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The external costs of port activity for port cities: An environmental efficiency analysis of Spanish ports

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Abstract

Port activity brings economic benefits to ports and port cities but also generates negative environmental externalities. These negative externalities derived from pollutants represent a social cost for port cities and coastal areas close to ports, and include costs derived from damages to urban buildings, damage to vegetation and damage to the health of the local population. This raises the question of whether ports may have scope to reduce external costs and thereby improve air quality in port cities and/or increase their existing level of service. To address this, we estimate the environmental efficiency of 37 Spanish ports observed in 2016 for which data on inputs, outputs and local external environmental costs are available. Using Data Envelopment Analysis, we estimate a hybrid model with non-separable good and bad outputs. Undesirable output is measured for the first time by local external costs of air pollution instead of tons of pollutants released, which better reflects the differential damages caused by the individual pollutants. Two definitions of undesirable outputs are used: total local external costs and local external costs per capita. In both versions of the model, we find evidence of high levels of environmental inefficiency in Spanish ports, with over half of the ports found to be inefficient. We rank efficient ports using a super-efficiency version of the model with external costs per capita and identify ports which appear to be references for best practice.

Keywords: Local external costs, port cities, environmental efficiency, Spanish ports, Data Envelopment Analysis, emissions from ships berthed

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1. Introduction

While the large increase in port traffic in recent decades has brought economic benefits by boosting economic and social development of ports–cities and coastal areas, it has also generated environmental concerns (Merico et al., 2019). Ports generate negative environmental externalities, with shipping activity and exhaust emission gases negatively affecting port-city air quality. These negative externalities represent a social cost for port cities and coastal areas close to ports, and include costs derived from damages to urban buildings, damage to vegetation and damage to the health of the local population. These environmental concerns are reflected in current regulation (e.g., MARPOL convention and EU Directives), which aims to reduce ship emissions by introducing minimum fuel quality standards and implementting new abatement technologies to reduce SOx, NOx and PM.

The relevance of the maritime transport sector on air pollutants emissions and its impact on air quality and human exposure in port-cities has been shown in a small but growing literature (Viana et al., 2014; Sorte et al., 2020). Merico et al (2019) underlined the importance of estimating the impact of harbour activities and the health effects on residents at local scale in port-cities or coastal areas where regulations are more stringent. They went on to evaluate the contribution of the Italian harbour of Bari to atmospheric gaseous and particulate pollutants. Other local-level studies include Contini et al. (2015), who estimated the contribution of tourist ship traffic to $PM_{2.5}$ concentrations in the urban area of Venice (Italy) and the efficiency of emission reduction strategies, and Merico et al (2017), who compared the impact of shipping on atmospheric pollution in four port-cities in the Adriatic/Ionian Sea: Brindisi (Italy), Venice (Italy), Rijeka (Croatia) and Patras (Greece). They highlight the importance of using comparable modelling strategies. This issue of comparability was also raised in the literature review carried out by Viana et al. (2014) on the contribution from the maritime transport sector to air quality degradation along European coastal areas. In their review they found substantial heterogeneity in measurement and modelling studies, particularly between those carried out for Northern and Southern Europe.

Sorte et al. (2020) provides a recent and comprehensive review of the literature measuring the contribution of harbour activities to air quality in port-cities. The studies they reviewed indicated that shipping and harbour activities are important contributors of atmospheric emissions and related concentrations of the main critical pollutants (PM_{10}, $PM_{2.5}$, NO_2 and SO_2). They also found that the studies they selected pointed to a large spatial variability of particulate matter and gaseous concentrations over distinct countries. On the positive side, they find that European mitigation strategies have proved their efficiency, leading for example, to decreases of SO_2 concentrations in several harbours.

The importance of identifying mitigation strategies that could be applied without hindering the economic competitiveness of the harbours involved was highlighted by Merico et al (2017). This raises the question of whether ports may have scope to reduce external costs and thereby improve air quality in port cities while maintaining their level of service. In particular, inefficient ports have the scope to maintain – or even increase - their level of service with lower external costs derived from pollutants. To address these issues, we estimate the environmental efficiency of 37 Spanish ports for which data on inputs, outputs and local external environmental costs are available for the year 2016. To do so, we use Data Envelopment Analysis techniques to estimate a hybrid model with non-separable good and bad outputs. This allows us to identity efficient ports and the inefficient ports for which they serve as a benchmark.

The emphasis in this paper is on local external costs, and as such this work is complementary to Tovar and Wall (2019), which estimated the environmental efficiency for Spanish Port Authorities using global external costs derived from CO_2 emissions. Our work makes several contributions. First, we use a new, previously-unavailable data set of local external costs where port air emissions from ships are converted to local external costs affecting the port city or immediate surrounding port area. We focus exclusively on emissions from ships while berthing, so we are ignoring emissions from land-based activities at the ports. However, ships emissions at ports accounts for the vast majority of port emissions (Habibi and Rehmatulla, 2009). To the best of our knowledge, ours is the first paper in port efficiency analysis to use local external costs instead of physical measures of pollution. This allows us to aggregate pollutants in a way that reflects their actual cost to society, as the damage levels are not the same across pollutants. Secondly, very few papers in the literature to date have focused on the relationship between port technical efficiency and the local effects of pollutants, and with the exception of Sun et al. (2017) and the present paper, all of these have focused exclusively on container ports. Thirdly, unlike previous frontier-based efficiency studies of the Spanish port sector, this is the first study as far as we are aware to use port data as opposed to Port Authority data for the analysis of technical efficiency. The use of port data as opposed to Port Authority data is crucial for this study as local external costs are calculated for individual ports due to the fact that their damage is felt in the immediate local area surrounding the port. As Port Authorities in Spain may manage several different ports in different locations (readers interested in the organization of the port system in Spain can consult Tovar and Wall, 2020), they are not an appropriate unit of analysis for a study of the relationship between technical efficiency and local external costs. Finally, from a methodological point of view, only one paper in the port environmental efficiency literature to date (Na et al., 2017) has used hybrid efficiency models to account for non-separability in good and bad outputs.

2. DEA and environmental efficiency in ports: a brief review of the literature

There is a small but growing literature that uses frontier techniques - and in particular, Data Envelopment Analysis (DEA) - to measure ports' environmental efficiency. In this section we summarize the main contributions to date (see Table 1).

