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Examining the relationship between relative size and technical efficiency in peripheral port markets: Evidence from Irish and North Atlantic Spanish ports

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Abstract

In peripheral port markets, a limited volume of traffic creates challenges in sustaining multiple competing Port Authorities (PAs). With a limited size, smaller ports have difficulty in attracting the necessary traffic flows to leverage capital for development. In many European jurisdictions, recent policy reform has sought to concentrate resources in dominant ports or amalgamate smaller PAs to increase competitiveness and rationalize investments. This paper formally examines the link between port size and achievable efficiencies through an efficiency analysis of Irish and Atlantic Spanish ports. To achieve this, the paper applies a two-step double bootstrap Data Envelopment Analysis (DEA) approach to examine the effect of relative size on technical efficiency across the two port systems in the period 2000-2015. The results indicate a positive relationship between size and technical efficiency amongst ports in peripheral regions. As the time-period covers the financial crisis, it is possible to further explore the effect of the recession and subsequent contraction in the market for port services on the relationship between size and technical efficiency. The findings indicate that the effect of size on technical efficiency becomes even stronger when market contraction is controlled for. Results also show that the efficiency gap between the larger and smaller ports increased considerably after the recession.

Keywords: Data Envelopment Analysis, Port Authorities, Peripheral Port Markets, Simar and Wilson Approach.

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1. Introduction

Achieving efficiencies in the production of port services is recognised as a key goal of regional and national policy makers around the world due to the importance of maritime transport in international trade (Brooks and Cullinane 2006). A key mechanism for achieving efficiencies has been the reform of Port Authorities who are responsible for the regulation and development of port infrastructure. The dominant paradigm has been the corporatisation of PAs, with public ownership retained and responsibility devolved to commercially orientated semi-state bodies (de Langen and Heij 2014; Brooks et al. 2017). Private sector participation under this approach is facilitated by public-private partnership mechanisms (most frequently involving licensing and concession contracts).

The promotion of competition between autonomous *PAs* and the intended associated benefits are a key components of reform in many jurisdictions (Ng and Pallis 2010).[1] Amongst the major European hub ports, increased competition and its associated effects on port company strategy have been widely documented (Notteboom, 1997; Notteboom and Winkelmans, 2001; Gouvernal et al., 2005; Notteboom, 2010). The largest hub ports act as load centres in hub and spoke networks competing for transhipment traffic. Increasing interdependency amongst nations and improvements in both technology and intermodal transport infrastructure have improved the capability of these ports to serve distant regions (Haralambides, 2002, 2017).

On the other hand, ports situated in regions that are relatively peripheral to major traffic lanes struggle to compete with the larger hub ports for contestable traffic. This restricts the spatial extent to which peripheral ports can compete for traffic, in most cases to the local hinterland. In peripheral regions it is questionable if the size of the market for port services can support multiple, independently competing *PAs* (Brooks et al., 2010). Port operations are capital intensive, requiring large fixed asset specific installations. *PAs* need sustained traffic flows to attract the capital necessary to develop infrastructure and increase their competitiveness. With limited traffic flows,

[1] In Spain for example the Royal Legislative Decree 2/2011 set objectives for the self-financing of State PA’s. In addition the decree relaxed the tariff system to increase the autonomy of the PA’s to set their own fees (Coto-Millán et al., 2016).

the capability of multiple *PAs* -operating in proximity- to attract adequate capital so as to remain competitive is highly challenged.

Recent national reforms in specific European jurisdictions have seen initiatives to boost the competitiveness of peripheral ports and avoid unnecessary duplication of resources in neighbouring competing ports. In Ireland, the National Ports Policy (2013) categorised ports into three tiers based on their capability to serve national traffic requirements. The National Ports Policy (NPP) is a move away from the previous policy of multiple independent competing ports. The NPP cites the wider trend toward consolidation in the shipping market and the use of larger ships as influencing factors. NPP states that Tier 1 ports are mandated to "lead the response of the State commercial ports sector to future national port capacity requirements" with Tier 2 ports also recognised as having a responsibility to develop additional national capacity. The remaining commercial ports are categorised Tier 3 ports of regional significance. The NPP also points out that all future state support for major infrastructure developments will respect this mandate, a position which has been reiterated in the National Development Plan 2040[2]. Similarly in France, most recent reform has decentralised regional ports, while the largest ones, the *"Grands ports Maritimes"*, are retained under state ownership (Debrie et al., 2013; Cariou et al., 2014). In Italy, the 2016 reforms went a step further. There, 24 independent PAs have been consolidated to 15 in a series of mergers, aimed to boost the capabilities of the newly formed PAs (Ferretti et al., 2018).

While the above refers to relatively policy-driven or top-down reforms, there are also strong examples of *PAs* themselves acting to pool resources (Notteboom et al., 2018). Most prominently, the ports of Copenhagen and Malmö merged to become a single entity in 2001. Similarly, in 2017, the ports of Ghent and Zeeland Ports merged to become the North Sea Port. Prioritisation of larger ports through tiering, or amalgamating smaller ports through mergers, should lead to efficiency gains. We explore this assertion, by examining the relationship between the relative size and the technical efficiency of PAs in peripheral regions.

[2] Under the NPP there is no exchequer funding available for port infrastructure development. Instead state support will prioritise the development of intermodal infrastructure for Tier 1 and Tier 2 ports.

2. Investigating the relationship between size and technical efficiency

Prior works on the relationship between port size and technical efficiency have shown mixed results regarding the significance of this relationship. Barros (2003), applying a second stage tobit regression, found that market share had a positive effect on technical efficiency in Portuguese *PAs*. Similar results were found in Barros and Athanassiou (2004), with the analysis extended to Portuguese and Greek Ports. Tovar and Wall (2017) found that relative size typically had a positive effect on the technical efficiency of Spanish *Pas*, between 2000-2012. Hidalgo Gallego et al. (2015) found a positive relationship between size and port utilisation, also in Spanish *PAs*. In contrast, Coto-Millán et al. (2000) found that, amongst Spanish *PAs,* it is the smallest ports that have the highest technical efficiency, while Inglada and Coto-Millán (2010) found a negative association between size and efficiency (technical and scale efficiency). Bonilla et al. (2002), Tongzon (2001), Gonzalez and Trujillo (2008) and Zahran et al. (2017) found no significant effect of size on efficiency in *PAs*.

