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Benchmarking Container Port Technical Efficiency in Latin America and the Caribbean

A Stochastic Frontier Analysis

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Abstract

This paper presents a technical efficiency analysis of container ports in Latin America and the Caribbean using an input-oriented stochastic frontier model. A 10-year panel is employed with data on container throughput, port terminal area, length of berths, and number of cranes available in 67 ports. The model has three innovations with respect to the available literature: (i) it treats ship-to-shore gantry cranes and mobile cranes separately, in order to account for the higher productivity of the former; (ii) a binary variable is introduced for ports using ships' cranes, treated as an additional source of port productivity; and (iii) a binary variable is used for ports operating as transshipment hubs. The associated parameters are highly significant in the production function. The results show an improvement in the average technical efficiency of ports in the Latin America and the Caribbean region from 36 percent to 50 percent between 1999 and 2009; the best-performing port in 2009 achieved a technical efficiency of 94 percent with respect to the frontier. The paper also studies possible determinants of port technical efficiency, such as ownership, corruption, terminal purpose, income per capita, and location. The results reveal positive, but weak, associations between technical efficiency with landlord ports and with lower corruption levels; stronger results are observed between technical efficiency with specialized container terminals and with average income.

This paper is a product of the Sustainable Development Department, Latin America and the Caribbean Region. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The author may be contacted at cbricenogarmendi@worldbank.org.

Produced by the Research Support Team

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1. Introduction

a. Context

The Latin America and the Caribbean (LAC) region is responsible for 8.0% of the world's GDP, is home to 8.5% of the world's population, and had an average annual economic growth of 4.9% during the period 2002–2012 (IMF, 2013), a higher rate than the worldwide average. Part of this consistent growth was brought about by an increasing interconnectedness to international markets that resulted in a notable growth of international trade. During the same period, the volume of merchandise exports grew by 44% and the volume of merchandise imports grew by 190% in South America. In the rest of the LAC region these two indicators increased by 50% and 55%, respectively (Unctad, 2013). The observed growth in trade has put pressure on the main international trade gateways of the region, and, as a result, LAC ports have been receiving significant attention from governments, regulators, and the private sector.

The importance of seaports to LAC's economic growth is rooted in the region's colonial history and natural endowment. Rather than intra-regional trade over land corridors, LAC's economy has long depended on seaborne international trade for income (from agricultural products and extractive industries exports) as well as consumer goods (from imports) purchased with the capital accrued from those commodity exports. Another determinant of the importance of maritime trade in LAC is the Panama Canal, a key element of the East-West main trade axis of the global economy, transforming the ports in Central America and the Caribbean into natural transshipment hubs, not only between the Northern and Southern hemispheres, but also between Asia, Europe, and both coasts of the USA. Because of the planned expansion of the Panama Canal by 2015 and, therefore, the traffic increase in the associated maritime routes, ports in the whole region have been under stress to prepare for higher demand and larger vessels.

Port expansions in countries such as Brazil, Argentina, and Mexico have been driven by the increase of exports and imports propelled by a significant growth in agricultural trade, moved as either bulk or container cargo. In other countries, such as Chile and Ecuador, ore and oil have been drivers of the expansion of the port sector, although merchandise trade of containerized commodities has also performed above expectations. This supply-led growth has taken place alongside a noticeable increase in household consumption and import demand for final, intermediate, and capital goods, propelled by the effect of appreciated exchange rates in many countries in the region. In 2011, LAC merchandise exports and imports reached US$886 and US$874 billion, respectively, 81% of which was mobilized through seaports (ECLAC, 2012).

