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Are larger and more complex port more productive? An analysis of Spanish port authorities

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Abstract

Several Spanish ports have grown substantially in recent decades. Ports in Spain are heterogeneous in that they differ substantially in terms of complexity, size and traffic mix. We measure the productivity of Spanish port authorities and identify the drivers of productivity taking into account this heterogeneity in order to provide more meaningful estimates of efficiency and productivity change. Using a sample of 26 ports observed over the period 1993-2016, we classify these ports into two different groups according to their overall size and their importance in terms of individual outputs. Segregating the sample into these two distinct groups permits us to draw a more precise picture of the consequences for productivity of the changes that have occurred in the sector in Spain over the last quarter of a century. Using Data Envelopment Analysis techniques, we calculate and decompose Malmquist productivity indexes using a metafrontier analysis. We use these indexes to estimate an Arellano-Bond Generalised Method Moments model to explain the differences in productivity change. Our results show that the group of large and complex port authorities had a considerable technological advantage, being closer to the metafrontier on average than the other group. Relative size, which can be interpreted as a measure of complexity of the port authority, has a strong positive influence on productivity growth. Specialisation in solids, container cargo and general bulk also increased productivity growth, but specialisation in liquids has no effect.

Keywords*:* DEA-Malmquist, Metafrontier, Technology gap ratio, Dynamic panel data method, Spanish Port Authorities, Productivity drivers.

1. Introduction

Spain has a long maritime tradition as a country and it is an important player in international maritime transport. The 25 most important ports worldwide include five from Spain, namely Valencia, Algeciras, Barcelona, Las Palmas and Bilbao, underlying the consolidation of the country in the maritime transport market and its strategic location as a stop on many international routes. Data on maritime traffic for 2016 confirm this upward trend and the importance of the Spanish port system as a logistic hub for cargo and passenger traffic (Medal-Bartual et al., 2016).

In a recent paper, Tovar and Wall (2017b) addressed the issue of how Spanish port authorities have reacted to a changing competitive environment by analysing the evolution of market concentration and the evolution of the output mix within the individual port authorities themselves. Ports may handle several outputs, yet still be specialised in one or few of these. Specialization in a particular output is one way of reacting to changing competitive conditions, and can be thought of as a way of gaining from economies of scale. Also, ports can gain from 'specialisation efficiencies' when specialization leads to greater technical efficiency from, among others, the use of specialist skills, learning by doing and product-specific scale economies.[1] On the other hand, however, Ducruet el al. (2010) argue that commodity specialisation can represent a weakness for ports as they may suffer if their main commodity cargo is particularly affected by adverse demand conditions.

An alternative strategy therefore would be to diversify output and take advantage of economies of scope by spreading costs over several types of traffic.[2] On these lines, De Langen (2002) highlights the importance of diversification strategies for smaller ports and Meyler et al. (2011) proposed that port authorities implement a "strategy of port activity diversification" to improve performance in adverse market conditions. Diversification can be viewed in this context as a risk-reduction strategy. The size of the port is key here, as a port authority may exhibit diversification across cargoes yet still be able to take advantage of scale economies. In particular, if the diversified port authority is large enough it may have sufficient infrastructure

[1] The term 'specialisation efficiencies' was initially introduced in the agricultural economics literature by Coelli and Fleming (2004).
[2] Port activity diversification can be measured by the weight of various traffic categories in overall seaport traffic (Huybrechts et al., 2002).

to handle large quantities of several cargoes, thereby benefitting from scale economies as well as economies of scope.

Tovar and Wall (2017a) show that Spanish port authorities have acted in different ways in recent decades, with some increasing their specialisation in certain outputs and taking advantage of scale economies, while others have tried hard to diversify more and reduce their dependence on a single output, thereby taking advantage of scope economies. This diversity of responses to changing market conditions might be expected given the variety of Spanish ports.[3] In a relatively recent analysis of Spanish ports, Reina and Villena (2013) concluded that less specialized ports were the most vulnerable and argued in favour of greater specialisation in order to deal with economic downturns. Moreover, González-Laxe and Novo-Corti (2012) argued that the unfavourable economic environment of the recent economic crisis led to a concentration of certain types of traffic in particular ports in Spain, leading to greater overall concentration and specialization in the system.

As pointed out by Tovar and Wall (2017b), Spanish ports vary widely in terms of their size and specialisation, including small, medium-sized and large ports, ports that act as gateways to their hinterland and ports that serve as hubs. Generally speaking, differences in types of infrastructure can be conceptualised as differences in technology and this can be reflected in different output mix strategies and differences in terms of productive performance.[4] The possible effects of technology differences on Spanish port productive performance where these differences between ports may be due to different degrees of specialisation, complexity and size, is the issue addressed in this paper, where our indicator of productive performance is Total Factor Productivity (TFP) growth.

When analysing the efficiency and productivity change of ports, the efficiency and productivity change measurements will be misleading in the presence of unobserved heterogeneity. This heterogeneity problem can be approached using a metafrontier approach, as has been recently shown by Chang and Tovar (2017a) in an analysis of South Pacific terminals. We avail of the concept of the metafrontier to account for differences in technology across ports. Using a panel

[3] In an analysis of specialisation in Spanish ports, González-Laxe (2012) concludes that they are becoming more and more specialised in terms of their traffic as well as in the services they offer.
[4] Technological change has affected port infrastructure, with some types of infrastructure being highly specialised whereas others permit a greater degree of flexibility (Tovar and Wall, 2017a).

data set of 26 Spanish port authorities observed over the period 1993-2016, we first divide the sample into two groups based on a criterion of complexity and size. To measure productivity and its components, we calculate Malmquist Productivity Indices with respect to the metafrontier and the group-specific frontiers and disaggregate these indices in their component parts of technical efficiency and technical change. The frontiers and productivity indices are calculated from output-oriented distance functions estimated using Data Envelopment Analysis (DEA), a non-parametric method widely used in the frontier literature. Finally, we also evaluate the influence of certain specific explanatory variables that may explain productivity differences among these port authorities using a dynamic panel estimation of Arellano and Bond (1991).

The paper proceeds as follows. In the next section we review the concept of metafrontiers and how they have been applied in the literature to measure and decompose productivity. Section 3 discusses the data used. In Section 4, we discuss the criterion used to separate the sample into two groups and present the results on total factor productivity, its decomposition and its drivers. Section 5 concludes.

2. Measuring productivity using metafrontiers

The concept of metafrontiers was introduced and refined in a series by papers by Battese and Rao (2002), Rao et al. (2004) and O'Donnell et al. (2005, 2008) with the aim of taking into account the differences in technology across production entities. The technique consists of enveloping the group-specific frontiers (representing the boundaries of group-specific technology sets, where the groups should be relatively homogeneous) with a new frontier called the metafrontier. The metafrontier can be thought of as the boundary of the metatechnology set under the assumption that all producers have potential access to the same technology (Battese and Rao, 2002; Battese et al., 2004). O'Donnell et al. (2008) had indicated that the cause of the differences among the technologies presented by the metafrontier and the group frontiers could be attributed to discrepancies between economic infrastructure and/or other characteristics of the production environment.

In this setting of group-specific frontiers and metafrontiers, Malmquist productivity indices can be calculated using distance functions estimated using stochastic frontier analysis or Data Envelopment Analysis (DEA). We will focus on DEA due to the ease with which it can handle multiple outputs.[5] The distance functions can take an input orientation or an output orientation, with the choice depending on whether the firm has control over inputs or outputs.[6] As we consider the ports in our sample closer to being output maximizers than input minimizers (see also Cullinane et al., 2004; Cheon et al., 2010; Chang and Tovar, 2017a,b), we will adopt an output orientation.