Chin and Low (2010) used DEA to analyse the productivity of 13 major East Asian ports. These authors use an externality-augmented production frontier that incorporated unwanted emissions into the production efficiency of each port and explore how environmental considerations affect efficiency rankings. Haralambides and Gujar (2012) analyse a sample of 16 Indian dry ports, and propose a novel eco-DEA model that simultaneously evaluates both the undesirable and the desirable outputs of port service production, where undesirable outputs were CO2 emissions from container transport. Their analysis used an output-oriented DEA model. Total CO2 emissions were also used as the undesirable output in two studies on Korean ports by Shin and Jeong (2013), who used a directional distance function approach, and Chang (2013), who used slack-based DEA model. Chang (2013) found Korean ports to be economically inefficiency but environmentally efficient when considering the economic and environmental performance simultaneously.

Port cities have also been the focus of DEA-based efficiency analysis. Lee et al. (2014) investigated the environmental efficiency of port cities using DEA. They found that the most environmentally-efficient port cities were those that implemented early pro-active measures to deal with emissions. They argue that his justifies the need to develop green shipping and port operations measures in accordance with IMO regulations. Port cities' sustainable development was addressed by Chen and Lam

(2018) who presented a two-stage DEA model to analyse the efficiency of 20 top world container ports and their cities using an integrated approach where the port output (container throughput) is one of the city inputs, where the city in turn generates good output (GDP) and bad output (CO2 emissions).

Na et al. (2014) and He et al. (2015) used DEA to study environmental efficiency in Chinese ports using CO2 emissions as the bad output. Na et al. (2014) analysed eight Chinese container ports, finding them to have relatively low levels of environmental efficiency. He et al. (2015), on the other hand, analysed the productivity of container rail transport for 12 Chinese ports using a Malmquist productivity index approach. Cui (2017) adapted the three-stage RAM-Tobit-Ram (Range-Adjusted Measure) to incorporate bad outputs (CO2) in a study of environmental efficiency of 10 Chinese ports over the period 2003-2013. They find that environmental efficiency declined from 2006, attributing this to the emphasis placed by ports on profits at the expense of environmental concerns.

Studies of U.S. ports have also been carried out. Thus, Cheon et al. (2017) used DEA to analyse economic and environmental performance for the top 10 U.S. seaports. The undesirable output in this case was total water pollution discharges from pollution incidents and environmental efficiency is calculated under the condition that ports have to minimize these incidents. They find that positive economic performance can be achieved in conjunction with good environmental practices. Liu and Lim (2017) use a DEA environmentally-sensitive hyperbolic distance function to evaluate environmental efficiency the top 20 U.S. ports, where toxic air pollutants were used as undesirable outputs.

Na et al. (2017) use a non-radial non-oriented slack-based DEA model to analyse the environmental efficiency of 8 Chinese container ports over the period 2005-

2014, identifying the potential to reduce CO2 emissions. These authors find that excess CO2 emissions in the ports decreased after 2011, coinciding with an energy conservation and emission reduction plan implemented at that time. Sun et al. (2017) analysed the environmental efficiency of 17 Chinese port enterprises (14 coastal and 3 inland) observed in 2013 using a non-radial DEA directional distance frontier. Through a second-stage multiple regression, they find that environmental efficiency is affected by port assets, berth quantity and geographical location.

The paper by Tovar and Wall (2019) can be considered complementary to the present work. These authors used input and output data from 28 Spanish Port Authorities to measure environmental efficiency measured in global terms (i.e., greenhouse gas emissions, using CO2 equivalents). Dong et al (2019) who analyzed environmental efficiency for 10 major container ports along the Maritime Silk Road using inseparable data envelopment analysis (DEA) model with slack-based measures (SBMs). Lin et al (2019) analyze the efficiency of 16 major container Chinese ports for the year 2017 using an inverse data envelopment analysis (IDEA) model and calculate excess input resource use, comparing the results from their IDEA model to a SBM DEA model. The efficiency of 21 Coastal Chinese ports for the years 2008-2012 was analyzed by Li et al (2020), who used a DEA approach based on the closest targets. These authors also provide analyses of benchmarking information, noting that few studies in the literature provides such analyses despite the fact that it provides an important pathway for inefficient DMUs. The final study in our review is Castellano et al (2020), which used an output-oriented DEA model to study hthe environmental performance of 24 Italian Port Authorities using data from 2016. Thrse authors used composite indicators for environmentla quality and green port activies in their analysis.

INSERT TABLE 1 ABOUT HERE

From the review of the literature, it can be seen that the papers estimating environmental efficiency in terms of air quality to date have all used physical measures of pollution as opposed to external costs. Moreover, very few of the efficiency papers to date have focused on the local effects of pollutants, and with the exception of Sun et al. (2017) and the present paper, all of these have focused exclusively on container ports. Slack-based models have frequently used, but to date there is only one paper (Na et al., 2017) that has accounted for the possibility of non-separability of good and bad outputs by using a hybrid radial-non-radial approach. This is the methodological approach we will follow.

Of the papers reviewed, ours can be considered complementary to Tovar and Wall (2019) in the sense that both papers analyse environmental efficiency for the Spanish port system using cross-sectional data for the year 2016 where bad outputs are emissions from ships in ports. However, the present study differs in some important aspects from Tovar and Wall (2019). Most importantly, Tovar and Wall (2019) studied global environmental effects as their bad output was tons of CO2 whereas the present paper studies local environmental effects where several different types of polluting emissions have been aggregated (monetized) into local external costs. Undesirable output is measured for first time by local external cost of air pollution instead of the usual procedure to date of using tons of pollutants released. Individual pollutants differ widely in the damage they cause so aggregating them in physical terms does not accurately reflect the actual damage they cause, which is better captured by the use of local external costs.

The difference between global and local emissions also means that different units of analysis have to be used. Thus, Tovar and Wall (2019) was concerned with

CO2 emissions so data from Port Authorities, which include multiple ports in some cases, could be used as all that mattered was the total emissions from each Port Authority, not the contribution of each individual port. However, for a study of local effects of emissions it, the specific location of the emissions matters, so the use of port-specific data is necessary.