An issue with drawing conclusions from these studies is that, in sampling PAs for analysis, major hub ports with a substantial amount of transhipment traffic are included alongside smaller ports serving regional demand. The relative size of the hub ports, compared to the small to medium sized ones that are the focus of our analysis, complicates the research. In this paper, we therefore sample exclusively from peripheral regions. Specifically, the paper looks at Irish state owned ports and spanish North Atlantic ports over the period 2000-2015. Ireland, as an island, has a limited hinterland while its relative distance from the major European markets and major trade lanes make it relatively uncompetitive in terms of major transhipment activity. Similarly, the North Atlantic Spanish region is limited in size. While the Spanish North Atlantic ports are less peripheral than the Irish ports to the major east-west and north-south trade lanes. The relative lack of transhipment activity in this region indicates a lack of competitiveness of ports in the region in attaining hub status.. This is clear from Table 1 where it can be seen that the volume of transhipment traffic in the largest port in the region (Bilbao) is far below the major hub ports in Europe.

Insert Table 1

In this paper, the sample consists of 15 ports, varying in size, as displayed in Table 2. To examine the relationship between size and a port's technical efficiency, the well-known two-step Simar-Wilson approach is applied (Simar and Wilson, 2007). The first step involves the measurement of a port's technical efficiency by using bootstrapped Data Envelopment Analysis (DEA), followed by a bootstrapped truncated regression (second step) to capture the relationship between contextual variables and technical efficiency measures. A major contribution of this study stems from our data set, covering as it does a long period of port activity before and after the 2008 economic crisis. In both analysed regions, the effects of the crisis resulted in a large scale contraction in market demand. Utilising the dataset we can measure the interaction effect between the contraction in ports system volume and size on technical efficiency. To achieve this a second interaction-based model is employed.

Insert Table 2

The remainder of the paper is structured as follows: Section 3 outlines the methodology in more detail and section 4 discusses the port data employed. Section 5 presents the analysis, starting with a qualitative analysis of efficiency scores and then present the results of the second stage estimation procedure. Finally, section 6 consists of conclusions.

3. Methodology

To measure the relationship between technical efficiency and relative size we employ the two-step double bootstrap DEA Approach outlined in Simar and Wilson (2007)[3]. DEA is one of two prominent approaches to estimate a production possibility frontier (or an input requirement frontier) and analyse efficiency[4]. The DEA method was developed by Charnes et al (1978), based on Farrel (1957), and it has been widely applied in port efficiency measurement (Barros 2006; Wu et al. 2010; Schøyen and Odeck 2013; Zahran et al. 2017; Nguyen et al. 2018). The method takes a set of *n* inputs (x_{in}) and *m* outputs (y_{im}), for a set of *i* decision making units (DMUs) -in our case *ports*, and estimates an efficiency frontier by creating a piece-wise surface that

[3] Efficiency measurement is primarily based on the concept of efficiency introduced by Farrell (1957). Farrell (1957) decomposes overall productive efficiency into two elements; technical efficiency and allocative efficiency. Technical efficiency measures the ability of a firm to obtain maximum outputs from a certain quantity of utilized inputs, and typically refers to physical quantities. Allocative efficiency relates to the optimal choice of input bundle to produce outputs given prevailing market prices of inputs and outputs. It is desirable to measure both, however as outlined in Gonzalez and Trujillo (2007), the lack of factor price information has frequently forced researchers to focus on technical efficiency. Similar data constraints limit the current study to the analysis of technical efficiency.

[4] The other approach is parametric stochastic frontier analysis (SFA).

envelopes the data. This is done by solving a linear programming problem for each data point *i*, commonly represented for an output-orientated model in its dual form:

$$\widehat{E}_i(\mathrm{y,x}) = \max_{\theta,\lambda} \theta \qquad (1)$$

s.t.

$$\sum_{i=1}^{I} \lambda_i y_{im} \geq \theta_m y_{im}, \qquad m = 1, \ldots, M$$

$$\sum_{i=1}^{I} \lambda_i x_{in} \leq x_{in}, \qquad n = 1, \ldots, N$$

$$\lambda_i \geq 0$$

Where $\widehat{E_i}$ is the efficiency estimate of the i^{th} DMU ($\widehat{E_i} \geq 0$), λ_i is a non-negative intensity vector used to scale individual observed activities for constructing the piece-wise linear technology and θ is the actual unobserved efficiency score. With an output oriented frontier, a port *i* is considered as technically efficient when $\widehat{E}_i = 1$, and as technically inefficient when $\widehat{E}_i > 1$ with $\widehat{E}_i - 1$ representing the proportional increase in output required to project DMU *i* to the frontier, holding inputs constant. The The DEA programme given by Eq. (1) represents the DEA-Charnes–Cooper–Rhodes (CCR) or DEA constant returns to scale model; to assume variable returns to scale, or the DEA-Banker–Charnes–Cooper (BCC) model, the constraint the constraint $\sum_{i=1}^{I} \lambda_i = 1$ is added.

The main advantage of DEA is that it does not require the specification of a production function and it performs better with smaller samples relative to SFA (Panayides et al. 2009). As mentioned above, the estimation procedure may assume an output orientation, whereby output is maximised holding inputs constant or, alternatively, an input orientation can be assumed where input requirements, rather than the production possibility frontier, are estimated. Typically, an orientation should be chosen based on the production units' capability to adjust inputs/outputs (Coelli et al. 2005). Given that the provision of port infrastructure is highly capital intensive, the capability of PAs to adjust inputs is restricted. In choosing an output orientation we therefore follow Gonzalez and Trujillo, (2008), Tovar and Wall (2017) and Zaharan et al. (2017).