Cargo in LAC is increasingly dispatched as container shipments, a situation that has led to an increasing trend of specialization of port terminals in container handling. At the regional level, container traffic more than doubled in the last decade from 17 million twenty-foot equivalent units (TEUs) in 2000 to 40 million TEUs in 2010 (World Bank, 2013b), with an average compound annual growth rate of 10%. More than one-third of these container flows can be traced to Brazil (19%) and

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Panama (16%) combined. In the case of Brazil, container traffic is driven by the size of its market, while in the case of Panama, transshipment is the leading factor. Mexico, Chile, and Colombia have 7% to 10% of the share of container flows each. Combined, Caribbean islands capture about 13% of containerized flows due to their strategic location connecting many intercontinental maritime routes (ECLAC, 2012). In Central America alone, containerized cargo represented only 40% of all cargo handled in 2003, by volume. By 2011 this share increased to 59% (COCATRAM, 2011). Another factor that has helped increase container traffic is larger ship sizes being acquired by shipping lines. According to CompairData (2013), the average capacity of container vessels servicing Latin America has doubled between 2000 and 2011, from roughly 2,000 TEUs to over 4,000 TEUs, a trend that has intensified since 2007.

On account of the continued maritime trade growth across LAC and the larger vessel sizes, many countries are already expanding their container handling facilities and setting in place institutional reforms to accommodate increasing demand. Beyond the major transshipment ports of the Caribbean and large container terminals of Brazil, Argentina, Uruguay and Chile, expansions can be seen even in the smaller sub-regions, such as Central America, where neighboring ports are competing for resources to retain and attract more direct liner services.

In terms of institutional reforms, from the early 1990s many LAC countries (including Argentina, Colombia, Chile, Brazil, Mexico, and Panama) started the dual processes of decentralization and concessions, transitioning ports to a landlord system with high foreign participation (Sanchez et al., 2004). In the last two decades, LAC countries have been very active in moving forward port service concessions. In our sample of 67 ports in the region, in 2009, almost two thirds had privately operated terminals under concession agreements.

b. Motivation

The dynamic growth in container shipments, ongoing investment in physical capacity, and institutional and market reforms indicate that both private and public actors in the region could benefit from a rigorous assessment of the current and achievable efficiencies in the LAC port sector. Several benchmarking studies have addressed efficiency calculations either through case studies or through estimation of technical efficiency frontiers; however, to the best extent of our knowledge none of these studies focused on a large sample of ports in LAC.

One of the reasons for the dearth of LAC-specific analyses to date has been the lack of data. In an effort to fill the existing gap of harmonized time series data and, therefore, develop an analysis of port technical efficiency in the region, we have put together a database that draws primarily on information provided in the Containerization International Yearbooks (Degerlund, 2009). While the information is available on a country-individual basis, the data are scattered over various publications and editions.

In order to assess port technical efficiency, we employed an econometric model based on a Stochastic Frontier Analysis (SFA). The model consists in the estimation of a production function for container terminals, in which cranes, berths, and terminal area are the inputs, while port container throughput is the output. As a result, time-varying technical inefficiency is calculated as part of the residual term, conditional on a set of independent variables, which is later transformed into a technical efficiency variable with range from 0 to 1. The results provide a guideline for understanding technical efficiency's explanatory factors and trends across time, sub-regions, and countries. Moreover, they are a valuable input for regulatory and operational decision making in the port sector.

The application of this model in LAC poses challenges in the attempt to consider all sources of productivity in container ports. The first challenge is the use of cranes mounted on vessels, which expedite the process of container handling, a routine usually seen more frequently in ports with limited infrastructure. Moreover, some ports in the Caribbean and in adjacent regions also benefit from quicker container turnaround due to the transshipment nature of their container traffic, *i.e.* transferring containers between vessels without requiring much terminal space and container processing time. In this paper we propose a methodology to account for the impact of these two characteristics on technical efficiency. The explicit inclusion of a variable that measures the impact of ships' cranes on productivity is a novel contribution.

In summary, we attempt to address several aspects of port technical efficiency: (i) the contribution of the different inputs related to container traffic; (ii) the level of technical efficiency in LAC ports and their relative position in the region; (iii) the growth of port technical efficiency between 1999 and 2009; and (iv) the explanatory factors of port technical efficiency.

The paper is structured as follows: Section 2 summarizes concepts and approaches used to assess efficiency, and the existing literature on port efficiency. Section 3 shows an analysis of the database. Section 4 provides a discussion of the model. Section 5 presents the estimation results and Section 6 provides an analysis of the results and benchmark of port technical efficiency in the region. Finally, Section 7 concludes.

