

where the α_i are individual port fixed effects to capture time-invariant port heterogeneity, and t and t^2 are the time trend and its square. The square of the time trend is also included in the frontier. The time-varying technical inefficiency term $u_{it} \geq 0$ is specified according to (12) and the equation to be estimated can be expressed in general terms as:

$$- lny^{*}_{Mit} = \alpha_i + \sum_{m=1}^{M-1} \alpha_m ln\left(y^{*}_{mit}/y^{*}_{Mit}\right) + \frac{1}{2}\sum_{m=1}^{M-1}\sum_{n=1}^{M-1} \alpha_{mn} ln\left(y^{*}_{mit}/y^{*}_{Mit}\right) ln\left(y^{*}_{mit}/y^{*}_{Mit}\right) + \sum_{k=1}^{K} \beta_k lnx_{kit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} lnx_{kit} lnx_{lit} + \sum_{k=1}^{K} \times \sum_{m=1}^{M-1} \beta_{kl} lnx_{kit} ln\left(y^{*}_{mit}/y^{*}_{Mit}\right) + \sum_{m}^{M-1} \gamma_m D_{mit} + t + t^2 + v_{it} - u_{it} \tag{14}$$

$$ln\sigma^2_{uit} = \delta_0 + \sum_{p=1}^{P} \delta_p z_{pit} + \delta_t t + \delta_{tt} t^2 \tag{15}$$

where the inefficiency determinants, z, will include a measure of connectivity and other control variables, and a time trend and its square are included. We describe these control variables as well as the outputs and inputs used in the following section.

4. Data

The dataset used to estimate the output distance function for individual Spanish ports is constructed by crossing information from different sources, with the connectivity variable coming from UNCTAD and the port-level production data coming from the Spanish State Ports Public Body (*EPPE)* and the port authorities.

Our dataset consists of 176 observations corresponding to a sample of 16 Spanish ports observed over the period 2006–2016.[7] The sources of the production-related information are the Spanish State Ports Public Body (*EPPE)* and the port authorities. While production information is available for 28 port authorities, several of these comprise multiple individual ports and the data could not be disaggregated at port level, so only information for single-port port authorities could be used. Our outputs comprise four types of merchandise - liquids (y_1), solid bulk (y_2), containerised merchandise (y_3), and general non-container merchandise (y_4), all measured in tons - and the number of passengers (y_5). The inputs used are labour (x_1), intermediate consumption expenditures (x_2), and the expenditure on capital asset services (x_3). Descriptive statistics of the output and input variables used are presented in Table 1.

The determinants of inefficiency to be used in the distance function are reported in the lower half of Table 1. Our principal interest is in the first of these, namely the Connectivity Index (*Connect*). This variable comes from the Port Liner Shipping Connectivity Index (PLSCI) database launched by UNCTAD in 2019. The PLSCI uses the same methodology applied to the country-level LSCI and covers more than 900 ports over the 2006–2019 period, from which we extract the indices for 2006–2016 for the 16 port authorities in our sample. The PLSCI comprises six components covering key aspects of port-level connectivity including number of scheduled ship calls, deployed total capacity, number of regular services to and from the port, number of liner shipping companies that provide services, ship sizes and the number of destination ports that can be reached without the need for trans-shipment (UNCTAD, 2019).

To better identify the effect of connectivity on efficiency we include a series of control variables as efficiency determinants. These include several indices of output concentration and relative specialization which have been found to be relevant determinants of efficiency in previous studies (Tovar and Wall, 2017). The output concentration measure we use is the (normalised) Herfindahl-Hirschman Index (HHI) for each port authority (see Al-Marhubi, 2000). The index is normalised to take values ranging from 0 to 1, where a value of 1 represents perfect specialization and values closer to 0 represent greater diversification. In order to have common units of measurement for outputs, we calculate the HHI for cargo traffic only. We also include indicators of relative specialization ($SPECy_{mi}$), known as the Bird Index (Frémont and Soppé, 2007) which capture whether a port authority is relatively more specialised in a *given* output (or subset of outputs). When the index takes values greater (less than) 1, the port is relatively more (less) specialised in that output than the system as a whole.

[7] The port authorities included are A Coruña, Alicante, Bahía de Algeciras, Bahía de Cádiz, Barcelona, Bilbao, Cartagena, Castellón, Ferrol-San Cibrao, Gijón, Málaga, Marín-Ría de Pontevedra, Santander, Sevilla, Tarragona and Vigo.