Formally, let $x_t \in \mathbb{R}^{+M}$ y $y_t \in \mathbb{R}^{+L}$ denote the input and output vectors in time t, and $t = 1, 2, \dots, T$. The production technology is defined as the capability of transforming inputs into outputs. Assume there are K group-specific technology sets, S^k, with $k = 1, 2, \dots, K$, defined as:

$$S_t^k = \{(x_t^k, y_t^k) \colon x_t^k \text{ can produce } y_t^k\} \tag{1}$$

The group-specific output sets (P^k) and output distance functions (D^k) represent the K group-specific technologies (O'Donnell et al., 2008):

$$P_t^k(x_t^k) = \{y_t^k \colon (x_t^k, y_t^k) \in S_t^k\} \tag{2}$$

$$D_t^k(x_t^k, y_t^k) = \inf_{\theta} \left\{\theta > 0 \colon \left(\frac{y_t^k}{\theta}\right) \in P_t^k(x_t^k)\right\} \tag{3}$$

O'Donnell et al. (2008) refers to the boundaries of the group-specific output sets as group frontiers, and an output-oriented measure of technical efficiency with respect to the group-k frontier is given by:

$$TE_t^k(x_t^k, y_t^k) = D_t^k(x_t^k, y_t^k) \leq 1 \tag{4}$$

where an observation (x_t^k, y_t^k) is technically efficient if and only if $D_t^k(x_t^k, y_t^k) = 1$.

Following Battese et al. (2004) and O'Donnell et al. (2008), we assume that all of these K technology sets are subsets of a common (unrestricted) output set, S^*, defined as:

[5] Recent studies by Schøyen and Odeck (2013) and Nguyen et al. (2016) that offer comprehensive literature reviews highlight that the majority of port efficiency studies have used DEA, due most likely to its flexibility in handling multiple inputs and outputs and lack of assumptions about production technology.
[6] Directional distance functions have also been used in several studies of technical efficiency in recent years, particularly in environmental economics, though there have been applications to ports (Tovar and Wall, 2015 and 2017c).

$$S_t^* = \{S_t^1 \cup S_t^2 \cup \ldots \cup \; S_t^k\} \tag{5}$$

The output set for *any* input vector x is defined as:

$$P_t^*(x_t) = \{y_t \colon (x_t, y_t) \in S_t^*\} \tag{6}$$

and the boundary of this output set is referred to as the output *metafrontier*. Analogous to the group-specific technologies, the metatechnology can be represented by the output *metadistance function*:

$$D_t^*(x_t, y_t) = \inf_{\theta} \left\{\theta > 0 \colon \left(\frac{y_t}{\theta}\right) \in P_t^*(x_t)\right\} \tag{7}$$

The corresponding output-oriented measure of technical efficiency with respect to the metafrontier is given by:

$$TE_t^*(x_t, y_t) = D_t^*(x_t, y_t) \leq 1 \tag{8}$$

where an observation (x_t, y_t) is technically efficient with respect to the metafrontier if and only if $D_t^*(x_t, y_t) = 1$.

The fact that the metafrontier envelops the group frontiers implies that:

$$D_t^*(x_t, y_t) \leq D_t^k(x_t^k, y_t^k) \tag{9}$$

This in turn implies that technical efficiency with respect to the metafrontier cannot be larger than technical efficiency with respect to any group-specific frontier:

$$TE_t^*(x_t, y_t) \leq TE_t^k(x_t^k, y_t^k) \tag{10}$$

The relation between the output distance functions with respect to the metafrontier and the group frontiers allows us to obtain a measure of how close a group-specific frontier is to the metafrontier. Thus, the *metatechnology ratio* (O'Donnell et al., 2008) or *technology gap ratio* (Battese et al., 2004) is defined as:

$$TGR_t^k(x_t^k, y_t^k) = \frac{D_t^*(x_t, y_t)}{D_t^k(x_t^k, y_t^k)} = \frac{TE_t^*(x_t, y_t)}{TE_t^k(x_t^k, y_t^k)} \leq 1 \tag{11}$$

As this is simply the ratio of metafrontier technical efficiency to group-k technical efficiency, an increase (decrease) in the technology gap ratio implies a decrease (increase) in the gap between the group-k frontier and the metafrontier. As noted by O'Donnell et al. (2008), a rearrangement of equation (11) provides a convenient decomposition of technical efficiency:

$$TE_t^*(x_t, y_t) = TE_t^k\left(x_t^k, y_t^k\right) \times TGR_t^k\left(x_t^k, y_t^k\right) \tag{12}$$

Thus, technical efficiency measured with respect to the metafrontier can be decomposed into the product of technical efficiency measured with respect to the group-k frontier and the technology gap ratio. The first of these captures, among other things, the existing state of knowledge and the economic environment characterizing group k, while the latter measures the distance between the group- k frontier and the metafrontier. O'Donnell et al. (2008) points out that this decomposition is useful because it allows evaluation of policies or programs aimed at either efficiency improvement within the firm or at the environment in which the firm operates.

Turning to productivity measures, the Malmquist Productivity Index (MPI), introduced by Caves et al. (1982) and extended by Färe et al. (1994), allows productivity change between two periods, t and $t+1$, to be defined exclusively in terms of distance functions. Using the metafrontier to measure distances, the output-oriented metafrontier MPI (MMPI) defined with respect to the technology in period t is given by:

$$MMPI_t^* = \frac{D_t^*(x_{t+1}, y_{t+1})}{D_t^*(x_t, y_t)} \tag{13}$$

and the MMPI defined with respect to period $t+1$ technology is:

$$MMPI_{t+1}^* = \frac{D_{t+1}^*(x_{t+1}, y_{t+1})}{D_{t+1}^*(x_t, y_t)} \tag{14}$$

To avoid having to choose one of the periods t and $t+1$ as the reference period, the MPI is defined as the geometric mean of (13) and (14):

$$MMPI_{t,t+1}^*(x_t, y_t, x_{t+1}, y_{t+1}) = \left[\frac{D_t^*(x_{t+1}, y_{t+1})}{D_t^*(x_t, y_t)} \times \frac{D_{t+1}^*(x_{t+1}, y_{t+1})}{D_{t+1}^*(x_t, y_t)}\right]^{1/2} \tag{15}$$

Rearranging, this can be decomposed into technical efficiency change and technical change (Färe et al., 1994):

$$MMPI_{t,t+1}^*(x_t, y_t, x_{t+1}, y_{t+1}) = \frac{D_{t+1}^*(x_{t+1}, y_{t+1})}{D_t^*(x_t, y_t)}\left[\frac{D_t^*(x_{t+1}, y_{t+1})}{D_{t+1}^*(x_{t+1}, y_{t+1})} \times \frac{D_t^*(x_t, y_t)}{D_{t+1}^*(x_t, y_t)}\right]^{1/2} \tag{16}$$

where the first term on the right-hand side is technical efficiency change ($TEC^{*}_{t,t+1}$) and the second term, inside the brackets, is technical change ($TC^{*}_{t,t+1}$), so that:

$$MMPI^{*}_{t,t+1}(x_t, y_t, x_{t+1}, y_{t+1}) = TEC^{*}_{t,t+1} \times TC^{*}_{t,t+1} \quad (17)$$

Defining the productivity index with respect to a group-k frontier, the Group-specific Malmquist Productivity Index (GMPI) can similarly constructed and decomposed as:

$$GMPI^{k}_{t,t+1}(x_t, y_t, x_{t+1}, y_{t+1}) = TEC^{k}_{t,t+1} \times TC^{k}_{t,t+1} \quad (18)$$