2. Methodological Review

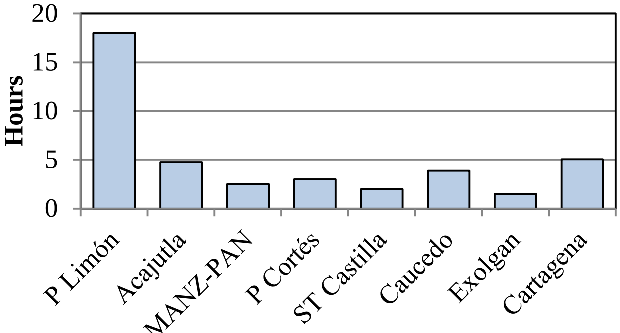
a. Port Efficiency and Other Measures of Performance

Oftentimes, port performance is associated with various measures of partial productivity, commonly defined as ratios of output volume to input volume, and with different measures of efficiency. The former productivity indicators are usually related to time variables that aim to assess, for example, how fast cargo is handled. Examples of these indicators include *moves per ship-hour, moves per crane-hour*, *ship delay*, *ship dwell time* and *ship productivity*, among other indicators (Box 1). These types of port indicators provide important operational efficiency measures and, combined, can draw a detailed picture of performance along the various stages of maritime shipping. However, there is a difficulty in gathering consistent time series data of partial productivity indicators for very large samples of ports. In LAC, for example, recent efforts to compile partial performance indicators in small sets of ports in the region include Kent (2011) and IADB (2013).

Box 1: Examples of Partial Performance Indicators

Ship Delay: This measure reflecting the availability of berth and gangs is calculated by subtracting the original scheduled time of the vessel's arrival at the port from the time the vessel arrives at the berth (second line tied) and is ready to work. Zero delay is ideal, but a delay of up to four hours can be absorbed in the vessel's itinerary.

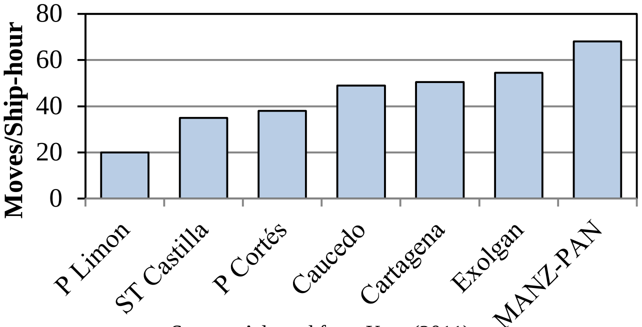
Figure i: Container Vessel Delay in Central American Ports



Source: Adapted from Kent (2011)

Ship Productivity: Probably the most commonly used measure of terminal performance, ship productivity is based on the number of moves per hour during a vessel's net berth time (see Figure 1). Net berth time is measured from the time the first gang appears on the vessel to the departure of the last gang from the vessel. Ship productivity is calculated by dividing the number of moves by net berth time measured in hours (moves/hour).

Figure ii: Ship Productivity for Calls Involving Moves between 500 and 1000



Source: Adapted from Kent (2011)

Efficiency is a relative concept that requires a clear definition of a benchmark, in order for operators to be compared among themselves and against their own performance over time (Liu, 2010). It can be defined in several ways, each serving a different purpose. Economic efficiency is achieved when resources are used in a way that production is maximized at the lowest cost. Allocative efficiency is achieved when production is at the level desired by society and the marginal benefit of the last unit produced equals its marginal cost. Lastly, technical efficiency, a pre-requisite for economic efficiency, is when a firm is producing the maximum output with the lowest quantity of inputs required.

Taking into account the various concepts and indicators of efficiency and performance, their strengths, drawbacks and computational challenges, in this paper we benchmarked technical efficiency by using an approach widely used in the port performance literature, the estimation of technical efficiency frontiers. For that purpose, the database compiled for this paper feeds an econometric estimation that assesses the inputs determining port throughput levels, including all physical assets required for port operations.

b. Approaches to Technical Efficiency Frontiers

The two main approaches used to calculate technical efficiency are Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA); both rely on the estimation of an efficiency frontier. The frontier is determined by the best possible performance drawing on information from the sample.