A number of approaches have emerged to examine the effect of contextual variables on efficiency scores generated by DEA. These approaches typically employ a second stage regression procedure, often using a censored or a truncated regression model to account for the bounded nature of the dependent variable; i.e. the estimated efficiency scores $\widehat{E_i}$ (Simar and Wilson 2007, 2011). Such models can be represented by:

$$E_i = z_i\beta + \varepsilon_i \tag{2}$$

where z_i represents contextual variables. The error terms ε_i are assumed to be independent and identically distributed $N(0, \sigma_\varepsilon^2)$ with left truncation at $1 - z_i\beta$ (Balcombe et al. 2008). Thus, E_i cannot take values smaller than unity, irrespective of the values that the elements in vector z_i may take (Badunenko and Tauchmann 2018a). Inferences in the second stage process relate the contextual variables as covariates to technical efficiency estimates that are assumed to be derived from some underlying Data Generating Process (DGP) based on a representative production technology. As outlined in Simar and Wilson (2007), replacing efficiency scores generated by the true DGP with estimates generated by DEA poses issues that make inference in "naïve" two-step approaches invalid.

Simar and Wilson (2007) stress the major shortcomings of naïve two-stage approaches. The first issue arises due to replacing E_i in Equation 2 with $\widehat{E_i}$; the DEA estimated efficiency scores. Although the error terms in Equation 2, where E_i is regressed on z_i, are assumed to be statistically independent across ports; the errors terms in a regression of $\widehat{E_i}$ on z_i cannot be treated as independent of $\widehat{E_i}$ since the latter are derived from the same sample. Thus the error terms of $\widehat{E_i}$ for each firm (port) i can be serially correlated. Secondly, conventional DEA results will, by construction, estimate some efficiency scores to be equal to one (i.e. full efficiency). However, according to Equation 2 the probability of a DMU achieving full efficiency ($E_i = 1$) is null and the aforementioned scores are an artifice of the finite sample. This is particularly a problem in large samples where multiple DMUs will achieve full efficiency.

Simar and Wilson (2007) suggest the use of a parametric bootstrap procedure to address the issue of serially correlated error terms. In this parametric bootstrap procedure standard errors and confidence intervals for $\hat{\beta}$ are estimated in which pseudo errors are drawn from the truncated normal distribution with left truncation $1 - z_i\hat{\beta}$ (Badunenko and Tauchmann 2018a).

The latter issue of unitary efficiency can be tackled by adopting one of the two following approaches proposed by Simar and Wilson (2007). In the first approach, observations with unitary efficiency are excluded from the truncated regression model. The estimated $\hat{\beta}$s and variance parameters of the remaining observations could be used further in the parametric bootstrap procedure mentioned above to eliminate the bias of serially correlated error terms. The second approach dealing with the problem of unitary efficiency, uses all observations in the truncated regression model and replaces the initial estimates using conventional DEA with bias-corrected scores, produced through a bootstrapping procedure, and as such is termed a *double bootstrap* approach. The second approach addresses the issue of serial correlation in the same way as the first approach does.

Since its introduction the Simar Wilson approach has become the most commonly used approach in two-step DEA regression analysis (Badunenko and Tauchmann 2018b). The Simar Wilson approach has also been applied by scholars to analyse the efficiency of PAs. Recent examples include Yuen et al. (2013), Bergantino et al. (2013), De Oliveira and Pierre Cariou (2015), Wanke and Barros (2015), and Tovar and Wall (2017). In this paper we use the double bootstrap approach of Simar and Wilson (2007) and the truncated regression for the second stage procedure. A bootstrapping procedure is subsequently used, to create confidence intervals through drawing from a truncated normal distribution with truncation at $(1 - z_i\hat{\beta})$ where $\hat{\beta}$ is the estimate of β in Equation 2. The authors show how, under a number of assumptions, this procedure produces consistent estimates of β. Most important is the assumption of separability, where the shape of the frontier is not dependent on z_i.

4. Data

The sample consists of the five largest Irish state owned ports and the 10 Spanish North Atlantic ports (table 2). Importantly, the ownership and governance structure across both jurisdictions are highly comparable. The Spanish ports were decentralised under Law27/1992 and Law62/1997. In Ireland, similarly, the Harbours Act of 1996 corporatised the former harbour authorities, creating decentralised autonomous port enterprises.[5] In both systems, therefore, PAs are decentralised and autonomous and while there is private sector participation in all ports, the state retains ownership of the infrastructure. PAs are therefore responsible for the development of infrastructure while ensuring that infrastructure is operated efficiently and effectively (in most cases through the appropriate regulation of private sector partners through the use of concession contracts and licensing).

The selection of inputs and outputs is a key element in any efficiency measurement exercise. There is significant diversity in the literature regarding what constitutes a port's output. This is often explained by the subject of analysis, i.e. a container terminal, a *PA*, etc., but also by the availability of data. There has been an extensive literature measuring Spanish PAs' technical efficiency. The major categories of cargo have been widely used as outputs, as well as the number of passengers (see Gonzalez and Trujillo 2007 for an extensive review), reflecting the multi-output nature of a port's production process. This however creates a certain difficulty, as discussed by Panayides (2009), when it comes to estimating an efficiency frontier using DEA; Increasing the number of outputs results in a loss of discriminatory power and overestimation of efficiency when there is significant heterogeneity in the output mix. As Panayides (2009) state, "*as the number of dimensions increase, the opportunity to differentiate one DMU from its peers also increases and as a result the DMU may be deemed efficient only due to the lack of comparator observations*".