3. Materials and Methods

3.1. Data envelopment analysis model used to measure environmental efficiency

To measure environmental efficiency in ports, the characteristics of our data - which will be explained in detail in the next section - need to be considered. Two fundamental characteristics are the non-separability of good and bad outputs and the quasi-fixed nature of our inputs. As we wish to take slacks into account as part of inefficiency, we use a version of the so-called hybrid model proposed by Tone and Tsutsui (2006) which combines radial and non-radial inefficiency measures. The Tone and Tsutsui (2006) model has been used by Na et al. (2017) in the context of ports.

In its most general form, the model considers non-separability in both inputs and outputs and uses a non-oriented approach. For n firms, Tone and Tsutsui (2006) decompose the input and output data set matrices into their separable and non-separable components. The separable and non-separable input data set matrices are given by $X^S \in R^{m_1 \times n}$ and $X^{NS} \in R^{m_2 \times n}$, where m_1 is the number of separable inputs and m_2 is the number of non-separable inputs. The output data set matrix is decomposed into separable good outputs, separable bad outputs, non-separable good outputs and non-separable bad outputs, denoted by $Y^{SG} \in R^{s_1 \times n}$, $Y^{SB} \in R^{s_2 \times n}$, $Y^{NSG} \in R^{s_3 \times n}$ and $Y^{NSB} \in R^{s_4 \times n}$, where s_1 is the number of separable good outputs, s_2 is the number of separable bad outputs, s_3 is the number of non-separable outputs and s_4 is the number of non-separable good bad outputs.

The production possibility set is

$$P_{NS} = \{(x^S, x^{NS}, y^{SG}, y^{SB}, y^{NSB} | x^S \geq X^S\lambda, x^{NS} \geq X^{NS}\lambda, y^{SG} \leq Y^{SG}\lambda, y^{SB} \geq Y^{SB}\lambda, y^{NSG} \leq Y^{NSG}\lambda, y^{NSB} \geq Y^{NSB}\lambda\} \tag{1}$$

and the model is defined for the k^{th} firm as:

$$\min \ \rho_k = \frac{1 - \frac{1}{m}\left(\sum_{i=1}^{m_1} \frac{s_i^{S-}}{x_{ik}^S} + m_2(1-\alpha) + \sum_{i=1}^{m_2} \frac{s_i^{NS-}}{x_{ik}^{NS}}\right)}{1 + \frac{1}{s}\left(\sum_{r=1}^{s_1} \frac{s_r^{SG+}}{y_{rk}^{SG}} + \sum_{r=1}^{s_2} \frac{s_r^{SB+}}{y_{rk}^{SB}} + (s_3 + s_4)(1-\alpha) + \sum_{r=1}^{s_4} \frac{s_r^{NSB+}}{y_{rk}^{NSB}}\right)} \tag{2}$$

subject to

$$\begin{aligned}
&x_k^S = X^S\lambda + s^{S-}\\
&\alpha x_k^{NS} = X^{NS}\lambda + s^{NS-}\\
&y_k^{SG} = Y^{SG}\lambda - s^{SG+}\\
&y_k^{SB} = Y^{SB}\lambda \mp s^{SB+}\\
&\alpha y_k^{NSG} = Y^{NSG}\lambda - s^{NSG+}\\
&\alpha y_k^{NSB} = Y^{NSB}\lambda + s^{NSB+}\\
&s^{S-} \geq 0, s^{NS-} \geq 0, s^{SG+} \geq 0, s^{SB+} \geq 0, s^{NSG+} \geq 0, s^{NSB+} \geq 0\\
&\lambda \geq 0, 0 \leq \alpha \leq 1
\end{aligned} \tag{3}$$

In this hybrid model, the non-separable inputs and outputs are radial while the separable inputs and outputs are non-radial. Note also that the slacks of the non-separable bad outputs (s^{NSB+}) have the reverse sign to those of the non-separable good outputs (s^{NSG+}). A firm is efficient if and only if $\rho_k = 1$, with values less than 1 denoting inefficiency.

In our empirical section we will estimate an output-oriented version of this model where all inputs are considered separable and there are no non-separable bad outputs. In this model the new production possibilities set is:

$$P_{NS} = \{(x^S, y^{SG}, y^{NSB} | x^S \geq X^S\lambda, y^{SG} \leq Y^{SG}\lambda, y^{NSG} \leq Y^{NSG}\lambda, y^{NSB} \geq Y^{NSB}\lambda\} \tag{4}$$

and the model is defined for the k^{th} firm as:

$$\min \ \rho_k = \frac{1}{1 + \frac{1}{s}\left(\sum_{r=1}^{s_1} \frac{s_r^{SG+}}{y_{rk}^{SG}} + (s_3 + s_4)(1-\alpha) + \sum_{r=1}^{s_4} \frac{s_r^{NSB+}}{y_{rk}^{NSB}}\right)} \tag{5}$$

subject to

$$\begin{aligned}
&x_k^S = X^S\lambda + s^{S-} \\
&y_k^{SG} = Y^{SG}\lambda - s^{SG+} \\
&\alpha y_k^{NSG} = Y^{NSG}\lambda - s^{NSG+} \\
&\alpha y_k^{NSB} = Y^{NSB}\lambda + s^{NSB+} \\
&s^{S-} \geq 0, s^{SG+} \geq 0, s^{NSG+} \geq 0, s^{NSB+} \geq 0 \\
&\lambda \geq 0, 0 \leq \alpha \leq 1
\end{aligned} \tag{6}$$

To further discriminate between ports, we will also estimate a super-efficiency version of this model where the evaluated port ($port_k$) is eliminated from the reference set in the program. Ports that were fully efficient in the original model (5)-(6) may therefore have super-efficiency greater than 1. This allows discrimination between efficient ports, which is particularly useful with relatively small data sets.

3.2. Data

We have data on inputs, good outputs and a bad (undesirable) output for 37 Spanish ports for the year 2016. The data is provided by the Spanish Public State Ports Body

(EPPE) and the ports themselves.

The inputs include *Labour*, measured by the number of port workers; *Intermediate*, which is intermediate consumption and includes expenses on all productive factors aside from labour and capital; and *Quays*, which is quay length measured in metres and which can be considered a quasi-fixed asset capturing capital.