In the case of DEA, the frontier is obtained by identifying the highest potential output under different input combinations through linear programming, and the degree of efficiency is measured by the distance between the observation and the frontier (Liu, 2010). A drawback of this methodology is that sample measurement error and random variation are simply assumed away and deviations from the frontier are attributed solely to inefficiency (Mortimer, 2002). On the other hand, the SFA approach relies on the parametric estimation of a production function with a stochastic component. The error term is composed of two random effects, one capturing the statistical noise and the other the technical efficiencies. Once the frontier is estimated, the efficiency is also measured by the distance between the observation and the frontier. Table 1 shows the main differences between DEA and SFA.

Table 1: Characteristics of DEA and SFA

DEA	SFA
Non-parametric approach	Parametric approach
Deterministic approach	Stochastic approach
Does not consider random noise	Considers random noise
Does not allow statistical hypothesis to be contrasted	Allows statistical hypothesis to be contrasted
Does not impose assumptions on the distribution of the inefficiency term	Imposes assumptions on the distribution of the inefficiency term
Does not include error term	Includes a compound error term: one of one side and the other symmetrical (two queues)
Does not require specifying a functional form	Requires specifying a functional form
Sensitive to the number of variables, measurement errors, and outliers	Can confuse inefficiency with a bad specification of the model
Estimation method: mathematical programming	Estimation method: econometric

Source: Trujillo et. al. (2013)

Along these lines, the frontier approach is known for having distinguished advantages and potential weaknesses. On the one hand, calculating an efficient frontier by utilizing data on factors of production is feasible in large-scale benchmarks with time series data. On the other, among the main critiques to these methodologies, is the fact that measurement error can play a role in the results and that stochastic frontiers might deliver biased estimates due to problems with the specification of the underlying production technology (Mortimer, 2002); we have carefully contemplated these points in the discussion of our methodology choice and estimation strategy.

After assessing the applicability, strength and weaknesses of both methods, and since we are also interested in understanding the dynamics between input and output variables, and the determinants of port technical efficiency, we have opted to carry out a Stochastic Frontier Analysis. One of the elements determining our choice is that this methodology benefits from the possibility to control for exogenous factors, such as the intervention of dummy variables for the utilization of ships' cranes and port transshipment activities, which are other determinants of port performance. In addition, the literature suggests that SFA is more accurate when the sample size reaches a threshold of 50 units (our database has 67 ports and spans 10 years) and distributional assumptions mirror actual distributions of noise and inefficiency. Along these lines, previous research indicates that SFA is more appropriate to deal with measurement error, which is likely to be present in large time series databases (Banker et al., 1993).

In a comparative analysis of the methodological merits of the Stochastic Frontier Analysis and Data Envelopment Analysis, Cullinane (2006a) found high correlations between the results obtained from both models (ranging between 0.63 to 0.80, depending on the specification), suggesting that DEA results are also robust under the distributional assumptions of SFA. We also performed a DEA analysis to compare with the results obtained using an SFA approach, and found a positive correlation of the technical efficiency term of 0.62. A detailed comparison of these results can be found in Annex 3.

c. The Stochastic Frontier Model

In the literature, Stochastic Frontier Analysis is a common tool used to measure firms' technical efficiency. The original idea of a frontier was proposed by Farrell (1957), but it was not until Aigner et al. (1977) and Meeusen and van den Broeck (1977) that frontier analysis was introduced as a regression method that incorporates an inefficiency term, which is later transformed into a technical efficiency variable ranging from 0 to 1. Subsequently, Battese and Coelli (1992) laid the ground for the application of time-varying frontier methods with panel data.

In short, the stochastic frontier approach is based on a production function that requires knowledge of the input variables explaining observed output. The basic form of the equation is given by:

$$y_{it} = \exp(\alpha + x'_{it}\beta + v_{it} + u_{it}), \quad \text{for } t \in \tau(i); i = 1,2,\dots,T. \qquad \text{(I)}$$

where y_{it} is output and x_{it} is a vector of inputs for each observation i and time period t. β is a vector of unknown parameters and α is a constant. $\tau(i)$ is a set of T_i time periods among existent time periods for which observations are available for the ith firm.