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[5]. In Ireland, the Harbours Act corporatized the 10 largest state owned ports, creating commercial state-owned enterprises. The government retained ownership as the sole shareholder with the resulting "port companies" given a largely commercial mandate. Most operating restrictions were removed except the requirement of ministerial approval for large-scale borrowing and the establishment of subsidiary companies. New boards of directors were established to be responsible to the minister for transport for the conduct and operation of the port companies. The Spanish State Port System consists of 46 ports, managed by 28 Port Authorities. In the terms established under Spanish Law27/1992 and Law62/1997, the Port Authorities are responsible for the management of the ports under their autonomy regime and the State Ports Authority (Puertos del Estado) is then responsible for the overall coordination of the 28 Port Authorities and for the execution of the port policy of the Government.. Puertos del Estado define the objectives of the whole state port system, as well as the general management of the Port Authorities, through the Business Plans agreed with them. When a Port Authority considers it necessary to establish objectives with a time horizon of more than four years, it must formulate a plan that must also be agreed with Puertos del Estado. In addition, Puertos del Estado approve the financial and investment programming of the Port Authorities, derived from the Business Plans agreed with them, and the consolidation of their accounts and budgets (Royal Decree 2/2011). While there have been further reforms in both jurisdictions in the intervening period, the fundamental structure of the PAs, as decentralised autonomous units, has been preserved.

In order to develop a parsimonious model and avoid estimation complexities a single aggregate output was used. We examined various means of aggregating outputs, based on cargo types and port activity. Given a lack of historical output price information, an issue arose in representing the relative value of different cargoes[6]. For that reason Zahran et al (2017) was followed and the revenue generated by the *PA* was chosen as a single output. A production process assuming an output orientation can be characterised as follows: the DMU, through available technology, transforms available resources (inputs) into output measured by the revenue generated by the PA.

As regards inputs, the standard factors of production, i.e. land, labour and capital, are employed. Land is measured by the surface deposit area of the port domain in squared meters (m^2). Labour is measured by total labour costs, obtained from audited annual reports, and deflated using Eurostat's Harmonised Index of Consumer Prices (HICP) in 2015 prices. Following Medal-Bartual et al. (2016), capital is approximated by the total stock of net assets. Again, this measure was taken from the audited annual accounts and deflated by using the HICP index in 2015 prices[7].

The next set of variables of interest are the contextual or z variables, as presented in equation (3). To measure the (relative) size of a *PA* we follow Tovar and Wall (2015) and measure the throughput of the port, relative to the total throughput of the port system measured in tonnes as follows[8]:

$$Relsize_i = \frac{tonnage_i}{tonnage_{sysj}} \quad (3)$$

Other variables considered in explaining efficiency were *specialisation* and *rate of unitisation*. Specialisation refers to the degree to which a *PA* concentrates in a particular output, relative to a differentiated output mix; the variable has been found to be a significant in Tovar and Wall (2017). To measure specialisation, we adopt the common normalised Herfindahl-Hirschman index (NHHI) given by:

6 The ports of Cork and Waterford do not disclose the prices that they charge. In addition this data is not available on a historical basis for the Irish ports.

7 Labour includes the wage bill for all direct employees and managers of the respective PAs. This information is taken from the annual accounts of the PAs. The value of the stock of net assets for each port were taken directly from the annual accounts of the PAs. The value of fixed assets in a given year reflect cost minus accumulated depreciation.

8 Tonnage is used to reflect cargo output as it allows for the aggregation of different types of cargo for comparative purposes.

$$NHHI_i = \frac{\sum_{m=1}^{M}\left(\frac{y_{mi}}{\sum_{m=1}^{M} y_{mi}}\right)^2 - \frac{1}{M}}{1-\frac{1}{M}} \tag{4}$$

where y_{mi} represents the m^{th} cargo output of port*, measured in tonnes*.

The unitisation rate is similar to the containerisation rate, commonly used as a measure of the type of output produced. We use unitisation rather than containerisation[9] to reflect the prevalence of RoRo (Roll-on/Roll-off) cargo in the Irish market and therefore aggregate LoLo (Lift- on/Lift-off) and RoRo cargo. RoRo cargo, similarly to containerised cargo, is parcelled and designed for easy transfer to other modes of transport. Unitised cargo is in direct contrast to bulk cargo, the latter consisting of goods that are primarily of low value and high volume, of a granular consistency and typically loaded *en masse*. Here, unitisation is measured simply as the percentage of traffic within the port that is unitised.

As mentioned above, we were also interested in examining the effect of the economic recession, in terms of *demand side shock* and subsequent market contraction. To capture this effect, we initially considered dummy variables. An issue arose however with regard to the varying intensity of the recessionary effect, following the initial shock and recovery. To capture this we therefore constructed a Market Contraction Index (MCI), whereby the effect of the recession is approximated by the amount of cargo, measured in tonnes, in the port system *j* in the given year $(cargo_{sysjt})$ relative to the previous maximum level of cargo attained within the port system ($max_{ij}^{t-1}\ cargo_{sysij}$); i.e.,

$$MCI_{sysij} = \frac{cargo_{sysjt}}{max_{ij}^{t-1}\ cargo_{sysi}}\ where\ j = 1,2 \tag{5}$$

Lastly, we have included three classes of control variables. Firstly, a *spatial* variable to account for the size of the natural hinterland, measured in terms of population. Secondly, following Tovar and Wall (2015), we included dummy variables for each year, to account for the evolution of efficiency over time. Finally, we included a regional dummy variable to account for any systematic variation resulting from being in either jurisdiction. Descriptive statistics for the control variables are presented in table 3.

[9] Unitization reflects both RoRo and LoLo traffic. Containerisation refers to traffic that is loaded in 20ft or 40ft containers for shipment.

Insert table 3

5. Results

To present the results of the efficiency analysis, we first examine the efficiency scores generated through the initial step, and then proceed to the results of the second stage (regression).