5. Results

The normalising output used to impose homogeneity of degree one is general merchandise (y_4). All outputs and inputs are expressed in terms of deviations from their means. The results of the output distance function are presented in Table 2, where the individual effects are not reported in order to save space. The coefficients on variables containing y_4 have been recovered from the homogeneity restrictions.

As can be seen, the econometric model performs quite well in that most of the parameters are statistically significant. The output distance function should be increasing in outputs and decreasing in inputs and this is complied with for all outputs and inputs at the sample mean, as is visible from the signs of the first-order parameters. Thus, for outputs, all the first-order terms are positive and highly significant. All the first-order input coefficients are negative, although only the coefficient for capital assets (x_3) is statistically significant. The positive coefficient on the time trend shows negative technical change, though the negative sign on the square of the time trend indicating that this has mitigated over the sample period. A possible explanation for this is that the period analyzed comprises the international economic crisis that began in 2008.

Having established that the estimated output distance function complies with the theoretical properties, we now turn to the determinants of technical inefficiency, which is our main focus of interest. Given the determinants of inefficiency discussed in the previous section, the efficiency Eq. (15) to be estimated is:

$$ln\sigma^2_{uit} = \delta_0 + \delta_{Conn} Connect_{it} + \delta_{HHI} HHI_{it} + \sum_{p=1}^{4} \delta_{Spec_{yi}} Spec_{y_{pit}} + \delta_t t + \delta_{tt} t^2 \tag{16}$$

The estimates for the determinants of inefficiency are presented in Table 3. Note that a negative sign on the coefficient of a variable implies a positive relationship between that variable and technical *efficiency*. Our primary interest is in the behaviour of the *Connect* variable. As can be seen, the coefficient is negative and highly significant, implying that there exists a strong positive relationship between connectivity and technical efficiency. Regarding the controls, the sign on HHI implies a positive relationship between overall output concentration and technical efficiency (though the coefficient is significant only at the 10% level), and there are also positive relationships between relative specialization and technical efficiency (although in the case of containers, this relationship is not statistically significant). Finally, the time trend variables were not significant.

The technical efficiency scores are summarized in Table 4, where it can be seen that overall technical efficiency was quite high, at 0.949, though this ranges considerably with a minimum value of 0.546.

Table 1
Descriptive statistics of variables.

Variable	Description	Mean	Std. Dev.	Min.	Max.
Outputs and inputs					
y_1	Liquid bulk cargo (tons)	7,100,440	8,664,243	0	27,344,044
y_2	Solid bulk cargo (tons)	4,304,164	4,065,432	234,910	18,905,283
y_3	Container cargo (tons)	4,720,379	10,795,711	565	60,178,589
y_4	General non-container cargo (tons)	2,509,648	6,319,415	305	55,476,501
y_5	Passengers (units)	688,529	1,429,903	0	5,618,048
x_1	Labour (units)	9,510,306	7,029,806	301,8105	37,020,055
x_2	Supplies (€ deflated)	11,579,396	10,921,719	178,7876	55,311,069
x_3	Capital assets (mill. € deflated)	33,452,208	28,173,379	572,4252	14,184,1050
Variables used to explain efficiency					
Connect	Connectivity Index	11.540	13.827	0.659	60.340
HHI	Normalised Herfindahl-Hirschman Index	0.281	0.163	0.059	0.754
SPECy$_1$	Relative specialization in output y_1	0.760	0.772	0.000	2.395
SPECy$_2$	Relative specialization in output y_2	1.899	1.259	0.099	4.910
SPECy$_3$	Relative specialization in output y_3	0.776	0.720	0.000	3.141
SPECy$_4$	Relative specialization in output y_4	1.030	0.826	0.000	3.092

Table 2
Output-oriented stochastic distance function.