Further decompositions of the MMPI are possible. It can be shown that MMPI can de decomposed as:

$$MMPI^{*}_{t,t+1} = TEC^{k}_{t,t+1} \times TC^{k}_{t,t+1} \times TGRC^{k}_{t,t+1} \quad (19)$$

where

$$TGRC^{k}_{t,t+1} = \frac{MMPI^{*}_{t,t+1}}{GMPI^{k}_{t,t+1}} = \left[\frac{TGR^{k}_{t+1}(x_{t+1},y_{t+1})}{TGR^{k}_{t}(x_t,y_t)} \times \frac{TGR^{k}_{t}(x_{t+1},y_{t+1})}{TGR^{k}_{t+1}(x_t,y_t)}\right]^{1/2} \quad (20)$$

TGRC refers to the change in the technology gap ratio measured as the geometric mean of two growth indices of the TGR (see Chen and Yang, 2011, and references therein for details) and can be thought of as the inverse of group catch-up (i.e., the extent to which the group frontier is catching up to the metafrontier). That is:

$$TGRC^{k}_{t,t+1} = \frac{MMPI^{*}_{t,t+1}}{GMPI^{k}_{t,t+1}} = \left(catch-up_{t,t+1}\right)^{-1} \quad (21)$$

Hence, group catch-up can be expressed as:

$$Catch-up_{t,t+1} = \frac{GMPI^{k}_{t,t+1}}{MMPI^{*}_{t,t+1}} = \left(TGRC^{k}_{t,t+1}\right)^{-1} \quad (22)$$

The value of $Catch-up_{t,t+1}$ is greater (less) than unity when the group frontier is moving closer to (further away from) the metafrontier. Hence, values greater (less) than unity denote positive (negative) catch-up.

Finally, in order to identify the drivers that explain the productivity change of Spanish port authorities we follow Chang and Tovar (2017a) by taking advantage of the panel data structure to specify a dynamic model in a second stage using the Arellano and Bond (1991) specifications.

The general specification of the econometric model is:

$$TFP_{i,t} = \sum_{s=1}^{S} \alpha_s TFP_{i,t-s} + \sum_{j=1}^{J} \beta_i X_{j,i,t} + \epsilon_{i,t} \tag{23}$$

where $TFP_{i,t}$ is productivity growth of port authority i calculated as $GMPI_{i,t,} - 1$, $TFP_{i,t-s}$ are the lagged dependent variables, X_{jit} is the set of control variables and ϵ_{it} is the idiosyncratic error.

This dynamic panel data specification has been recommended in the literature because there are well-known problems in using the Malmquist TFP index as a dependent variable in econometric specifications that can be solved by using appropriate econometric methods.[7]

3. Data

The data we use corresponds to the Spanish port system and our sample contains 624 observations comprising a panel data set of 26 port authorities observed over the period 1993-2016.[8] The main sources of this information are the Spanish Public State Ports Body (EPPE), which publishes accounts and management reports, and the port authorities, which provide information in their annual reports and their websites. The port authorities in the sample vary widely in terms of size and specialisation, with some managing ports whose activity involves cargo and passenger traffic whereas others run ports whose main activity is cargo and passenger transport is virtually non-existent. The fact that the ports under consideration are in the same country also has the advantage that the accounting data used are uniform and comparable. Moreover, these ports face the same regulations and the remaining environmental factors are either equal or very similar for all of them.

[7] Although this index does not suffer from boundary problems, such as those for DEA efficiency scores, its estimates are seriously affected by serial correlation (Simar and Wilson, 2007). Indeed, some authors suggest the use of the dynamic GMM model to eliminate problems of serial correlation that arise when the TFP measure, as estimated by DEA, is used as a dependent variable (Zhengfei and Oude Lansink, 2006).

[8] The port authorities included are A Coruña, Alicante, Avilés, Bahía de Algeciras, Bahía de Cádiz, Baleares, Barcelona, Bilbao, Cartagena, Castellón, Ceuta, Ferrol-San Cibrao, Gijón, Huelva, Las Palmas, Málaga, Marín y Ría de Pontevedra, Melilla, Pasajes, Santa Cruz de Tenerife, Santander, Sevilla, Tarragona, Valencia, Vigo and Vilagarcía.

In order to estimate the distance function technology for the ports in our sample, we need information on their outputs and inputs. Regarding outputs, port activity is multi-product. Port infrastructure service provision may be viewed in terms of the merchandise handled and the passengers using the port. The tons of different types of merchandise for each of the sampled port authorities are known by type: bulk liquids, bulk solids, general containerised merchandise, general merchandise not in containers and passenger numbers. Information is available on the following outputs: liquids (y_1), solid bulk (y_2), containerised merchandise (y_3), general non-container merchandise (y_4), and passengers (y_5). The inputs used are labour (x_1); intermediate consumption expenditures (x_2); capital assets, including the port authority's capital assets (x_3); and the deposit surface area (x_4). Descriptive statistics of the data are presented in Table 1.

Table 1. Descriptive statistics of variables

Variable	Description	Mean	Std. Dev.	Min.	Max.
Outputs and inputs used to calculate efficiency scores					
y_1	Liquid bulk cargo (tons)	5,305,818	6,863,994	0	27,344,044
y_2	Solid bulk cargo (tons)	3,203,973	3,420,341	3,425	19,658,167
y_3	Container cargo (tons)	3,976,167	9,715,641	0	60,178,589
y_4	General non-container cargo (tons)	1,823,185	2,162,910	77,496	10,834,853
y_5	Passengers (units)	903,617	1,560,948	0	7,782,400
x_1	Labour (units)	209	110	58	613
x_2	Supplies (€ deflated)	9,859,132	9,350,020	539,709	68,390,000
x_3	Capital assets (mill. € deflated)	326.452	323.493	142.130	1,870.002
x_4	Deposit surface area (m^2)	909,268	1,110,653	11,345	5,039,802
Number of observations: 624					

4. Empirical specification and results

In order to divide the sample into groups according on the basis of size and complexity, we consider that port authorities should be significant players at national level in more than one output. For each port authority i, we calculate the shares of each individual output (y_{mi}) in overall system output (y_{mSYS}). We label this measure of the size or importance of the port in a certain output as $NATSHAREy_{mi}$, defined as:

$$NATSHAREy_{mi} = \frac{y_{mi}}{y_{mSYS}} \tag{24}$$

As an additional interpretation of this, Tovar and Wall (2017a) show that that the *NATSHARE* measure of port size in a given output comprises both relative specialization in that output compared to other ports as well as the overall relative size of the port. To see this, an index of relative specialisation (Bird Index) for each of the outputs for port authority i ($RELSPECy_{mi}$) can be defined as:

$$RELSPECy_{mi} = \frac{y_{mi}/Y_i}{y_{mSYS}/Y_{SYS}} \tag{25}$$

where y_{mi} is the total traffic of output *m* in port authority *i*, Y_i is total traffic of port authority *i* $Y_i = \sum_m y_{mi}$, y_{mSYS} is the total traffic of cargo *m* in the system ($y_{mSYS} = \sum_i y_{mi}$), and Y_{SYS} is the total traffic of the system ($Y_{SYS} = \sum_m y_{mSYS}$). This index of specialisation or polarization indicates the degree of specialisation *in a given cargo* compared to the degree of specialisation in that cargo of the system as a whole. Clearly, values greater (less) than 1 indicate higher (lower) relative specialisation of the port authority in that output. On the other hand, a measure of the overall relative size of the port ($RELSIZE_i$), can be defined as the ratio of total port cargo output to total system port cargo in a given year:

$$RELSIZE_i = \frac{Y_i}{Y_{SYS}} \tag{26}$$

From (24), (25) and (26) it follows that:

$$NATSHAREy_{mi} = RELSPECy_{mi} * RELSIZE_i \tag{27}$$

Large and complex port authorities were then defined as those for which the average value of $NATSHAREy_{mi}$ over the whole sample period was greater than the sample average for at least two outputs. The average values of $NATSHAREy_{mi}$ for the sample period are reported in Table 2. Those greater than the average for the system as a whole are marked in bold, and the final column assigns the port authorities to one group or another according to the criterion of whether the port has at least two outputs for which its average share of national output over the sample period is greater than the national average (Cluster 1) or not (Cluster 2).