Efficiency Estimates

Applying the double bootstrap methodology of Simar and Wilson (2007), we first estimate bias corrected efficiency scores (Table 4). We estimate efficiency scores both under constant returns to scale (CRS) and variable returns to scale (VRS) in order to ascertain the appropriate technology. Following Coelli et al. (2005), scale efficiency in an output orientated technology equals:

$$SE_i = E_{ci}/E_{vi} \qquad (6)$$

Where scale efficiency SE_i, is given by the ratio of efficiency under constant returns to scale (E_{ci}) to efficiency under variable returns to scale (E_{vi}). The CRS assumption is valid only if $SE_i = 1$ globally (Coelli et al. 2005). As can be see in Table 4, several DMUs exhibit scale inefficiency. Thus for qualitative analysis of efficiency scores, and the second stage estimation procedure, VRS is assumed.

Insert Table 4

We first look at the evolution of efficiency scores over time. To achieve this, average technical efficiency scores, for ports and jurisdictions, are reported for the pre-recessionary (2000-08) and (2009-15) periods. Here, it can be seen that average technical inefficiency across jurisdictions has decreased from the first period to the second. Illustrating annual efficiency changes (Figure 1), inefficiency was largely cyclical and strongly correlated to economic growth over the period. This is not surprising, as ports are nodes in a transport network that exists to serve international trade. Further, ports are capital-intensive infrastructure systems that require large, fixed, asset specific installations. As a result, given a sudden reduction in demand, ports will typically be subject to over-capacity as they cannot easily reduce their rate of input consumption, notably *capital*. Interestingly, a divergence was observed between North Atlantic Spanish and Irish Ports, with regard to the effects of the recession. The initial effects of the recession were stronger in Irish ports, with a much sharper decline in efficiency, following the financial crash, with the strongest effect observed in 2009. Nevertheless, efficiency in Irish ports has largely recovered while it has continued to decrease in Spain. The relative improvement in efficiency in Irish ports compared to Spanish ports may be influenced by the faster rate of recovery in the Irish economy as illustrated in figure 2.

Insert Figure 1

Insert Figure 2

Examining differences across jurisdictions overall, it can be seen that average inefficiency in Irish ports has been slightly lower in both periods as measured under VRS technology. It is important to note however that the larger number of Spanish ports in the sample may have influenced this result. Examining efficiency at the individual port level, there appears to be no obvious advantage of being in either jurisdiction. Dublin is the best performing port in both periods, with efficiency scores well above the most efficient Spanish ports, A Coruña and Gijon. The remaining Irish ports however are rather dispersed in terms of efficiency rankings in both periods.

To qualitatively examine the relationship between efficiency scores and the variables of interest identified in section 4, in Figure 3 we plot the average technical efficiency score against the average variable levels. A clear pattern emerges for relative scale, as those ports with higher efficiency are also those with the larger scale. There is no such pattern for the remaining variables, including, notably, NHHI: One can see no clear pattern, with highly concentrated ports tending both towards higher- and lower efficiency. The same applies in the case of less concentrated ports. While we explore this formally in the next section, this result indicates that scale is likely the best predictor of technical efficiency scores. To examine this relationship over time in Figure 3, the average efficiency of the top 20% of our ports, in terms of size, is plotted against the bottom 20%. It can be seen that the efficiency gap between the larger and smaller ports increased considerably after the recession.

As displayed in Table 4, scale efficiency decreased from the pre- to the post-recessionary period. Notably the ports with the highest rate of average scale inefficiency, such as Marin Pontevedra, Vilagarcía, Waterford and Drogheda, were also the ports with the lowest average tonnage per year.

We can examine whether scale inefficiency is caused by increasing or decreasing returns to scale. This can be done by exploring further the relationship between efficiency scores generated by a VRS assumption versus those generated by assuming non-increasing returns to scale. This is done by employing the indicator:

$$\text{SEIN} = E_{ni} / E_{vi} \qquad (7)$$

Here, SEIN indicates the degree to which there are increasing returns to scale available and is determined by the ratio of efficiency under the non-increasing returns to scale assumption (E_{ni}), to efficiency under the variable returns to scale assumption (E_{vi}). Calculating SEIN for the four ports we find average scores of 1.11 (Marin Pontevedra), 1.31, (Vilagarcía) 1.07 (Waterford) and 1.28 (Drogheda). These scores indicate that the four ports could increase their respective scale efficiency by increasing their scale.

Insert Figure 3

Second Stage Process

In the second stage process, we estimate two models to measure the effect of the variables of interest (namely Relative Size, NHHI and Unitisation) on technical efficiency. The first model estimates the effect of these variables without controlling for the effect of market contraction. In the second model, we include the MCI variable (5) and interact it with the variables of interest to examine if the intensity of effects changes with the size of market contraction. As the truncated regression employed is a non-linear model, the estimated coefficients do not represent the marginal effects of the relevant variables. To derive these, we differentiate the expected value of the dependent variable with respect to the variables of interest, as shown in Table 5. Furthermore, in model 2, as the variables of interest are interacted, the interpretation of the effect of variables changes relative to model 1. We now have to consider the effect of a variable in conjunction with the interaction effect (Drichoutis 2011). The marginal effect, as presented in Table 5, is the marginal effect of the variable of interest with the MCI at its mean value. To examine how the effect of the variable of interest changes with MCI, we calculate the marginal effect of the variable of interest conditional on several values of the MCI. To choose values, we start at 75 and continue in intervals of five until we reach 100 (we choose 75 as a starting value as it roughly corresponds to the minimum value of the MCI as presented in Table 5).