Variable	Estimate	Std. Err.	*p*-Value	Variable	Estimate	Std. Err.	*p*-Value
y_1	0,2535	0,0359	0,000	y_4•y_5	−0.0025	0.0020	0.206
y_2	0.4375	0.0423	0.000	x_1•x_2	0.0561	0.0523	0.284
y_3	0.1345	0.0177	0.000	x_1• x_3	−0.0687	0.0574	0.231
y_4	0.1395	0.0204	0.000	x_2• x_3	0.2114	0.1063	0.047
y_5	0.0350	0.0114	0.002	y_1•x_1	0.0066	0.0082	0.417
x_1	−0.0021	0.0202	0.919	y_1•x_2	−0.0519	0.0283	0.066
x_2	−0.0747	0.0695	0.282	y_1• x_3	−0.0011	0.0344	0.974
x_3	−0.1900	0.0797	0.017	y_2•x_1	−0.0034	0.0189	0.856
y_1•y_1	0.0374	0.0077	0.000	y_2•x_2	−0.0144	0.0431	0.738
y_2•y_2	0.1068	0.0387	0.006	y_2• x_3	0.0804	0.0621	0.195
y_3•y_3	0.0233	0.0057	0.000	y_3•x_1	−0.0039	0.0089	0.663
y_4•y_4	0.0202	0.0078	0.010	y_3•x_2	0.0262	0.0173	0.131
y_5•y_5	0.0017	0.0046	0.720	y_3•x_3	−0.0670	0.0205	0.001
x_1•x_1	−0.0505	0.0519	0.330	y_4•x_1	−0.0063	0.0192	0.742
x_2•x_2	−0.1555	0.1348	0.249	y_4•x_2	0.0189	0.0303	0.534
x_3•x_3	−0.1640	0.1774	0.355	y_4•x_3	−0.0015	0.0297	0.958
y_1•y_2	−0.0493	0.0171	0.004	y_5•x_1	0.0070	0.0063	0.269
y_1•y_3	0.0156	0.0070	0.025	y_5•x_2	0.0212	0.0130	0.102
y_1•y_4	−0.0017	0.0082	0.834	y_5 x_3	−0.0107	0.0108	0.324
y_1•y_5	−0.0020	0.0031	0.507	t	0.0579	0.0220	0.008
y_2•y_3	−0.0417	0.0127	0.001	tt	−0.0053	0.0015	0.000
y_2•y_4	−0.0193	0.0152	0.203	D_1	−0.1903	0.1219	0.119
y_2•y_5	0.0035	0.0049	0.474	D_3	0.2143	0.2212	0.333
y_3•y_4	0.0034	0.0122	0.784				
y_3•y_5	−0.0006	0.0031	0.838	Constant	1.0864	0.1684	0.000

No of observations. 176.
Log likelihood: 164.31.

Table 3
Determinants of efficiency in stochastic output distance function.

Variable	Estimate	Std. Err.	*p*-Value
Connect	−0.1960	0.0681	0.004
HHI	−7.6848	4.4246	0.082
SPECy$_1$	−7.3342	3.6741	0.046
SPECy$_2$	−5.6571	2.5276	0.025
SPECy$_3$	−4.5121	3.2377	0.163
SPECy$_4$	−3.1636	1.6133	0.050
t	0.4579	0.5728	0.424
tt	−0.1143	0.0740	0.122
Constant	21.0496	11.2053	0.060

No of observations. 176.

We look more closely at the relationship between connectivity and efficiency by calculating the marginal effects of connectivity on technical efficiency. Having estimated (16), the conditional expectation of the technical efficiency scores can be calculated using the following formula (Kumbhakar and Lovell, 2000):

Table 4
Summary technical efficiency scores.

Variable	Mean	Std. Dev.	Min.	Max.
Technical efficiency	0.945	0.094	0.546	1.000

$$E[exp(-u_{it})] = 2[1-\Phi(\sigma_u)]exp\left(\frac{\sigma_u^2}{2}\right) \tag{17}$$

We use the estimated coefficients reported in Table 3 to predict technical efficiency using (17). To analyse the impact on connectivity on efficiency, we set the determinants of technical efficiency other than connectivity at their sample mean values and vary the value of the variable *Connect* across its range of observed values, recalculating the predicted technical efficiency score each time.

Some summary results from this analysis are represented in Fig. 1, which shows how the technical efficiency scores change as the value of the connectivity index ranges from its first to ninth deciles. The

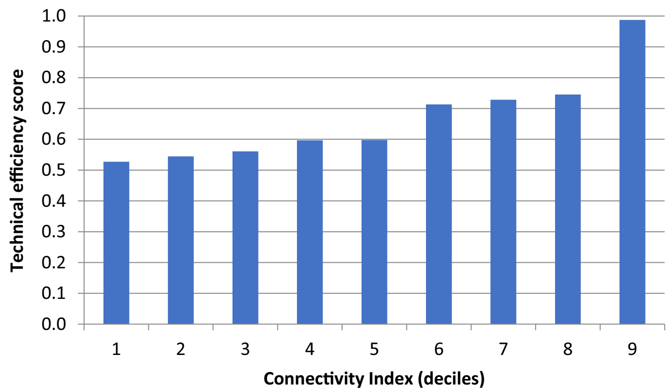

Fig. 1. Relationship between connectivity and technical efficiency scores.