The calculations in Table 2 illustrate the differences in terms of size and complexity across port authorities in the sample. Thus, Barcelona has output shares greater than the national average for all five outputs, while Santa Cruz de Tenerife, Bilbao and Algeciras have higher than national average output shares for four outputs. At the other end of the scale, Alicante, Avilés, Cádiz, Málaga, Marín-Pontevedra, Melilla, Sevilla, Vigo and Vilagarcía have no output with a national share greater than the average. There is a small group of highly specialized port authorities which are relatively large players in one output. For example, Gijón and Ferrol-San Cibrao account for 18% and 9% of national solid bulk respectively, Castellón accounts for 5.5% of national liquid bulk, and Ceuta has an average national share of passenger traffic of almost 10%. These port authorities have very low traffic in the remaining outputs, however. As can be seen in the last column of the table, Cluster 1, which contains those port authorities with national shares greater than the average for at least two outputs over the sample period, comprises 11 members, with the remaining 15 assigned to Cluster 2.

Before proceeding with our results for the metafrontier analysis based on the groups we have selected, it should be noted that other criteria could have been used to group port authorities according to size and complexity.

Table 2. Average NATSHARE by port authority and assignment to groups

	Liquids (y_1)	Solid (y_2)	Containers (y_3)	General (y_4)	Passengers (y_5)	Cluster
A Coruña	**0.056**	**0.043**	0.000	0.015	0.003	1
Alicante	0.001	0.016	0.010	0.008	0.011	2
Avilés	0.005	0.031	0.000	0.028	0.000	2
Algeciras	**0.149**	0.026	**0.314**	**0.089**	**0.195**	1
Cádiz	0.002	0.021	0.010	0.032	0.013	2
Baleares	0.017	0.020	0.017	**0.127**	**0.191**	1
Barcelona	**0.073**	**0.050**	**0.160**	**0.130**	**0.104**	1
Bilbao	**0.121**	**0.057**	**0.054**	**0.075**	0.007	1
Cartagena	**0.115**	**0.044**	0.005	0.005	0.002	1
Castellón	**0.055**	0.028	0.009	0.009	0.000	2
Ceuta	0.012	0.001	0.001	0.017	**0.097**	2
Ferrol-San Cibrao	0.010	**0.095**	0.000	0.012	0.001	2
Gijón	0.009	**0.182**	0.002	0.012	0.001	2
Huelva	**0.099**	**0.065**	0.000	0.013	0.003	1
Las Palmas	0.032	0.012	**0.086**	**0.067**	**0.060**	1
Málaga	0.018	0.016	0.008	0.010	0.025	2
Marín-Pontevedra	0.000	0.010	0.003	0.012	0.001	2
Melilla	0.001	0.001	0.002	0.012	0.022	2
Pasajes	0.001	0.027	0.000	**0.040**	0.000	2
S.C. de Tenerife	**0.059**	0.013	**0.034**	**0.065**	**0.200**	1
Santander	0.003	**0.041**	0.001	0.026	0.015	2
Sevilla	0.002	0.029	0.008	0.019	0.000	2
Tarragona	**0.137**	**0.113**	0.008	0.017	0.000	1
Valencia	0.021	**0.049**	**0.250**	**0.127**	0.018	1
Vigo	0.001	0.006	0.018	0.030	0.028	2
Vilagarcía	0.002	0.005	0.000	0.004	0.000	2

One possible classification criterion could be dedication to container traffic, due to the highly specialized infrastructure it requires and the increasing capacity needed to service larger vessels.[9] In principle, this would appear to fit well with the objective of classifying port authorities according to size and, to a lesser extent perhaps, complexity. It turns out that our criterion captures the relevance of the port authorities in terms of container traffic as Cluster 1 includes all six port authorities with container traffic above the national average: Algeciras, Baleares, Barcelona, Bilbao, Las Palmas, Santa Cruz de Tenerife and Valencia. Moreover, these ports are by far the most important container ports, and accounted for an average of around 90% of Spanish container traffic over the sample period. Apart from this, there may be other interesting sources of heterogeneity apart from differences in technology such as, for example, differences that may exist between port authorities located on the Atlantic and Mediterranean seaboards due to their relation to different international maritime routes. While such a criterion may be relevant for identifying possible differences between ports in terms of their location, it clearly would not serve to classify ports according to differences in technology in terms of size and complexity, which is our objective.[10]

Tables 3 and 4 show the technological gap ratios and their components for both clusters. For the full sample period (1993-2016), we can see from Table 3 that the large and complex port group (Cluster 1) had a TGR of 0.965 whereas that for the remaining group had a TGR of 0.812. The conditions under which Cluster 1 port authorities operate therefore permit these ports to produce much more output from a given set of inputs: the maximum output that is feasible for Cluster 1 ports with their technology (and inputs) is about 97% of that which could be achieved using the metatechnology, whereas Cluster 2 ports can only produce a maximum of 81% of the output achievable with the metatechnology. Looking at the components of the TGR, it can be seen that Cluster 1 ports are more technically efficient with respect to the metafrontier, with average technical efficiency (TE) scores of 0.904 compared to 0.729 for Cluster 2, reflecting their technological advantage. Moreover, they are also more efficient with respect to their group frontier, with average TE scores of 0.935 compared to 0.894 for Cluster 2. Overall, these results

[9] Another interesting possibility, suggested by a referee, is the ratio of cargo to deposit surface area. However, we found that this criterion grouped small specialised port authorities together with large complex ones. When we divided the sample into two clusters based on the average size of the cargo/deposit area ratio, one of the groups included small ports such as, for example, Ceuta, Melilla and Málaga with large and complex ones such as Algeciras and Tenerife. Similarly, the other group included small specialised ports such as Pasajes and Avilés with the large, complex ports of Barcelona and Valencia.

[10] Indeed, the application of this criterion would lead to a classification where small Atlantic ports such as Pasajes and Aviles are grouped with the large, complex port of Bilbao, while the Mediterranean seaboard includes small ports such as Malaga and Melilla with large one such as Barcelona and Valencia.

imply that large and more complex ports have not only a technological advantage over other ports but that they are better able to exploit their technology in terms of productive efficiency.

Table 3. Technological gap ratios by group: 1993-2016

	TE^{*}	TE^{k}	TGR
Cluster1	0.904	0.935	0.965
Cluster2	0.729	0.894	0.812

To check how the TGR has evolved for the two clusters of ports over the 24-year sample period, we divide the sample into two sub-periods. A natural division would be to divide the sample into two subsamples of equal size, which would be achieved by dividing the overall sample into the 12-year sub-periods 1993-2004 and 2005-2016. However, instead of this division, we note that the 2007 was the beginning of the recent global economic crisis, which caused severe disruption to several sector, including port traffic. Hence, we divide the sample into 'pre-crisis' and 'crisis' periods, corresponding to 1993-2006 and 2007-2016 respectively.