Examining the control variables first, hinterland population size has a negative and significant effect on technical efficiency (at the 10% level) in both models. As to be expected, this indicates that proximity to a large population centre has a positive effect on the probability of a port achieving technical efficiency in generating revenue. However, the effect of hinterland population size on technical efficiency is not statistically significant at the 5% or 1% level. Examining the year dummies in model 1, it can be seen that none of the years has a significant effect. However, in model 2, the year dummies corresponding to the post-recessionary period are significant and have negative signs (switching from positive in model 1), indicating a positive effect on efficiency. This result is unexpected, given that average technical efficiency declined in the post-recessionary period, displayed in Figure 1. A possible explanation for this could be that the negative effect of the recession in model 2 is captured primarily in the MCI variable introduced in model 2. This variable is negative, indicating that, as MCI rises (i.e. traffic relative to the previous year rises) technical efficiency similarly improves and vice versa. One possible conjecture is thus that, controlling for the effect of market contraction, efficiency improved following the recession. Finally, the lack of significance of the country dummy variable would support the argument that there is no significant advantage in being in either jurisdiction, as regards the probability of improved technical efficiency.

Moving to the variables of interest, and examining firstly the effects of model 1, it can be seen that the average mean effect for both size and unitisation are positive, albeit more significant for size. This is more evident when we look at the marginal effects in Table 6. As both variables are measured on the same scale (i.e. percentage), both effects are directly comparable. It is clear that size has a much higher effect than unitisation. NHHI is not statistically significant; indicating that, on average, there has not been a significant relationship between efficiency scores and concentration of traffic over the period.

Examining marginal effects in model 2, it can be seen again that size and unitisation have a positive effect while NHHI is insignificant. In Table 7, the change in effect as the market contracts is displayed. Examining size first, it can be seen that, as the market contracts, the magnitude of the estimated marginal effect increases significantly. This is largely consistent with the qualitative analysis of the change in technical efficiency of the top 20% of ports in terms of size, as displayed in Figure 3. In contrast, for unitisation, the significance of this effect on the probability of a port being inefficient decreases as the market contracts. The sign further switches as we reach the minimum of the MCI. One possible explanation for this is that unitised trade is more closely linked with the wider underlying activity of a region, relative to bulk trade which is typically concerned with large industrial production and the movement of raw materials. As such, the relative effect of a domestic recession is likely to affect unitised trades to a greater extent than bulk. Finally, the NHHI variable is again insignificant in model 2.

Insert Table 5

Insert Table 6

Insert Table 7

6. Conclusions

In this article we employed the DEA double bootstrap procedure of Simar and Wilson (2007) to examine the relationship between technical efficiency and port size in peripheral regions over the period 2000-15. Purposely sampling Irish and North Atlantic Spanish ports of various sizes that compete in limited markets, we find evidence of a positive relationship between technical efficiency and size. The magnitude of the positive effect of a port's size on technical efficiency becomes stronger when we account for potential interactions between post-recessionary market contractions (MCI) and size.

The evidence put forward, both qualitatively and quantitatively, clearly points toward a positive relationship between scale and technical efficiency across the two port systems. As discussed in section 2, this is not necessarily consistent with the literature, which provides mixed evidence of a positive relationship between scale and technical efficiency in *PA* operations. The discrepancy between the strong evidence in this study and contrary evidence elsewhere is likely to be a question of sample. This study has considered a range of small- to medium-sized gateway ports from two peripheral port regions. Other studies have included transhipment hubs which, as discussed in Notteboom et al. (2000), have a different operational model from ports without transhipment operations.

Higher degrees of technical efficiency imply a competitive advantage for larger ports within peripheral regions relative to smaller ports. The scale efficiency analysis in section 5 indicates that the smallest ports in the sample are scale inefficient and facing increasing returns to scale. With a limited volume, it is questionable as to whether there is scope for these ports to increase scale and achieve higher efficiencies. Our evidence would suggest the concentration or amalgamation of resources to create larger ports within regions with limited traffic could lead to more efficient outcomes.

While the results of this research indicate that a positive relationship exists between port size and technical efficiency across the peripheral traffic regions of Ireland and North Atlantic Spain a broader analysis would be required to ascertain if these findings can be generalized to small ports in other peripheral areas.

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Tables and Figures

Table 1: Transhipment Incidence of Major Western Mediterranean and North West Atlantic Ports

Port	TEU	Transhipment (%)
Bilbao	610,131	2
Algeciras	4,070,701	91
Valencia	4,469,754	51
Barcelona	1,749,974	25
Antwerp	8,635,169	29
Le Havre	2,303,750	17
Rotterdam	11,865,910	36

Source: (Notteboom et al., 2014)

Table 2: Irish and North Atlantic Spanish Ports

Port	**Traffic (tonnes)**	**Revenue (€)**
Avilés	5,108,851	17,273,601
Bilbao	32,399,823	66,511,912
El Ferrol	12,759,526	18,632,334
Gijon	21,178,589	46,936,764
A Coruña	13,764,237	27,871,516
Pasaia	3,738,537	14,798,088
Marin-Pontevedra	2,114,083	9,634,104
Santander	5,559,820	20,417,982
Vigo	4,027,462	27,496,589
Vilagarcía	1,024,904	5,365,487
Dublin	22,204,000	79,508,000
Cork	9,708,000	29,956,316
Waterford	1,497,000	6,903,614
Shannon Foynes	10,871,000	12,151,864
Drogheda	1,227,000	3,196,536

Source: Authors own compilation

Table 3: Summary Statistics

Variable	Unit	Obs	Mean	Std. Dev.	Min	Max
Outputs:						

Revenue	€ (2015 prices)	240	25,659,023	21,388,328	1,877,855	98,816,828
Inputs:						
Land	m^2	240	956,310	834,984	100,443	3,132,019
Labour	€ (2015 prices)	240	6,699,467	4,646,796	463,188	26,400,000
Capital	€ (2015 prices)	240	271,718,536	279,123,174	25,022,409	1,210,969,087
Contextual Variables:						
Population	People	240	1,868,926	738,844	531,159	2,797,653
Relative Size	%	240	12%	11%	1%	44%
NHHI	%	240	32%	20%	0%	80%
Unitisation	%	240	17%	22%	0%	74%
MCI	Index value	240	94	7.05	78.5	100