Table 5
Change in output from effect of connectivity on technical efficiency.

	Quartile 1	Quartile 2	Quartile 3
Connect	3.396	5.280	11.519
TE	0.549	0.598	0.741
$\%\Delta Y: Q1 \rightarrow Q2$		9.0	
$\%\Delta Y: Q2 \rightarrow Q3$		24.0	
$\%\Delta Y: Q1 \rightarrow Q3$		35.1	

predicted technical efficiency scores range from 0.527 for the first decile value of the connectivity index to 0.987 for the ninth decile value.

The efficiency scores can be used to estimate the change in output that arises from differences in connectivity. To see this, note that by the definition of the output distance function, we have $u_i = \frac{y_i}{y^*}$ where y_i is observed output of port i and y^* is frontier output. For two ports ($i = 1$, 2) with the same frontier output, we then have that $\frac{u_1}{u_2} = \frac{y_1}{y_2}$, so that the ratio of efficiency scores gives us the ratio of outputs that we would observe. We illustrate this in Table 5 below for the values of *Connect* at its first, second and third quartiles and the corresponding estimated technical efficiency scores.

The bottom part of Table 5 shows the percentage changes in output as the value of the connectivity index changes (which thereby changes the technical efficiency values). As can be seen, as the connectivity index goes from its first to second quartile value, output would be an expected 9% higher, ceteris paribus. As we go from the second to third quartile, output would be 24% higher, and if we go from the first to the third quartile, it would be 35.1% higher. Therefore, even relatively moderate changes in connectivity correspond to much greater expected level of output.

6. Discussion and conclusions

We have explored the relationship between port-level maritime connectivity and technical efficiency for a sample of Spanish ports observed over the period 2006–2016 using a stochastic output distance function approach. A novel dataset was constructed by crossing information on port-level connectivity from UNCTAD with production data with information provided by Spanish port authorities for individual ports. This is the first paper to investigate the relationship between port efficiency and maritime connectivity using port-level connectivity indices. Controlling for unobserved heterogeneity and a series of port characteristics relating to their output structure in terms of their output concentration and specialization, our results show that there is a strong positive correlation between connectivity and efficiency.

We quantify the effect of connectivity on port performance and show that even relatively modest changes in connectivity have large impacts on expected output. Thus, compared to ports with an index of connectivity equal to its first quartile sample value, we find that ports with a connectivity index value corresponding to the second quartile sample value would have an expected output 9% greater, while ports with third quartile connectivity indices would have over 35% higher expected output.

Our results point to a clear relationship between port efficiency and connectivity and provide a quantitative approximation of the benefits of improved connectivity. This implies that studies of port efficiency should be careful to try to include connectivity variables reflecting ports' integration into shipping networks. As such, our conclusions are in line with those of Schøyen et al. (2018), who also found a positive impact of connectivity measures (country-level in their case) on port technical efficiency. These authors concluded that researchers needed to go beyond benchmarking ports' pure technical efficiency and take account of connectivity measures including integration in supply chains.

The question remains as to how the connectivity of individual ports can be increased. Several policy options have been discussed in the literature. These have been summarized by UNCTAD (2019), which points to seven key policy measures. Firstly, it has been noted that digital and physical connectivity are complementary, so that increased digitalization should be encouraged. Two related measures are the promotion of greater links among domestic, regional and global networks - by eliminating restrictions affecting regional or domestic cabotage markets and permitting international lines to also carry domestic trade and feedering cargo – and an emphasis on competition when it comes to assigning port concessions to terminal operators. A fourth policy measure is the modernization of ports, with continuous investment in technological, institutional and human capacities. On this point, UNCTAD underlines the importance of cooperation between public and private companies. Another recommended policy measure is that of widening the hinterland[8] by attracting business from domestic production centres and neighbouring countries,[9] which can be promoted by investment in corridors (Van den Berg and De Langen, 2011) and the facilitation of cross-border trade and transit (Lind et al., 2021). Sustainability also has a role to play in connectivity, with increased demands by stakeholders – including shipping lines, social partners and the port-city community – for ports to comply with social, economic and environmental sustainability criteria. A final measure is to promote continuous and accurate monitoring of trends in the global shipping network, trade geography, fleet deployment and port performance.