Table 4 presents the TGR and its components for the periods 1993-2006 and 2007-2016. As can be seen, the TGR has increased for both groups from the first period to the second, although the increase for Cluster 2 is quite small. The technical efficiency scores with respect to both the metafrontier and the group frontiers also evolved positively for each group.

Table 4. Technological gap ratio by cluster: sub-periods 1993-2006 and 2002-2016

	1993-2006			2007-2016		
	TE^{*}	TE^{k}	TGR	TE^{*}	TE^{k}	TGR
Cluster1	0.888	0.931	0.951	0.926	0.941	0.984
Cluster2	0.716	0.885	0.811	0.748	0.906	0.814

The calculations for the individual port authorities for the full sample period and for the two sub-periods are presented in Table 5. For the overall sample period (1993-2016), the port authorities of Algeciras from Cluster 1 and Ceuta and Ferrol from Cluster 2 form part of the metafrontier, with TE indices with respect to the metafrontier equal to 1 for each sub-period. A number of ports are efficient with respect to their group-specific frontier: Algeciras, Baleares, Tenerife and Tarragona for Cluster 1, and Castellón, Ceuta, Ferrol and Melilla for Cluster 2.

Looking at the sub-periods, we can identify some port authorities which were not completely technically efficient with respect to their group frontier in the pre-crisis period that become completely efficient in the second period. These port authorities, which have learned to take full advantage of their group technological possibilities in the second period, are A Coruña, Cartagena and Valencia from Cluster 1, and Gijón and Pasajes from Cluster 2. On the whole, the port authorities from Cluster 1 were relatively more efficient in the period 1993-2006, and the port authorities in Cluster 2 made more notable progress in group-efficiency in the second period.

Finally, this table illustrates the importance of measuring each port authority's efficiency with respect to its group technological frontier as well as the metafrontier in order to get a truer picture of their productive efficiency performance. If this is not done, the port authorities' measured technical inefficiency would be exaggerated, greatly in some cases. Thus, in Cluster 1, A Coruña appears quite inefficient with respect to the metafrontier, with a TE score of 0.864 for the overall sample period, but turns out to be relatively highly efficient within its group with a TE score with respect to its group-specific frontier of almost 0.97. There are far more glaring cases in Cluster 2, with Alicante and Vigo scoring quite poorly in efficiency terms with respect to the metafrontier (with TE scores below 0.50) but having TE scores of over 0.90 with respect to their group frontier (as high as 0.97 in the case of Vigo). These port authorities are inefficient relative to port authorities operating with the metatechnology, but use their group technology quite efficiently.

Table 5. Technological gap ratio by port authority

	1993-2016			1993-2006			2007-2012		
	TE^*	TE^k	TGR	TE^*	TE^k	TGR	TE^*	TE^k	TGR
Cluster 1									
A Coruña	0.864	0.968	0.914	0.805	0.946	0.854	0.998	1.000	0.998
Algeciras	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Baleares	0.999	1.000	0.999	0.998	1.000	0.998	1.000	1.000	1.000
Barcelona	0.686	0.738	0.924	0.591	0.659	0.896	0.819	0.850	0.962
Bilbao	0.860	0.923	0.931	0.842	0.924	0.911	0.886	0.920	0.961
Cartagena	0.972	0.995	0.976	0.951	0.991	0.958	1.000	1.000	1.000
Huelva	0.984	0.997	0.987	0.981	1.000	0.981	0.989	0.994	0.995
Las Palmas	0.697	0.702	0.994	0.777	0.781	0.993	0.586	0.590	0.995
S.C. de Tenerife	0.996	1.000	0.996	0.993	1.000	0.993	1.000	1.000	1.000
Tarragona	0.924	1.000	0.924	0.933	1.000	0.933	0.911	1.000	0.911
Valencia	0.938	0.963	0.970	0.895	0.937	0.949	0.999	1.000	0.999
Cluster 2									
Alicante	0.493	0.938	0.541	0.355	0.972	0.377	0.686	0.890	0.771
Avilés	0.919	0.991	0.927	0.934	1.000	0.934	0.898	0.979	0.916
Cádiz	0.591	0.877	0.668	0.697	0.993	0.702	0.443	0.714	0.621
Castellón	0.966	1.000	0.966	0.996	1.000	0.996	0.924	1.000	0.925
Ceuta	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Ferrol-San Cibrao	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Gijón	0.812	0.839	0.958	0.683	0.725	0.933	0.992	1.000	0.992
Málaga	0.709	0.845	0.827	0.726	0.827	0.861	0.685	0.869	0.781
Marín-Pontevedra	0.699	0.909	0.777	0.641	0.878	0.749	0.780	0.953	0.817
Melilla	0.977	1.000	0.977	0.960	1.000	0.960	1.000	1.000	1.000
Pasajes	0.845	0.906	0.935	0.769	0.839	0.923	0.951	1.000	0.951
Santander	0.494	0.662	0.751	0.444	0.598	0.747	0.565	0.753	0.757
Sevilla	0.455	0.871	0.518	0.421	0.819	0.507	0.503	0.943	0.533
Vigo	0.498	0.973	0.512	0.574	0.998	0.575	0.392	0.937	0.423
Vilagarcía	0.483	0.594	0.823	0.543	0.619	0.901	0.398	0.559	0.716

The Malmquist Metafrontier Productivity Indices (MMPI) for each port authority, both for the full sample period and also for the two sub-periods (1993-2006 and 2007-2016) are presented in Table 6, where the MMPI is disaggregated into technical efficiency change (TEC) and technical change (TC). Looking at the average figures for each group, it is clear that the larger and complex port authorities in Cluster 1 outperform the other group in productivity terms over the sample period, reporting average annual productivity growth of 1.2% compared to a slight negative annual average productivity growth (-0.8%) for the group of smaller, less complex port authorities. Average annual productivity was positive for Cluster 1 and negative for Cluster 2 in the first period, while in the second (crisis) period it was negative for both clusters. In terms of the components of the MMPI, technical efficiency change was positive for the whole sample period for both groups. It was positive for both clusters in the first period and negative for both clusters in the second. Cluster 1 experienced positive average annual technical change for the whole sample period and for both sub-periods, whereas Cluster 2 had negative annual average technical change over the whole sample period and for both sub-periods.

Looking at individual port authorities, the effects of negative technical change attributable to the economic downturn in the second sub-period were particularly noticeable in Santa Cruz de Tenerife (Cluster 1) and Ceuta, Ferrol and Vilagarcía (Cluster 2). For example, Santa Cruz de Tenerife showed strong average annual productivity growth in the period 1993-2006 (3.3%) but its negative technical change in 2007-2016 had the effect that its average annual productivity for this period and for the full sample period was negative. A Coruña (Cluster 1) and Vilagarcía (Cluster 2) suffered similar effects, with positive annual average productivity growth on the period 1993-2006 turning negative in 2007-2016, with average productivity for the whole sample period also being negative as a consequence. Generally, port authorities performed worse in terms in productivity in the second sub-period although the results are quite different between the two groups. Thus, in Cluster 1, only one port authority, Algeciras, performed better in the second sub-period, while in Cluster 2 eight of the fifteen port authorities performed better. Finally, the best performing ports in terms of average annual productivity growth in Cluster 1 were Valencia (6.8%), Barcelona (6.3%) and Bilbao (3.1%), and in Cluster 2 were Santander (3.7%), Gijón (3.5%), Alicante (2.7%) and Sevilla (2.6%).