The bad output is *External Cost*, which represents the cost of emissions of NOx, SOx, and PM (PM_{10}, $PM_{2.5}$) from ships berthed at Spanish ports (Tovar, 2019). Most in-port emissions are generated while berthing (Styhre et al. 2017). The emission released by vessels while in hoteling or berthing mode in Spanish ports during 2016 has been calculated as part of an EU-funded research project. The methodology used to calculate these emissions is the fleet activity–based emission estimation ('bottom–up' approach). This uses more refined and disaggregated data than the alternative 'top-down' approach, and is based on technical characteristics. In particular, emissions are calculated using data type of vessel (which determines auxiliary engine power), the time the vessel was at berth and an emission factor). For details, see Tovar and Wall (2019).

The ExternE Impact Pathway Approach (bottom-up) methodology was adopted to calculate the external costs derived from emissions (see Tichavska and Tovar, 2017, for a review of methodologies). This approach traces a chain of causal relations that begins with pollutant emissions. Once an inventory of the emissions has been carried out, their dispersion in the atmosphere is modelled in order to estimate the impact of the emissions on air quality, with calculations made of the concentration of each pollutant in the area affected. The health effects of air pollutants are measured using exposure-response functions grounded in epidemiological studies. The final step is to monetize the impacts. In the case of health impacts, this involves placing a value on the adverse effects derived from medical treatment; losses of wages and productivity; and damages arising from mortality and morbidity, where the latter are valued using contingent valuation methods. This process permits a detailed estimation of the external costs per pollutant.

While a full bottom-up approach based on the Impact Pathway Approach would be the ideal, this would be hugely costly and require extensive local data. We therefore follow an accepted approach in the literature in environmental efficiency studies where external costs of shipping emissions are calculated using emissions conversion factors (ECFs) from major European reports in a top-down fashion (see, e.g., Nunes et al, 2019 and the literature referred to therein).

In the literature to date, cost conversion factors from the BeTa, CAFÉ, NEEDS and HEATCO projects have been used (Nunes et al., 2019). However, BeTa is the only report that makes specific reference to damage from shipping-related air pollution in seaports. An alternative approach is to complement the BeTa urban conversions factors with rural factors derived from the CAFÉ project under different specifications. However, as Tichavska and Tovar (2015) illustrate, external costs under BeTa are very similar to the average of the (four) external external costs calculated using BeTa urban factors complemented with each of the four rural specifications from CAFÉ. As such, we believe that our procedure, which is the same as that followed in a complementary paper to this (Tovar and Wall, 2019) is appropriate.

INSERT FIGURE 1 ABOUT HERE

Figure 1 shows the ranges of external costs derived from NOx, SOx, and PM for the port included in our study[1]. On the one extreme, 9 of the 37 ports in our study have

[1] For details, see Spengler and Tovar (2021). Note that in the figure there are more than 37 ports. Due to zero values for some variables, which caused problems to implement our empirical model,

local external costs of less than €1million. At the other extreme, the large ports of Algeciras, Barcelona Bilbao and Valencia all have external costs over €20 million, with Barcelona standing out with external costs of over €70 million.

In our empirical section we will present the results from two different models, one using total local external costs and another using the local external costs per capita. Descriptive statistics for both variables are presented in Table 2.

INSERT TABLE 2 ABOUT HERE

The good outputs we use are *Ships*, *Cargo Traffic* and *Passenger Traffic*. Passenger traffic is measured in number of passengers. Cargo traffic is divided into two outputs, namely *Container Cargo* (general containerized merchandise) and *Non-Container Cargo*, where the latter is the sum of liquid bulk, solid bulk and general non-containerized merchandise. Both cargo traffic outputs are expressed in tons. Finally, *Ships* is the aggregate weight of ships in gross tonnage (GT) that berthed at the port during the year and which acts as a proxy for the size of ships. An alternative would be to aggregate by number of ships. However, as ship size heavily influences emissions (Tichavska and Tovar, 2015b), we opt for aggregating by size, which we measure by weight.

As emissions – and thereby local external costs - are generated by ships, we assume that the desirable output *Ships* and the undesirable output are non-separable. All other good outputs and the inputs are considered separable.

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we had to eliminate six of these ports, reducing the sample to 37. The ports eliminated were all very small ports which lacked certain types of traffic.

4. Results and discussion

4.1. Results

The results from the hybrid model with ships and local external cost as non-separable good and bad outputs are summarised in Table 3, with the scores for each individual port presented in Table 4.

The results from two different models are presented. Model 1 uses total local external costs, whereas Model 2 uses local external costs per capita.

INSERT TABLE 3 ABOUT HERE

We begin with the results for Model 1, which uses total local external costs as the undesirable output, and from Table 3 we see that of the 37 ports, only 12 were efficient. The three very large ports of Barcelona, Algeciras and Valencia were all efficient, as were several of the very small ports such as La Savina, Puerto del Rosario and Los Cristianos. The relatively large ports of Bilbao, Santa Cruz de Tenerife, Las Palmas and Palma were found to be inefficient but other ports with important volumes of traffic such as Gijón and Huelva were efficient. Thus, the efficient ports are represented by a mix of ports covering all size ranges.

With regard to the inefficient ports, Bilbao stands apart from the rest, having by far the highest score (0.783), and the only score greater than 0.500. The remaing ports all have values below 0.500 and can be considered highly inefficient. However, among these, three different groupings can be made. The first comprises the ports of Santa Cruz de Tenerife (0.485) and Alicante (0.464). There is then something of a gap to the next group, comprising five ports – Santa Cruz de La Palma, Melilla, Las Palmas, Bahía de Cádiz and Málaga - with scores ranging from 0.266-0.377. The remaining 17 ports all have scores below 0.173, and can be classified as extremely inefficient. Indeed, the average of the scores for the inefficient ports is 0.177, and these 17 are the ones that have lower scores than this average.

INSERT TABLE 4 ABOUT HERE

In Model 1, care needs to be taken when comparing efficiency scores as part of the bad output is not controllable by the port. The reason is that the bad output in this model, namely the local external costs from all pollutants, partly depends on the size of the local population: in particular, the costs of SO_2 and PM all depend on population. This may penalise ports that are located in larger port cities: two ports with similar levels of good output and which emit the same levels of air pollutants will generate different levels of local external costs if their populations are different, with higher levels of external costs for the port with the larger surrounding population. In these circumstances, to make meaningful comparisons we should compare ports with similar local populations. For example, the ports of Pasajes, Los Cristianos and Alcudia all have populations in the range of 16,200-19,300 inhabitants. Whereas Los Cristianos is efficient, the other two are highly inefficient. Similarly, a meaningful comparison can be made between the two Atlantic ports of Gijón (pop. 273,000) and Vigo (pop. 293,000). It can be seen that Gijón is efficient whereas Vigo is highly inefficient with a score of 0.12.