According to our results, the implementation of some or all of these measures to increase connectivity would be expected to have substantial effects on port efficiency performance. Moves in this direction are underway in Spain, with initiatives such as the Ports 4.0 Fund entering a new phase in 2021. The objective of this initiative is to promote and incorporate innovation in Spanish ports by funding projects related to improvements in logistics efficiency in infrastructure, operational or service provision, digitisation of processes and intelligent platforms and environmental sustainability.[10] The Spanish State Ports Public Body also announced at the beginning of 2021 an increase in investment in the sector projected to reach €4.5 billion by 2024, with a focus on connectivity, security, environmental sustainability and digitilisation.[11] In light of our results, these measures will be expected to have a substantial on technical efficiency in Spanish ports.

[8] The spatial development of the ports' hinterland is beyond the scope of this paper but readers interested in spatial development of the hinterland of the main Spanish ports can consult Garcia-Alonso et al. (2016).

[9] While location is one of the most relevant factors for capturing port traffic, Grecco et al. (2017) note that alternative factors such as connectivity and service quality become increasingly important as the geographical scope of port competence widens.

[10] http://www.puertos.es/Documents/Notas%20de%20Prensa/29102020NPPuertos40es_esen_gbTC.pdf

[11] https://www.diariodelpuerto.com/noticia1392

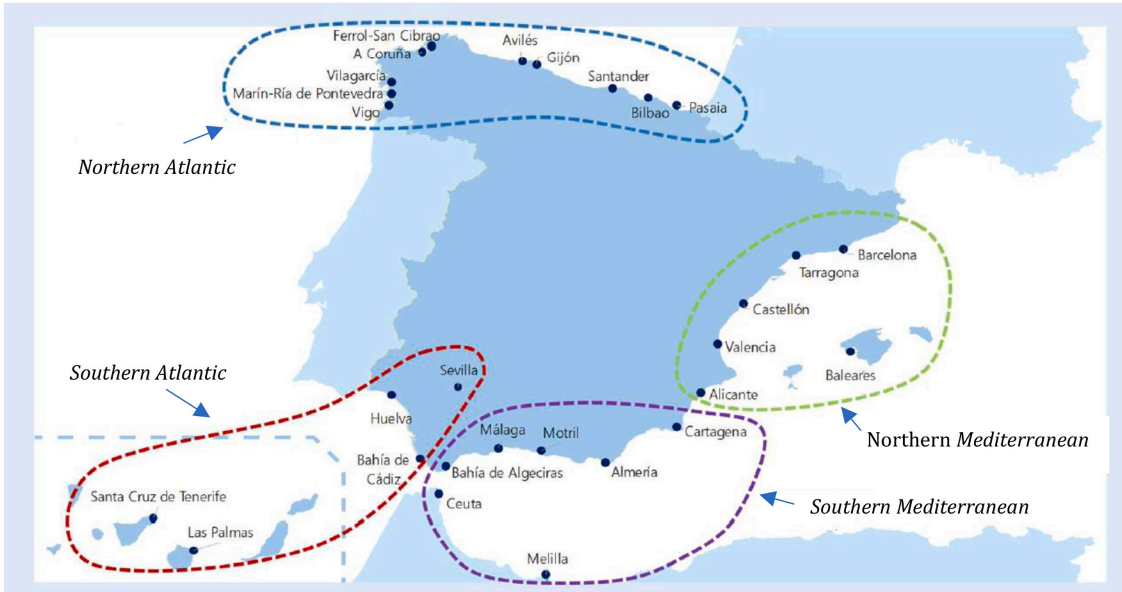

Fig. 2. Spanish ports – Atlantic and Mediterranean seaboards.