Legend:
Relative Size: Cargo output in port relative to the market, equation (3)
NHHI: Normalised Herfindahl-Hirschman index, equation (4)
Unitisation: percentage of cargo that is unitised
MCI: Market Contraction Index, equation (5)

Source: Authors own compilation

Table 4: Average Technical Efficiency Scores

	Pre-Recession			Post-Recession		
Port	CRS	VRS	Scale	CRS	VRS	Scale
Avilés	1.62	1.52	1.07	1.49	1.46	1.02
Bilbao	1.32	1.29	1.02	1.41	1.37	1.03
El Ferrol	1.48	1.48	1	1.55	1.49	1.04
Gijon	1.24	1.25	0.99	1.27	1.3	0.98
A Coruña	1.27	1.25	1.02	1.27	1.25	1.01
Pasaia	1.9	1.91	1	1.87	1.82	1.03
Marin-Pontevedra	1.45	1.3	1.11	1.61	1.46	1.11
Santander	1.49	1.49	1	1.92	1.9	1.01
Vigo	1.31	1.34	0.98	1.59	1.63	0.98

Vilagarcía	2.07	1.5	1.39	2.18	1.84	1.19
Dublin	1.15	1.13	1.02	1.11	1.12	0.99
Cork	1.41	1.38	1.02	1.56	1.49	1.05
Waterford	1.39	1.37	1.01	1.67	1.48	1.14
Shannon Foynes	1.66	1.66	1	1.47	1.46	1.01
Drogheda	1.99	1.36	1.47	1.78	1.72	1.02
Ireland	**1.52**	**1.38**	**1.1**	**1.52**	**1.45**	**1.04**
Spain	**1.52**	**1.43**	**1.06**	**1.62**	**1.55**	**1.04**

Legend:
CRS: Technical efficiency measured under constant returns to scale
VRS: Technical efficiency measured under variable returns to scale
Scale: Scale efficiency