To control for the issue of population, we estimate a second hybrid model (Model 2) where we use the local external costs per capita. The summary statistics in Table 3 show that the average efficiency score was higher for this model, with 17 efficient ports compared with 12 for Model 1. Among the inefficient ports in this model, three ports have higher values than 0.500: Alicante (0.6785), Las Palmas (0.6511) and

Santa Cruz de Tenerife (0.6125). These are followed by a group of five ports with scores ranging from 0.206-0.319, namely Málaga, Bahía de Cádiz, Melilla, Santa Cruz de La Palma and Vigo. The remaining 12 ports all have values below 0.150 and can be classified as extremely inefficient. It should be noted that the average of the scores for the inefficient ports for this model is 0.195, and the latter group contains all ports with scores below this value.

In Table 4, it can be seen that all the ports that were efficient in Model 1 are also efficient in Model 2. The change in definition of the bad output to control for population has therefore not penalized the ports that were efficient when population was not accounted for, and the increase in the number of efficient ports in Model 2 corresponds to ports that were inefficient in Model 1. On the other hand, focusing on the external costs per capita has clearly benefitted some ports with relatively large local populations. This is particularly noteworthy in the cases of Bilbao, Palma and A Coruña, which are all ports with relatively large local populations that go from inefficient in Model 1 to efficient in Model 2. Similarly, the three insular ports were ranked in terms of efficiency scores in Model 1 as follows: Tenerife (pop. 203,585), Las Palmas (pop. 378,998) and Palma (pop. 402,949), in that order. In Model 2, this order is reversed to Palma, Las Palmas and Tenerife, which is in line with their populations.

In Model 2, almost half of the ports (17 out of 37) have efficiency scores of 1. In order to distinguish among these ports, we re-estimate a super-efficiency version of the model which permits the scores to be greater than 1 and therefore allows them to be ranked. The results are presented in the final column of Table 4. The top-ranked ports are Puerto del Rosario, Barcelona and Los Cristianos, whereas the lowest –ranked are Bilbao, A Coruña and SS de la Gomera.

One of the advantages of the DEA methodology is that it permits easy identification of the so-caller ‘peers’, or efficient ports which serve as benchmarks. These efficient ports act as benchmarks in the sense that they serve to identify, in conjunction with other ports, the section of the production frontier where an inefficient port would be projected. It should be highlighted that not all efficient ports necessarily act as benchmarks, as the size or output mix may be such that a port could be efficient because there are no other ports with which it can usefully be compared. Table 5 below efficient ports in Model 2 ranked by their super-efficiency scores, which are reported in the second column. The final column shows the number of times these efficient ports served as benchmarks in Model 2.

INSERT TABLE 5 ABOUT HERE

As can be seen, 11 of the 17 efficient ports served as benchmarks for other ports. The other six efficient ports which do not serve as benchmarks are therefore found to be efficient because they were either exceptionally strong performers or had an atypical input-output mix. To clarify this, looking at the super-efficiency scores in Table 5 it can be seen that these six ports are among the worst performers, which implies that they are efficient because of their input-output mix rather than them being strong performers.

The ports that most often served as benchmarks were Valencia, Puerto del Rosario, Los Cristianos and La Savina. The very large ports of Algeciras, Barcelona and Valencia all served as benchmarks for multiple ports, as do the middle-sized ports of Gijón, Huelva, Castellón and Cartagena. Ports aiming at improving their environmental efficiency should pay special attention to the characteristics and practices of these ports, as well as the small ports of Puerto del Rosario, Los Cristianos and La Savina, to see what lesson can be learned from them.

As an example of an interesting comparison that can be made on the basis of our results, we can take the cases of Las Palmas and Palma. These share several features in common which make them attractive candidates for comparison. Both are insular ports, located in cities that are the capitals of their provinces and that have very similar populations, and which have substantial passenger as well as cargo traffic. Table 6 below summarises their situation.

INSERT TABLE 6 ABOUT HERE

The fact that their populations are so similar means that their ratio of total external costs is very close to their ratio of external costs per capita. Their composition of outputs differs substantially is important respects, where it can be seen that Las Palmas, a regional hub with important port container transhipment traffic (Tovar el al, 2015), has 13 times more container traffic than Palma, even though their non-container traffics are quite similar in volume. Both ports are inefficient in Model 1, with Las Palmas being more efficient. The situation changes in Model 2, where both ports improve their efficiency score when considering per capita local external costs. Las Palmas remains inefficient but Palma now appears as efficient. From Table 5, however, we have seen that Palma does not serve as a benchmark for any other ports, implying that the change of definition of bad output means that Palma has become efficient because of its specific input-output mix. This is partly a consequence of the relatively small number of observations in our dataset.

The comparison between these ports highlights that care must be taken when defining the variables used (in this case, the bad output) as this may substantially alter efficiency scores. While in many cases there were no substantial changes in the efficiency scores from Model 1 to Model 2, in some cases there were ports that were highly inefficient in Model 1 which become efficient in Model 2. The port of Palma is a prime example of this, but the same occurs in the cases of A Coruña, Ibiza and SS de la Gomera. Checking the super-efficiency scores shows that these ports become efficient because the change in the definition of the bad output leads to them having an atypical input-output mix. Defining our bad output to control for local population addresses the penalization suffered by ports such as Las Palmas (and Bilbao) that have relatively large local populations, whose efficiency scores improve. However, a collateral effect of this is that some inefficient ports have become efficient by default, and these cases should be identified. Super-efficiency scores help in this respect, permitting discrimination between efficient ports.

4.2. Discussion

The results of the models of environmental efficiency that we have presented show that more than half of the Spanish ports in our sample are environmentally inefficient, with high levels of inefficiency in several ports. With the aim of reducing the negative local environmental impact of port activity, incentives for the introduction of technical solutions, such on-shore power supply (OPS), and market-based solutions such as environmentally-differentiated port dues, have been promoted in recent years in Spain. In spite of these measures, however, our results indicate plenty of scope for reductions in local external costs through improvements in efficiency.