Table 6. MMPI, TEC and TC by port authority

	1993-2016			1993-2006			2007-2016		
	TEC*	TC*	MMPI	TEC*	TC*	MMPI	TEC*	TC*	MMPI
Cluster 1									
A Coruña	1.004	0.986	0.989	1.008	0.997	1.005	0.998	0.972	0.972
Algeciras	1.000	0.969	0.969	1.000	0.938	0.938	1.000	1.011	0.976
Baleares	1.001	1.001	1.003	1.002	1.013	1.015	1.000	0.987	1.000
Barcelona	1.023	1.039	1.063	1.068	1.042	1.113	0.967	1.035	1.035
Bilbao	1.005	1.026	1.031	1.034	1.035	1.070	0.968	1.015	1.003
Cartagena	1.000	1.000	1.000	1.000	1.007	1.007	1.000	0.992	0.986
Huelva	0.998	0.987	0.984	1.000	0.991	0.991	0.994	0.981	0.972
Las Palmas	0.996	1.020	1.016	1.049	1.024	1.075	0.931	1.014	0.946
S.C. de Tenerife	1.005	0.994	0.999	1.008	1.025	1.033	1.000	0.955	0.979
Tarragona	0.990	1.024	1.014	0.997	1.029	1.026	0.980	1.018	1.000
Valencia	1.030	1.038	1.068	1.054	1.041	1.097	0.999	1.034	1.035
Mean Cluster 1	***1.005***	***1.008***	***1.012***	***1.020***	***1.013***	***1.034***	***0.985***	***1.001***	***0.991***
Cluster 2									
Alicante	1.048	0.980	1.027	1.055	0.957	1.009	1.039	1.011	1.050
Avilés	0.991	0.990	0.981	1.000	0.983	0.983	0.980	0.999	0.985
Cádiz	0.978	0.982	0.960	0.997	0.984	0.981	0.953	0.980	0.950
Castellón	1.000	0.984	0.984	0.997	0.972	0.969	1.004	1.001	1.010
Ceuta	1.000	0.935	0.935	1.000	0.908	0.908	1.000	0.971	0.944
Ferrol-San Cibrao	1.000	0.960	0.960	1.000	0.951	0.951	1.000	0.972	0.946
Gijón	1.035	1.001	1.035	1.062	1.008	1.070	1.000	0.991	0.987
Málaga	0.968	0.945	0.915	1.000	0.907	0.907	0.929	0.997	0.952
Marín-Pontevedra	1.029	0.987	1.015	1.030	0.992	1.023	1.026	0.980	1.002
Melilla	1.000	1.007	1.007	1.000	0.989	0.989	1.000	1.030	1.060
Pasajes	1.030	0.994	1.024	1.056	1.002	1.058	0.998	0.985	0.992
Santander	1.023	1.014	1.037	1.014	1.013	1.028	1.035	1.014	1.042
Sevilla	1.022	1.004	1.026	1.096	0.999	1.094	0.933	1.011	0.968
Vigo	0.977	0.998	0.975	0.992	0.978	0.970	0.958	1.025	0.990
Vilagarcía	1.029	0.971	0.999	1.062	0.977	1.037	0.988	0.963	0.954
Mean Cluster 2	***1.009***	***0.983***	***0.992***	***1.024***	***0.975***	***0.998***	***0.990***	***0.995***	***0.989***

Tables 7 and 8 show the Group Malmquist Productivity Indices (GMPI) and the degree of catch-up for the full sample period and the two sub-periods respectively. For the full sample, we can see from Table 7 that average annual GMPI was higher for Cluster 2 (2.4%) than Cluster 1 (1.7%) and that this was due to greater relative improvements in technical efficiency with respect to the group frontier. With respect to their group frontiers, Valencia, Barcelona and Las Palmas have experienced large improvements in technical efficiency relative to the Cluster 1 frontier. For Cluster 2, Vilagarcía made huge improvements in efficiency followed by Marín-Pontevedra, Gijón, Pasajes, Sevilla and Santander, all of which made significant improvements. The frontier for Cluster 2 also moved relatively closer to the metafrontier over the sample period, showing larger positive average annual catch-up.

Looking at GMPI and catch-up by sub-period, in Table 8 we can see that the Cluster 1 port authorities group experienced strong productivity growth in terms of its own frontiers in the first period but negative average annual productivity growth in the second period. Cluster 2 port authorities, on the other hand, experienced increases in average annual productivity growth in both sub-periods. In the second period, the highest and lowest productivity scores were represented by Valencia and Tenerife respectively for Cluster 1, whereas for Cluster 2, Alicante and Santander performed particular strongly, with the latter's performance due mainly to large improvements in technical efficiency. With regard to catch-up, both clusters' frontiers moved closer to the metafrontier in the period 1993-2006, though catch-up was relatively larger for Cluster 2. In the second period, average catch-up was zero for Cluster 1, whereas the Cluster 2 group frontier moved closer to the metafrontier over the same period.

As a final empirical exercise, we try to identify variables that determine or drive productivity growth. To do so, we follow the strategy of Chang and Tovar (2017a), who analysed productivity in Chilean and Peruvian port terminals, and use the econometric method of dynamic GMM originally proposed by Arellano and Bond (1991) to identify terminal port productivity drivers. Chang and Tovar (2017a) included indexes of specialisation in container cargo and bulk cargo in their model, finding that a greater degree of containerisation was positively related to TFP growth and that greater specialisation in bulk cargo reduced TFP growth. They also included a public/private ownership variable in their model, but this is not relevant in our case as the Spanish port authorities all follow the landlord model.

Table 7. MMPI, GMPI and catch-up by port authority: 1993-2016

	TEC_k	TC_k	$GMPI^k$	$MMPI$	*Catch-up* $\left(\frac{GMPI^k}{MMPI}\right)$
Cluster 1					
A Coruña	1.004	0.987	0.990	0.989	1.001
Algeciras	1.000	0.975	0.975	0.969	1.006
Baleares	1.000	1.014	1.014	1.003	1.011
Barcelona	1.022	1.038	1.060	1.063	0.997
Bilbao	1.000	1.028	1.028	1.031	0.997
Cartagena	1.001	1.015	1.016	1.000	1.016
Huelva	0.998	1.000	0.998	0.984	1.014
Las Palmas	1.019	1.022	1.042	1.016	1.025
S.C. de Tenerife	1.000	1.002	1.002	0.999	1.003
Tarragona	1.000	1.005	1.005	1.014	0.992
Valencia	1.026	1.035	1.062	1.068	0.995
Mean Cluster 1	***1.006***	***1.011***	***1.017***	***1.012***	***1.005***
Cluster 2					
Alicante	1.017	1.073	1.091	1.027	1.063
Avilés	1.000	1.004	1.004	0.981	1.023
Cádiz	0.981	1.008	0.989	0.96	1.030
Castellón	1.000	0.996	0.996	0.984	1.012
Ceuta	1.000	0.941	0.941	0.935	1.007
Ferrol-San Cibrao	1.000	0.975	0.975	0.96	1.015
Gijón	1.042	1.016	1.059	1.035	1.023
Málaga	1.006	0.976	0.982	0.915	1.073
Marín-Pontevedra	1.047	1.011	1.059	1.015	1.043
Melilla	1.000	1.013	1.013	1.007	1.006
Pasajes	1.036	1.006	1.042	1.024	1.018
Santander	1.029	1.030	1.060	1.037	1.022
Sevilla	1.031	1.036	1.068	1.026	1.041
Vigo	0.998	1.032	1.030	0.975	1.056
Vilagarcía	1.092	0.966	1.055	0.999	1.056
Mean Cluster 2	***1.019***	***1.006***	***1.024***	***0.992***	***1.034***