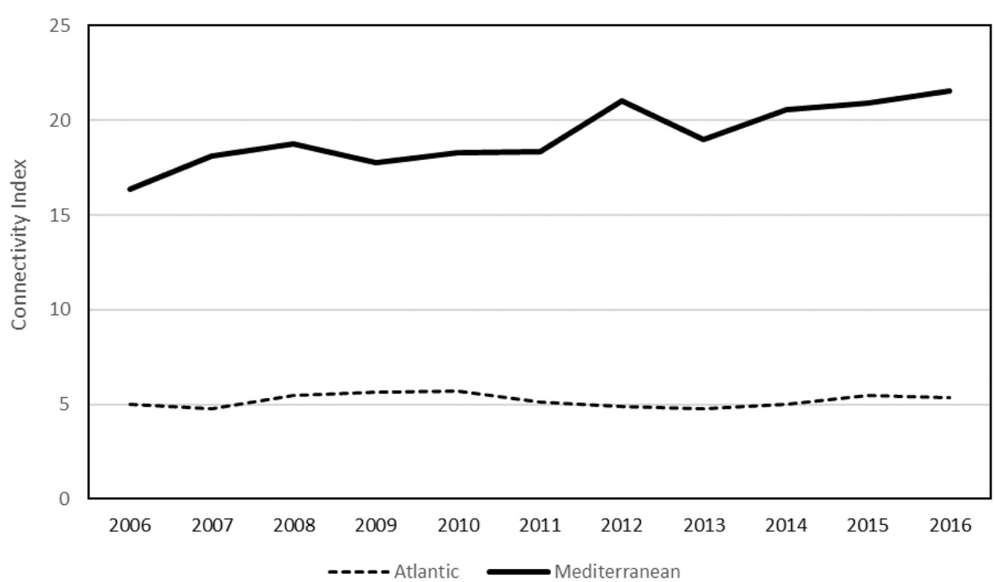

Fig. 3. Connectivity in Atlantic and Mediterranean ports: 2006–2016.

Finally, the question arises as to whether policy measures with regard to connectivity should take into account aspects such as port location. To shed some light on this, Fig. 2 shows the distribution of Spanish ports by seaboard.

Our sample includes ports from each of these seaboards represented in Fig. 2, namely Northern Atlantic (7 ports), Southern Atlantic (2 ports), Southern Mediterranean (3 ports) and Eastern Mediterranean (4 ports). The increasing amount of trade with the East in recent decades has meant that Mediterranean ports have gained influence at the expense of Atlantic ports.[12] This is illustrated in Moura et al. (2018), who also find that the connectivity of the Mediterranean ports (proxied in their case by container throughput) is in line with the evolution of Spanish maritime trade flows. To check whether this is reflected in the PLSCI used in this paper, we calculate the average connectivity indices from our data for the nine Atlantic and seven Mediterranean ports over the sample period. These are presented in Fig. 3.

Fig. 3 illustrates that the differences between the connectivity of the Atlantic and Mediterranean ports is striking. The connectivity of the Atlantic ports is much smaller on average over the sample period. Moreover, average connectivity for this set of ports remained basically unchanged over the period, with the index increasing by just over 7% from 2006 to 2016. The connectivity of Mediterranean ports, on the other hand, is not only much higher but also increased considerably, with an increase in the average index of over 31% from 2006 to 2016. This is in line with the findings of Moura et al. (2018). The results of our estimation of the relationship between connectivity and efficiency therefore imply that differences in efficiency between Mediterranean and Atlantic ports will be reinforced to the detriment of the latter.

[12] It should be noted that things could change again if, in spite of environmental concerns, the northern sea route through the Arctic becomes a real alternative for maritime transport due to the commercial benefits derived from the shorter transit.

This comparison illustrates an increasing divergence between the two sets of ports and points to a need for specific policy attention to be given to the Atlantic ports in order to break the potentially vicious circle between lower trade, lower connectivity and lower efficiency. If they are to increase their competitiveness, policy measures to increase efficiency and connectivity, such as, for example, marketing strategies and measures to increase service quality and reduce costs faced by clients, are needed to counteract the relative geographical disadvantage of their location. For a discussion of the literature on the options open to Port Authorities to counteract geographical location, a factor beyond the control of ports, see Martínez-Moya and Feo-Valero (2017).

Our research can be extended in various ways. A more complete analysis of connectivity would include measures of land connectivity and/or intermodal connectivity, and it would be particularly interesting to see how these impact on port efficiency. On the other hand, alternative measures of port connectivity to the PLSCI could be explored, such as ASC-based measures. The PLSCI uses equal weights for each of its components but it is to be hoped that in the future there will be panel data available with disaggregated individual components, which would allow alterative weighting to be considered. It would also be interesting to see if our results for Spain hold for other countries. In this sense, it is our hope that our work will encourage research on the relationship between port efficiency and port-level connectivity measures.

Declaration of Competing Interest

None.

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