There are various ways to achieve reductions in the local external costs of emissions. Generally, when it comes to reducing emissions in port, a distinction can be made between technical measures (such as alternative fuels and OPS) and operational and logistic measures. Time at berth can be reduced by more efficient port operations and administrative procedures, all of which increase energy efficiency and reduce emissions and costs.. Ports must strive to ensure that ships spend the minimum time possible at berth, as this is a determining factor in emissions of gases with negative local effects. When this is not an option, as in the case of cruise passenger traffic, greater reliance must be placed on technical solutions such as OPS, exhaust scrubber technology or low sulphur fuels. This is the strategy followed by, for example the Port of Seattle, in collaboration with regional government and the cruise industry (see https://www.portseattle.org/page/cruise-accomplishments-sustainability). A case can also be made to facilitate service to larger ships, as there are economies of scale in ship emissions (Cullinane and Cullinane, 2019). The flip-side of this argument, however, is that economies of scale at sea through larger ships increases the demand for energy at ports, increasing pressure on OPS systems.

The high level of inefficiency we have found in Spanish ports points to weaknesses in existing policies aimed at environmental sustainability. In particular, the incentives provided by environmentally-differentiated port dues for complying with environmental requirements suffer the drawback that these dues represent a small proportion of shipping costs. The recognition that market forces alone will not solve environmental problems and that more stringent regulatory invention may have a role has been made by Cullinane and Cullinane (2019), and the widespread environmental inefficiency we have found in our study supports this. It would appear that there is a role for more ‘stick’ given the apparent lack of success of ‘carrot’ incentives, with a move towards the compliance of the ‘polluter pays’ principle. Successful regulatory intervention will require cooperation and coordination between the IMO and regional powers to avoid shipping companies diverting to ports where less stringent environmental regulations are in place-needed. The success of any incentive scheme or regulatory initiative will ultimately depend on technical, operational, organizational and market conditions. Carefully-considered combinations of technical measures and measures to increase efficiency in port operations and wide-ranging enforceable regulation so as to avoid opportunistic behaviour have an important role to play. For example, OPS (or 'cold-ironing') will reduce the problem of emissions with local effects, but ports may not adopt this technology if there is no legal or regulatory requirement to do so. Even if OPS is adopted, reductions in inefficiency are still of crucial importance in order to keep the energy supplied by OPS to its minimum efficient level. Reductions in emissions with local effects will primarily benefit the port city and local area surrounding the port but if inefficiency exists, more energy than would be strictly necessary will be used, generating an excess of emissions with no improvement in the environmental sustainability of port activity from a holistic perspective.

5. Conclusions

Using a DEA approach, we estimate environmental efficiency for 37 Spanish ports for the year 2016 with a hybrid model comprising radial and non-radial efficiency measures. Whereas previous papers have used physical measures of air pollutant, in this paper the undesirable output is measured by the local external costs associated with vessel emissions of pollutants, which is assumed to be non-separable from the number of vessels serviced in the port, one of our good (desirable) outputs. A benefit of using external costs is that air pollutants can be aggregated into a single variable in a meaningful way, which is of particular interest when available datasets are relatively small, which is often the case.

We estimate versions of the model using total local external costs and local external costs per capita. In both cases we find substantial inefficiency, with over the half of the ports being inefficient. As total external costs depend in part on the size of the local population, which is outside the control of the ports, the use of this variable will tend to penalize ports located in areas with large local populations. The use of per capita local external cost controls for this population effect and the number of efficient ports increases substantially when bad outputs are defined with this variable. Estimation of a super-efficiency version of this model permits us to discriminate between efficient ports and therefore rank them in term of efficiency performance. Combining this with an analysis of the frequency with which an efficient port serves as a benchmark for inefficient ports, we find that several of the ports that become efficient when using the per capita local costs did so by default, in the sense that their particular input-output mix precluded comparison with other ports. On the other hand, by comparing the super-efficiency rankings with the number of times each port serves as a benchmark for other ports, we are able to identify a set of ports that appear to be best-practice references for the inefficient ports in our sample.

Overall, our study, which is the first as far as we are to use local external costs as a means of aggregating polluting emission from ships in ports, highlights the environmental inefficiency of several Spanish ports. Our results show that over half the ports in our sample have scope to improve their environmental efficiency. This points to the importance of complementing technical solutions and price-incentive schemes with measures to improve the efficiency of port operations as a means to reduce local external costs. Incentives for OPS and environmentally-differentiated port dues have been promoted in recent years in Spain, and it would be interesting to see how successful these initiatives have been in increasing the environmental efficiency of the ports over time. This will be possible to analyse when new data for external costs appear, permitting the use of panel data analysis, and will the subject of future research.

By identifying inefficient ports, our study provides indications as to which ports the authorities should first direct their attention. Given their levels of emissions, these ports have considerable scope to expand their production or, equivalently, produce the same with much lower emissions levels. Other ports may be emitting more pollutants, but if they are identified as efficient, their level of economic activity provides greater justification for their levels of emissions.

We conclude by highlighting some limitations of our study. A weakness of our study is that we have a relatively small sample size observed in one year only. As new data appear for local external costs, the use of panel data techniques will permit us to track the evolution of environmental efficiency over time and permit a comparative analysis of the effectiveness of environmental measures implemented in different ports. Another option would be to try to obtain similar data for other ports in Europe for the same year. In either case, the increase in the number of observations will also help reduce the number of ports that appear efficient due to their input-output mix, thereby permitting better identification of best-practice ports. Another limitation of the paper is that only ship emissions during hotelling are considered. While this is the largest source of in-port emissions by ships, studies have reported that emissions from manoeuvring have a non-negligible impact on local air quality (e.g., Merico et al., 2016). As such, our measure of local external costs will underestimate the real impact on the local population. Incorporating emissions from manoeuvring would permit us to assess whether these emissions affect the efficiency ranking of the ports in our sample. Similarly, the small sample size given we have only one year's data precludes from including additional variables containing information on the fleets arriving at each port. The characteristics of the ships attended to by the ports (size, type, age, etc) is a major factor in determining pollution levels and hence external costs, and in the future we hope to be able to extend our sample over time in order to be able to incorporate these additional variables. It would also be interesting to collect data on land-based port activities to obtain a more complete picture of emissions associated with all aspects of port activity.