Table 8. MMPI, GMPI and catch-up by port authority: 1993-2006 & 2007-2016

	1993-2006					2007-2016				
	TEC^k	TC^k	$GMPI$	$MMPI$	*Catch-up*	TEC^k	TC^k	$GMPI$	$MMPI$	*Catch-up*
Cluster 1										
A Coruña	1.006	0.999	1.006	1.005	1.001	1.000	0.970	0.970	0.972	0.998
Algeciras	1.000	0.945	0.945	0.938	1.008	1.000	1.013	1.013	0.976	1.038
Baleares	1.000	1.029	1.029	1.015	1.013	1.000	0.995	0.995	1.000	0.995
Barcelona	1.054	1.046	1.102	1.113	0.990	0.980	1.027	1.006	1.035	0.972
Bilbao	1.020	1.039	1.060	1.070	0.990	0.974	1.013	0.987	1.003	0.984
Cartagena	1.001	1.022	1.024	1.007	1.017	1.000	1.005	1.005	0.986	1.019
Huelva	1.000	1.023	1.023	0.991	1.033	0.995	0.969	0.965	0.972	0.993
Las Palmas	1.063	1.026	1.090	1.075	1.014	0.962	1.018	0.979	0.946	1.034
S.C. de Tenerife	1.000	1.034	1.034	1.033	1.001	1.000	0.961	0.961	0.979	0.982
Tarragona	1.000	1.013	1.013	1.026	0.988	1.000	0.995	0.995	1.000	0.995
Valencia	1.046	1.043	1.091	1.097	0.994	1.000	1.026	1.026	1.035	0.991
Mean Cluster 1	***1.017***	***1.020***	***1.038***	***1.034***	***1.004***	***0.992***	***0.999***	***0.991***	***0.991***	***1.000***
Cluster 2										
Alicante	0.980	1.083	1.062	1.009	1.053	1.064	1.060	1.129	1.050	1.075
Avilés	1.000	1.015	1.015	0.983	1.033	1.000	0.989	0.989	0.985	1.004
Cádiz	1.001	1.014	1.015	0.981	1.035	0.955	1.001	0.956	0.950	1.006
Castellón	1.000	0.974	0.974	0.969	1.005	1.000	1.025	1.025	1.010	1.014
Ceuta	1.000	0.913	0.913	0.908	1.005	1.000	0.978	0.978	0.944	1.036
Ferrol-San Cibrao	1.000	0.970	0.970	0.951	1.020	1.000	0.981	0.981	0.946	1.037
Gijón	1.074	1.024	1.100	1.070	1.028	1.000	1.007	1.007	0.987	1.020
Málaga	1.036	0.973	1.008	0.907	1.111	0.966	0.982	0.948	0.952	0.996
Marín-Pontevedra	1.064	1.011	1.076	1.023	1.052	1.025	1.010	1.036	1.002	1.034
Melilla	1.000	0.999	0.999	0.989	1.010	1.000	1.030	1.030	1.060	0.972
Pasajes	1.063	1.013	1.077	1.058	1.018	1.000	0.998	0.998	0.992	1.006
Santander	1.014	1.039	1.053	1.028	1.025	1.048	1.019	1.068	1.042	1.025
Sevilla	1.061	1.044	1.108	1.094	1.013	0.992	1.026	1.017	0.968	1.051
Vigo	0.998	1.052	1.050	0.970	1.083	0.997	1.007	1.004	0.990	1.014
Vilagarcía	1.120	0.954	1.068	1.037	1.030	1.056	0.982	1.037	0.954	1.087
Mean Cluster 2	***1.027***	***1.005***	***1.033***	***0.998***	***1.035***	***1.007***	***1.006***	***1.013***	***0.989***	***1.025***

In our model we wish to test whether size and specialisation influence productivity growth. In line with Chang and Tovar (2017a), we use control variables that capture the relative importance of different types of cargo for each port authority, and a one-period lag of productivity growth. In particular, we used the variable $RELSIZE_i$ to capture the size of the port authority and the specialization variables $RELSPECy_m$ for each cargo.

When using the whole sample, the model did not function well in that the validity of the instruments was rejected. As the period from 2007 was one of severe economic crisis and hence may be considered as not representative of port authority performance since the early 1990s, we estimated the model using the subsample 1993-2006 corresponding to the pre-crisis period and the model performed well, with the instruments proving valid and the hypothesis of zero autocorrelation of the first-differenced errors not rejected. As the years 2008-2011 were the most disruptive for port traffic, we re-estimated the model dropping these four years, and again the model performed well. This is our chosen model, and the results are presented in Table 9, where a time trend has also been included. As can be seen, TFP growth in this model is found to depend on previous values, as we would expect, with the lag being significant at the 10% level. The size of the port authority, which captures its complexity, is also found to positively influence productivity growth. Of the variables capturing the degree of specialization in each cargo, we find that port authorities that are relatively specialized in solid bulk, containerized cargo and general merchandise have higher productivity growth, whereas being specialised in liquid bulk has no effect on productivity. A conclusion of our results would appear to be that large port authorities have the best of both worlds as they can take advantage of both diversification and specialization insofar as the can handle large quantities of several types of traffic.

Table 9. Determinants of productivity growth –GMM estimation

Variables	Coefficient	Std. Error	*p*-value
$TFP_{i,t-1}$	-0.0869	0.0445	0.051
$RELSIZE$	15.5819	2.8956	0.000
$RELSPECy_{SOL}$	0.1708	0.0601	0.005
$RELSPECy_{LIQ}$	-0.1128	0.0937	0.229
$RELSPECy_{CONT}$	0.1154	0.0456	0.011
$RELSPECy_{GM}$	0.1310	0.0421	0.002
t	0.0017	0.0026	0.512
Constant	-0.9961	0.2778	0.000

Sargan test of overidentifying restrictions: $\chi^2(125) = 132.78$. Prob > χ^2 = 0.300
Arellano-Bond test for zero autocorrelation in first-differenced errors: Prob > z = 0.760

5. Conclusions

In this paper we have analysed the productive performance of Spanish port authorities over the period 1993-2016. This was carried out while recognising that differences in technology may exist among port authorities due to differences in infrastructures and complexity. These differences may in turn affect port authority productivity, and this is the issue we have addressed in our work.

To capture differences between technologies, we divided the 26 Spanish port authorities in our dataset into two groups based on a criterion of size and complexity. The group containing large and complex port authorities comprised 11 members, with the remaining 15 in the group of smaller and less complex port authorities.

Our results show that the group of large and complex port authorities had a considerable technological advantage, being closer to the metafrontier on average than the other group. Within their groups, the larger and more complex port authorities were also more technically efficient, thereby showing greater capacity to take advantage of their (superior) technology than the other group was of exploiting theirs. When looking at sub-periods, we find that both groups increased their technical efficiency in 2007-2016 compared to the pre-crisis period 1993-2006. The degree of catch-up (i.e., the extent to which the group frontier moves closer to the metafrontier) was higher for the less complex port authorities over the whole sample period and for each sub-period.

Total factor productivity was also higher for the group of large and complex port authorities, who had an average annual productivity growth of 1.2% over the whole period compared to an average annual reduction of -0.8% for the smaller and less complex entities. Average annual productivity growth for the large and complex port authorities was positive in the first sub-period and negative in the second, whereas it was negative in both sub-periods for the smaller and less complex port authorities.