The SFA key features are the assumptions imposed over the error term, which help to disentangle statistical noise (random shocks) from the residual term representing inefficiency. In (I), v_{it} are assumed to be a two-sided independent and identically distributed $N(0,\sigma_v)$ random error. Moreover, u_{it} are assumed to be a one-sided independent and identically distributed random variable associated with technical inefficiency, which is later transformed into a technical efficiency variable for the calculation of the frontier. Henceforth, we will use *inefficiency* to refer to the random term u_{it}, and *efficiency* to refer to the variable that characterizes the frontier and ranges from 0 to 1.

In the attempt to study potential explanatory variables for efficiency, up until Battese and Coelli (1995), most papers used to adopt a two-stage approach, first estimating the stochastic frontier, and then using exogenous factors to explain efficiency with the specification of a second regression model. Nevertheless, the second stage disregards the fact that, in the first, the efficiency term is assumed to be an independent and identically distributed variable, leading to biased results. Battese and Coelli (2005) developed a one-stage model incorporating the explanatory factors of efficiency by fitting a conditional mean model to u_{it} in the estimation. The model is given by:

$$u_{it} = z_{it}\delta + w_{it} \qquad \text{(II)}$$

where z_{it} is a set of explanatory variables associated with technical inefficiency over time, δ is a vector of unknown parameters and w_{it} is defined by the truncation of a normal distribution with mean zero and standard deviation σ^2. These assumptions are consistent with u_{it} being a non-negative truncation of the normal $N(z_{it}\,\delta,\sigma_u)$ (Battesi and Coelli, 1995).

Once the assumptions are set, technical efficiency in each observation can be computed by comparing the observed output in each firm against the output if there were no inefficiencies of production. These estimates are calculated with the equation below:

$$TE_{it} = exp(-z_{it}\delta - w_{it}) \qquad \text{(II)}$$

TE_{it} or technical efficiency is a variable ranging between 0 and 1, in which the maximum value represents the technical efficiency frontier.

d. Application of Frontier Analysis in the Port Sector

The application of frontier analysis in the port sector is relatively recent, starting with a study by Liu (1995), which measured the efficiency of 28 public and private ports in the UK for the period between 1983 and 1990. The author concluded that port ownership, one of the considered inputs, did not have a significant impact on output (turnover). Aside from port ownership, the study considered other input variables such as labor and capital. Similarly, Tongzon and Heng (2005) used SFA to shed light on the relationship between ownership and efficiency of 25 ports across Asia and Europe, using container throughput as the output variable, and terminal quay length, terminal surface, and the number of quay cranes as inputs. They concluded that private sector participation can improve the efficiency of port operations.

Coto-Millan et al. (2000) used SFA to measure the efficiency of 27 Spanish ports with a translog cost function, finding a negative relationship between port size and efficiency in the sample. More recently, to assess the evolution of Spanish port efficiency, Gonzalez and Trujillo (2009) used a translog distance production function with a panel data from 17 Spanish ports from 1990 to 2002, showing that the average technical efficiency had changed little over time. Similarly, Estache et al. (2002) used SFA to measure the efficiency of 13 Mexican ports following a port reform. The variables included in the study were the volume of merchandise handled (output), the number of workers and the length of docks (the last two as inputs).

Notteboom et al. (2000) is an example of a region-wide analysis of port efficiency (with 36 European terminals) using terminal quay length, terminal surface area, and terminal gantry cranes as inputs, and terminal traffic in twenty-foot-equivalent units (TEUs) as the output variable. The authors conclude that terminals of hub ports, on average, are more efficient than those in feeder ports. More recently, Trujillo et al. (2013) applied SFA to the Africa region, analyzing a total of 37 ports. Using interactions among several input variables, the paper concludes that landlord ports show the highest level of efficiency. The overall average port efficiency for the period was low, 30%.

To the best extent of our knowledge, Stochastic Frontier Analysis has never been used to analyze port performance across LAC, although other studies have discussed port efficiency in the region relying on partial performance indicators or on Data Envelopment Analyses applied to a limited group of ports, countries or sub-regions of LAC. For example, Kent (2011) and IADB (2013) present a review of a set of partial productivity indicators in Central America ports, such as port productivity or port delay. Moreover, a survey of 19 LAC ports by Sanchez et al. (2003) provides measures of port efficiency specifically focused on time performance and terminal productivity, associating these variables with country competitiveness (measured in terms of waterborne transport costs). The study does not seek to provide a relative assessment (ranking) of the region's ports or a measure of the evolution of efficiency over time.