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Table 1. DEA literature to date on environmental efficiency in ports

Author (year)	Data	Methodology	Input and desirable outputs variables	Undesirable output
Chin & Low (2010)	156 Origin–Destination pairs between 13 major East Asian ports. Year: 2009	SBM-DEA model	**Inputs**: -Frequency of shipping services -Bilateral trade flows **Outputs**: -Annual container capacity flows	- NOx, SO2, CO2 and particulate matter emissions during transportation between origin and destination.
Haralambides & Gujar (2012)	16 dry ports in India. Years: 2006-2008	-Eco-DEA	**Inputs:** -Container (n) -Equipment (n) -Labor (n) -Terminal area (m^2) **Outputs:** -Throughput (TEU)	- CO2 emissions during transportation of containers to and from the dry ports.
Chang (2013)	23 ports in Korea Year: 2010	-SBM-DEA model. -Consider undesirable both in the objective and in the constraint functions.	**Inputs:** -Labor (n) -Quay (m) -Terminal area (m^2) -Energy consumed (TOE) **Outputs:**	- CO2 emissions of port including emissions at landside and seaside.
Shin & Jeong (2013)	8 container terminals at Busan port (5) and Kwangyang port (3). Years: 2007-	-DEA DDF model -Luenberger productivity index.	**Inputs:** -Quay (m) -Container crane (n) -Container yard (m^2) **Outputs:** -Throughput (TEU)	- CO2 emissions of container terminal
Lee, Yeo & Thai (2014)	27 world's top port cities. Year: 2011	-SBM-DEA model	**Inputs:** -Labor population (n) **Outputs:** -GRDP (US $) -Throughput (TEU)	-NOx, SO2, and CO2 in port emissions (seaside).
Na, Ji & Choi (2014)	8 container ports in China Years: 2005–2011.	-Non-radial, non-oriented SBM-DEA model	**Inputs:** -Berth (m) -Port area (m^2) -Gantry cranes (n) -Yard cranes (n) **Outputs:** -Throughput (TEU)	- CO2 emissions including emissions at landside and seaside.
He, Liao & Huang (2015)	12 ports in China Years: 2009–2014.	-DEA Malmquist productivity index -Ray and Desli decomposition	**Inputs:** -Infrastructure investment -Energy consumption. **Outputs:** -Logistics volume -Foreign trade volume	- CO2 emissions per unit of goods accumulated

Author (year)	Data	Methodology	Input and desirable outputs variables	Undesirable output
Cheon, Maltz & Dooley (2017)	The top 10 U.S. ports Year: 2004.	-Bootstrap DEA undesirable good DEA	**Inputs:** -Berth (m) -Crane ton. **Outputs:** Througput (TEU)	-Total Number of pollution incidents -Total water pollution volumes
Cui (2017)	10 Chinese ports Year: 2004-2013	-Three-stage DEA model: RAM-Tobit-RAM -Strong disposability is assumed for undesirable outputs	**Inputs** -Labor (n) -Annual cash investment -Berth (n) **Outputs** -Throughput (TEU) -Cargo (Tons) -Main business income	-CO_2 emissions of port (landside)
Liu & Lim (2017)	The top 20 U.S. container ports Year: 2005.	-A DEA hyperbolic distance function -A DEA environmentally sensitive hyperbolic oriented efficiency with pollution as inputs	**Inputs:** -Berth (feet) -Crane (n). **Outputs:** Throughput (TEU)	-SOx and PM2.5 air emissions derived from container ships*
Na, Choi, Ji & Zhang (2017)	8 container ports in China Years: 2005–2014.	-Non-radial, non-oriented, inseparable input–output SBM-DEA model	**Inputs:** Inseparable: -Gantry cranes (n) -Yard cranes (n) Separable: -Berth length (m) -Port area (m^2), **Outputs:** Separable: -Throughput (TEU)	- CO_2 emissions including emissions at landside and seaside
Sun, Yuan, Yang, Ji & Wu (2017)	17 Chinese port enterprises: (4 coastal and 3 inland) Year: 2013	-Non-radial DEA DDF-VRS preference model. -Regression model	**Inputs:** -Staff (n) -Fixed assets (RMB) **Outputs:** -Operating cost (RMB) -Net profit (RMB) -Throughput (Tons)	NOx air emissions of port enterprise
Chen & Lam (2018)	20 world container port-cities Year: 2013	-Two-stage SBM-DEA model estimating efficiency for ports and cities	**Inputs** - Ports: -Terminal area (h) -Berth (m) -Quay cranes (n) - Cities: Land area (h) Energy consumption (TOE) -Labor (n), -Throughput (TEU).	Cities: CO_2 emissions

Author (year)	Data	Methodology	Input and desirable outputs variables	Undesirable output
			Outputs - Ports: Throughput (TEU) - Cities: GDP ($)	
Tovar & Wall (2019)	28 Spanish Port Authorities Year = 2016	- Radial DEA DDF - Two main types of DDF: (i) simultaneously expanding good and reducing bad output (ii) only reducing bad output	**Inputs:** -Labor (n) -Intermediate expenditure (€) -capital assets (€) **Outputs:** -Ships (GT) -Cargo (Ton) -Passenger traffic (n)	The external global cost derived from the emissions (CO_2) from ships at berth
Dong, Zhu, Li, Wang & Gajpal (2019)	10 container ports worldwide Year = NA	Inseparable SBM-DEA model	**Inputs:** -Quay cranes (n) -Berth length (m) **Outputs:** -Throughput (TEU)	CO_2 emission of each container port
Lin, Yan, & Wang (2019)	16 Chinese container ports Year = 2017	Inverse data envelopment analysis (IDEA) model	**Inputs:** -Berths (n) -Equipment (n) -Employee (m) -Cost (Millions RMB) **Outputs:** -Throughput (Millions Tons) -Profit (Millions RMB)	CO_2 and NOx emission of each container port
Castellano, Ferretti, Musella, & Risitano (2020)	24 Italian Port Authorities Year = 2016	Output-oriented DEA model	**Inputs:** -Investments (€) -Terminal area (m^2) -Employees (n) - A composite indicator GPE **Outputs:** -Solid bulk (Ton) -Liquid bulk (Ton) -Containers (TEU)	A composite indicator (EQI) built from the emissions of: PM_{10}, NH_3, NO_2, C_6H_6, SO_2