Figure 1. Technical Efficiency (VRS) Over Time across the Port Systems

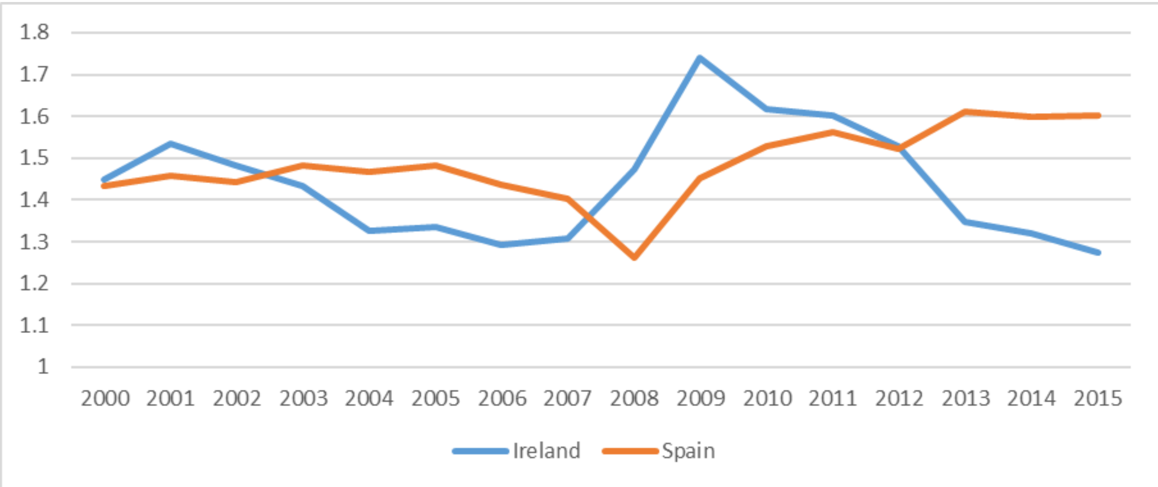

Figure 2. Post Recessionary Market Concentration Index change

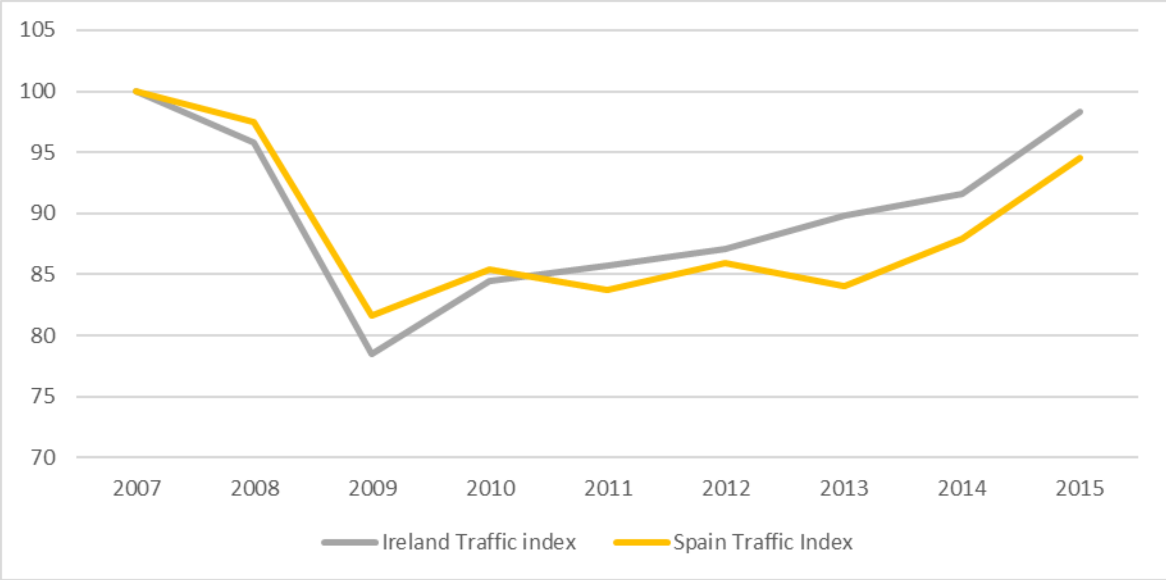

Figure 3: Technical Efficiency vs Contextual factors

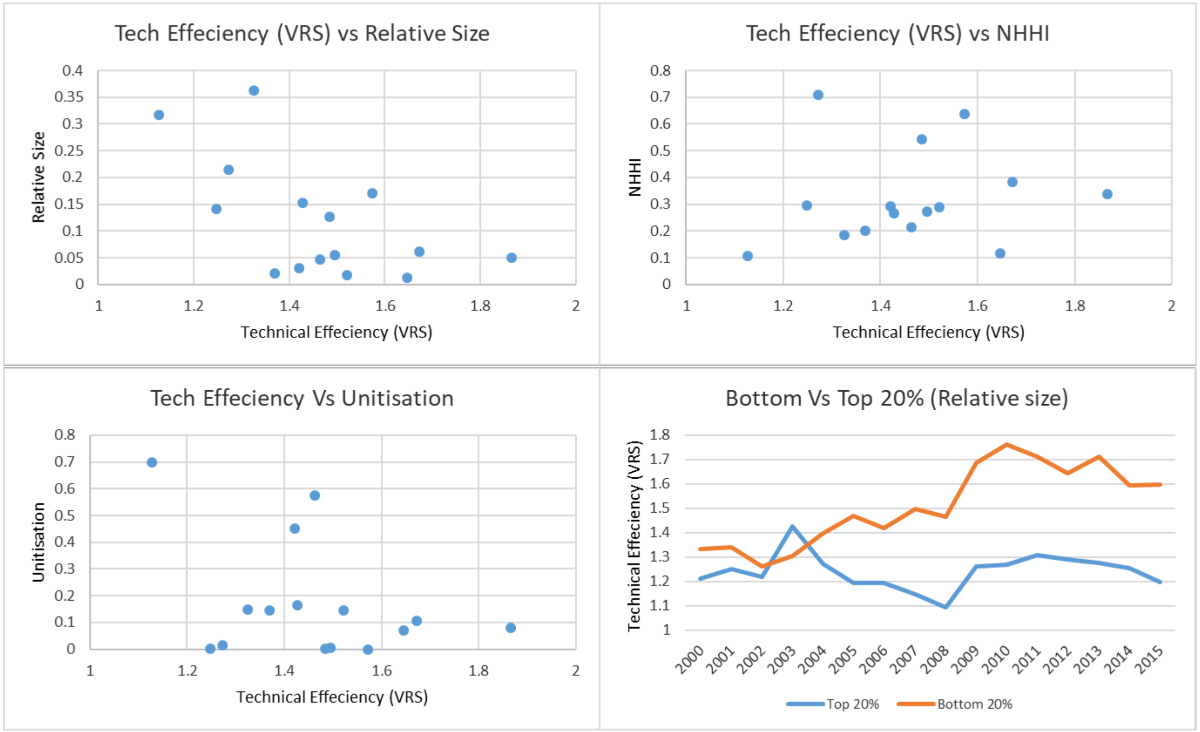

Table 5: Result of Second Stage Regression

	Model 1		Model 2	
Variable	Coefficient	SE	Coefficient	SE
Hinterland Population	-5E-05*	2.73E-05	-4.76E-05*	(2.56E-05)
RelSize	-1.49***	(0.24)	-7.57***	(2.62)
NHHI	0.11	(0.13)	-0.45	(1.49)
Unitisation	-0.25**	(0.1)	2.07	(1.27)
MCI	NA	NA	-0.09***	(0.02)
(MCI)*RelSize	NA	NA	0.07**	(0.03)
(MCI)*NHHI	NA	NA	0.01	(0.02)
(MCI)* Unitisation	NA	NA	-0.03*	(0.01)
2001	0.08	(0.11)	-0.04	(0.1)
2002	0.05	(0.11)	-0.01	(0.1)
2003	0.05	(0.11)	0.07	(0.1)
2004	0	(0.12)	0.01	(0.1)
2005	0	(0.11)	0.01	(0.1)
2006	-0.08	(0.12)	-0.06	(0.1)
2007	-0.08	(0.12)	-0.07	(0.1)
2008	-0.16	(0.12)	-0.39***	(0.12)
2009	0.13	(0.11)	-1.49***	(0.36)
2010	0.14	(0.11)	-1.09***	(0.28)
2011	0.17	(0.11)	-1.13***	(0.29)
2012	0.1	(0.11)	-1.03***	(0.26)
2013	0.1	(0.11)	-1.08***	(0.27)
2014	0.09	(0.11)	-0.81***	(0.22)
2015	0.08	(0.11)	-0.27**	(0.13)
Country Dummy (1=IRE)	-0.04	(0.04)	0.03	(0.05)
_cons	1.65***	(0.12)	10.34***	(1.86)

***Statistically significant at 1% confidence level instead of 0.01%

**Statistically significant at 5% confidence level instead of 0.05%

*Statistically significant at 10% confidence level instead of 0.10%

Table 6: Mean Marginal Effects

	Relative Size	NHHI	Unitisation
Model 1	-1.14 ***	0.08	-0.19**
Model 2	-1.11 ***	0.07	-0.24 ***

Table 7: Interaction effect

With MCI at	Relative Size	NHHI	Unitisation
75%	-2.62***	-0.02	0.15
80%	-2.26***	0.004	0.03
85%	-1.83***	0.03	-0.09
90%	-1.32***	0.05	-0.18
95%	-0.86***	0.06	-0.23*
100%	-0.45***	0.05	-0.22*