We finished our analysis by investigating the extent to which the overall size of the port authorities and their specialisation in different cargoes may affect total productivity growth. We did this by using the total factor productivity growth estimates as the dependent variables in a GMM regression. We find that relative size, which can be interpreted as a measure of complexity of the port authority, has a strong positive influence on productivity growth. Specialisation in solids, container cargo and general bulk also increased productivity growth, but specialisation in liquids has no effect. We can conclude that large and complex port authorities, which are large enough to be specialized in several outputs, have a comparative advantage in that they are able to benefit from self-reinforcing scale and scope economies.

We conclude by drawing attention to some of the implications of our results for regulatory and policy purposes. Recall that one of the advantages of metafrontier analysis is that it allows evaluation of policies or programs aimed at either efficiency improvement within the firm or at the environment in which the firm operates. From a regulatory perspective, the importance of 'comparing like with like' is highlighted by our results: several port authorities, especially (though not exclusively) those in the group of smaller, less complex entities, appear highly inefficient if they are compared to the (overall) metafrontier but when they are compared with port authorities with the same technology they appear highly efficient. Notable examples here are Alicante, Cádiz and Vigo, while in the group of large and complex port authorities A Coruña stands out.

We find that the smaller, less complex port authorities have been catching up to the larger ones, especially in the second half of the sample period where they showed greater growth in technical efficiency and greater movement of their technology towards the metafrontier. While some of these smaller, less complex port authorities are relatively efficient in terms of their group, this group is relatively more inefficient on average with respect to its frontier compared to the larger port authorities. This suggests that they have plenty of scope for improving their productivity without making large investments to increase their size or complexity, i.e., efficiency gains are possible without 'adopting' another technology. While making investments to increase their size and complexity, thereby taking advantage of economies of scope and scale, would in principle permit them to increase their productivity, it would appear sensible to take advantage of their existing technological possibilities by increasing their efficiency before contemplating large and risky investments.

References

Arellano, M. and Bond, S., (1991). Some tests of specification for panel data Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, 58(2), 277–297.

Battese, G.E. and Rao, D.S.P., (2002). Technology Potential, Efficiency and a Stochastic Metafrontier Function, *International Journal of Business and Economics*, 1 (2), 1-7.

Battese, G, Rao, D.S.P. and O'Donnell C.J. (2004). A metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies. *Journal of Productivity Analysis*, 21, 91-103.

Caves, D.W., Christensen, L.R. and Diewert, W.E., (1982). The economic theory of index numbers and the measurement of input, output, and productivity. *Econometrica*, 50 (6), 1393-1414.

Chang, V. and Tovar, B. (2017a). Metafrontier analysis on productivity for West Coast of South Pacific terminals. *Transportation Research Part A: Policy and Practice*. 103, 118-134.

Chang, V. and Tovar, B. (2017b). Heterogeneity unobserved and efficiency: A latent class model for west coast of South Pacific terminals. *Journal of Transport Economic and Policy*, 51(2), 139-156.

Chen, K.-H. and Yang, H.-Y. (2011). A cross-country comparison of productivity growth using the generalised metafrontier Malmquist productivity index: With application to banking industries in Taiwan and China. *Journal of Productivity Analysis* 35, 197-212.

Cheon S., Dowall, D. and Song D-W. (2010). Evaluating impacts of institutional reforms on port efficiency changes: Ownership, corporate structure, and total factor productivity changes of world container ports. *Transportation Research Part E*, 46, 546–561

Cullinane, K.P.B., Song, D.-W., Ji, P. and Wang, T. (2004). An application of DEA windows analysis to container port production efficiency. *Review of Network Economics* 3(2), 184-206

Coelli, T. and Fleming, E. (2004). Diversification economies and specialisation efficiencies in a mixed food and coffee smallholder farming system in Papua New Guinea. *Agricultural Economics*, 31, 229-239.

De Langen, P. (2002). Clustering and Performance: the case of maritime clustering in The Netherlands. *Maritime Policy and Management*. 29, 209-221.

Ducruet, C., Van der Beek, D.J. and Koster, H.R.A. (2010). Commodity variety and seaport performance. *Regional Studies*, 44(9), 1221-1240.

Färe, R., Grosskopf, S., Norris, M. and Zhongyang, Z. (1994). Productivity growth, technical progress and efficiency change in industrialised countries. *American Economic Review*, 84(1), 66-83.

González-Laxe, F. (2012). La nueva gestión portuaria española. *Boletín Económico del ICE*, nº 3024.

González-Laxe, F. and Novo Corti, I. (2012). Spanish port competitiveness: Port system response to economic crisis. Working Paper. Universidad de A Coruña.

Huybrechts, M., Meersman, H., van de Voorde, E., Van Hooydonk, E., Verbeke, A. and Winkelmans, W. (2002). *Port competitiveness: an economic and legal analysis of the factor determining the competitiveness of seaports*. Editions De Boeck Ltd, Antwerp.

Medal-Bartual, A; Molinos-Senante, M. and Sala-Garrido, R. (2016). Productivity change of the Spanish port system: Impact of the economic crisis. *Maritime Policy & Management*, 43(6), 683-705.

Meyler, L., Moiseenko, S. and Volkogon, V. (2011). Diversification of the seaport activity as an effective post-crisis strategy. Paper presented at the European Conference on Shipping Intermodalism & Ports (ECONSHIP), Chios, Greece.

Nguyen, H.-O., Nguyen, H.-V., Chang, Y.-T. and Chin, A.T.H. and Tongzon, J. (2016). Measuring port efficiency using bootstrapped DEA: The case of Vietnamese ports. *Maritime Policy & Management*, 43(5), 644-659.

O'Donnell, C.J., D.S.P. Rao and Battese, G.E. (2005). Metafrontier frameworks for the study of firm-level efficiencies and technology gaps. Working paper, University of Queensland, Brisbane.

O'Donnell, J., Rao, D.S.P. and Battese, G.E. (2008). Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. *Empirical Economics*, 34 231–255.

Rao, D.S.P., O'Donnell C.J. and Battese G.E, (2004). Metafrontier functions for the study of inter-regional productivity differences. CEPA Working Paper, No.1/2003, School of Economics, University of Queensland, Brisbane.

Reina, R. and Villena, F. (2013). Concentration of goods traffic in Spanish ports during the period 2000-2009. *Regional and Sectoral Economic Studies*, 13, 59-72.

Schøyen, H. and Odeck. J. (2013). The technical efficiency of Norwegian container ports: A comparison to some Nordic and UK container ports using Data Envelopment Analysis (DEA). *Maritime Economics & Logistics*, 15(2), 197–221.

Simar, L., and Wilson, P., (2007). Estimation and inference in two-stage, semi-parametric models of production processes. *Journal of Econometrics.* 136, 131-164.

Tovar, B. and Wall, A. (2015). Can ports increase traffic while reducing inputs? Technical efficiency of Spanish port authorities using a directional distance function approach. *Transportation Research Part A*, 71, 128-144.

Tovar, B. and Wall, A. (2017a). Specialisation, diversification, size and technical efficiency in ports: an empirical analysis using frontier techniques. *European Journal of Transport & Infrastructure Research*, 17 (2), 279-303.

Tovar, B. and Wall, A. (2017b). Competition strategies in the Spanish port system in recent decades and their relation with port authority efficiency. In Pettit, S. and Beresford A. (eds) *Port Management: Cases in Port Geography, Operations and Policy*. Kogan Page Ltd. United Kingdom, 376-406.

Tovar, B. and Wall, A. (2017c). Dynamic cost efficiency in port infrastructure using a directional distance function: Accounting for the adjustment of quasi-fixed inputs over time. *Transportation Science*, 17(2), 296-303.

Zhengfei, G. and Oude Lansink, A., (2006). The source of productivity growth in Dutch agriculture: A perspective from finance. *American. Journal of. Agricultural Economics,* 88, 644-656.