Author (year)	Data	Methodology	Input and desirable outputs variables	Undesirable output
Li, Li, Zhao & Zhu (2020)	21 coastal ports in China Year: 2008–2012.	A DEA approach based on the closest targets	**Inputs:** -Length of productive quay -Number of productive berths **Outputs:** - Cargo throughput	NOx, Sox air emissions from ships while in the port
Present Study	28 Spanish Port Authorities Year = 2016	-Non-radial, non-oriented, inseparable input–output SBM-DEA model	**Inputs:** -Labor (n) -Intermediate expenditure (€) -Quays (m) **Outputs:** -Ships (GT) -Non-Container cargo (Ton) -Container cargo (Ton) -Passenger traffic (n)	-Local external cost -Local external cost per capita Both derived from the emissions (NOx, SOx, and PM (PM_{10}, $PM_{2.5}$) from ships at berth

* In this case the pollutants have been treated as inputs

Note: SBM = Slacks-based measure model; DEA =Data Envelopment Analysis; NCR = North Central Region; n = number; m2 = squared meter; m = meter; TEU = Twenty equivalent unit; TOE = Ton oil equivalent; GRDP = Gross regional domestic product; PTEE = Pure technical environmental efficiency, EP = Port economic performance, ENP = Port environmental performance, MPR = Maximum pollution reduction, VRS = variable returns to scale, DDF = Directional Distance Function, RAM = Range Adjusted Measure; h = Hectare; NA = Not available; GT = Gross Tone: Environmental Quality Index (EQI) and Green Port Efforts (GPE),

Table 2. Descriptive statistics

Variable	Units	Mean	Min.	Max.	Std. Dev.
Output (Good)					
Ships	GT	56,149,817	345,073	400,999,443	91,148,707
Cargo Traffic: Container	Tons	4,516,726	2	60,178,589	13,223,474
Cargo Traffic: Non-container		8,597,283	56,019	36,680,576	10,606,522
Passenger Traffic	Number	845,471	595	4,220,710	1,104,703
Output (Bad)					
Local external cost	€	7,964,160	20,567	71,479,006	13,957,080
Local external cost per capita:	€	273	1	7,933	1,299
Inputs					
Labour	Number	142	5	552	115
Quays	Metres	6,788	254	25,424	6,135
Intermediate	€m.	5,578,752	311,861	26,538,325	6,744,899

Table 3. Summary of hybrid SBM efficiency scores

Efficiency scores *Model (Pollutants)*	Mean	Min.	Max	Std. Dev.	Number of Efficient Ports
Model 1 (Total)	0.443	0.001	1.000	0.424	12
Model 2 (Per capita)	0.565	0.001	1.000	0.438	17

Table 4. Directional distance function efficiency scores for each port

Port	Model 1 *Local External Costs: Total*	Model 2 *Local External Costs: Per Capita*	Model 3 *Local External Costs: Per Capita Super efficiency*
A Coruña	0.0017	1.0000	1.0071
Alcudia	0.0643	0.0633	0.0633
Algeciras	1.0000	1.0000	1.1753
Alicante	0.4638	0.6785	0.6785
Almería	0.0589	0.1030	0.1030
Arrecife	1.0000	1.0000	1.1306
Avilés	0.0010	0.0010	0.0010
Bahía de Cádiz	0.2723	0.3170	0.3170
Barcelona	1.0000	1.0000	1.3960
Bilbao	0.7826	1.0000	1.0082
Cartagena	1.0000	1.0000	1.0507
Castellón	1.0000	1.0000	1.0760
Ceuta	0.1697	0.1473	0.1473
Ferrol-San Cibrao	1.0000	1.0000	1.0698
Gijón	1.0000	1.0000	1.1077
Huelva	1.0000	1.0000	1.1149
Ibiza	0.1211	1.0000	1.0160
La Estaca	0.0056	0.0056	0.0056
Las Palmas	0.3432	0.6511	0.6511
La Savina	1.0000	1.0000	1.1452
Los Cristianos	1.0000	1.0000	1.1817
Mahón	0.1592	0.0621	0.0621
Málaga	0.2655	0.3191	0.3191
Melilla	0.3635	0.2747	0.2747
Motril	0.0363	0.0337	0.0337
Palma	0.1731	1.0000	1.0932
Pasajes	0.0027	0.0038	0.0038
Puerto del Rosario	1.0000	1.0000	1.5915
Santa Cruz de La Palma	0.3768	0.2277	0.2277
Santa Cruz de Tenerife	0.4854	0.6125	0.6125
Santander	0.0167	0.0163	0.0163
Sevilla	0.0752	0.1118	0.1118
SS de La Gomera	0.0127	1.0000	1.0070
Tarragona	0.0223	0.0470	0.0470
Valencia	1.0000	1.0000	1.1728
Vigo	0.1156	0.2060	0.2060
Vilagarcía	0.0078	0.0104	0.0104

Table 5. Efficient ports as benchmarks

Port	Model 2 Super-efficiency score	Model 2 Times as a benchmark
Puerto del Rosario	1.5915	14
Barcelona	1.3960	4
Los Cristianos	1.1817	14
Algeciras	1.1753	6
Valencia	1.1728	15
Lasavina	1.1452	12
Arrecife	1.1306	6
Huelva	1.1149	4
Gijón	1.1077	3
Palma	1.0932	0
Castellón	1.0760	5
Ferrol	1.0698	0
Cartagena	1.0507	2
Ibiza	1.0160	0
Bilbao	1.0082	0
A Coruña	1.0071	0
SS de la Gomera	1.0070	0

Table 6. Comparison of results for ports of Las Palmas and Palma

Port	Population	External	Container Cargo	Non-Container Cargo	Passengers	Efficiency scores	
						Model 1	*Model 2*
Las Palmas	378,998	18,879,729	8,696,174	7,773,121	1,718,790	0.343	0.651
Palma	402,949	6,629,878	646,207	8,352,561	2,469,453	0.173	1.000

Figure 1. Local external costs corresponding to ship emissions: 2016