Ramos and Gastaud (2006) applied DEA to MERCOSUR using five inputs (number of cranes, number of berths, number of employees, size of terminal area, and amount of yard equipment) and two output variables (annual TEUs handled and average number of containers handled per hour/ship. By considering five inputs, three years (2002-2004) and twenty-three ports, the paper finds that 60% of ports in MERCOSUR are efficient during that three year period.

Wilmsmeier et al. (2013) applied DEA to analyze technical efficiency evolution in 16 container terminals in LAC and 4 container terminals in Spain between 2005 and 2011. The authors focused on evaluating the impact of the financial crisis on productivity and efficiency, concluding that these terminals were particularly exposed to demand shocks and have difficulty to react effectively to these changes.

3. Data

This paper gathered data from 67 ports with container terminals in 27 countries in the region, covering 18 ports in Central America and Mexico, 14 ports in the Caribbean and 35 ports in South America (Table 2). All are gateways for imports/exports traded in containers for each country, representing around 90% of the container cargo handled by the region.

Table 2: Summary of the Ports in the Sample

Region	Country	Container Ports
Central America and Mexico	**Costa Rica**	Puerto Caldera, Puerto Limón
	El Salvador	Acajutla
	Guatemala	Puerto Barrios, Puerto Quetzal, Santo Tomás de Castilla
	Honduras	Puerto Castilla, Puerto Cortés
	Mexico	Altamira, Ensenada, Lázaro Cárdenas, Manzanillo-MEX, Progreso, Veracruz
	Nicaragua	Corinto
	Panama	Balboa, Colón CT, Puerto Manzanillo-PAN
Caribbean	**Aruba**	Oranjestad
	Bahamas	Freeport
	Barbados	Bridgetown
	Cuba	Havana
	Dominican Republic	Caucedo, Rio Haina
	Martinique	Fort-De-France
	Guadeloupe	Pointe-A-Pitre
	Jamaica	Kingston
	Netherlands Antilles	Willemstad
	Puerto Rico	San Juan
	Saint Lucia	Vieux Fort
	Trinidad and Tobago	Point Lisas, Port of Spain
South America	**Argentina**	Buenos Aires (excl. Exolgan), Exolgan, Rosario, Zarate
	Brazil	Belém, Fortaleza, Iitajaí, Manaus, Paranaguá, Pecém, Rio De Janeiro, Vitória, Rio Grande, Salvador, Santos, São Francisco do Sul, Sepetiba, Suape
	Chile	Antofagasta, Arica, Iquique, Lirquén, San Antonio, San Vicente, Valparaíso
	Colombia	Barranquilla, Buenaventura, Cartagena, Santa Marta
	Ecuador	Guayaquil
	Peru	Callao, Paita
	Uruguay	Montevideo
	Venezuela	La Guaira, Puerto Cabello

The database was primarily populated from information published in Containerization International Yearbook from various years. It spans 10 years (1999–2009) and contains key port infrastructure indicators such as berth length, port area, number of mobile and quay cranes[3], and number of ship-to-shore (STS) gantry cranes. It also includes annual container throughput in TEUs. Since the focus of this paper is on container terminals, the database is limited to output measures related to the volume of containerized cargo. This is the same approach as in Coto-Millan et al. (2000), supported by the fact that a large portion of the cargo in Latin America is dispatched in containers and this proportion is rapidly increasing, as discussed in Section 1. The original data are available at the terminal level; however, figures were aggregated at the port level when needed for comparative purposes.

The database includes data for ports with a wide range of sizes and infrastructure endowments (Table 3). On average, Caribbean ports in the sample move annually about 455,000

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[3] Only cranes with over 14 tons capacity were considered, a capacity required to handle a 20-foot container.

TEUs, driven by the transshipment activity anchored in Puerto Rico, Jamaica, Bahamas, Dominican Republic, among other smaller countries. That is more throughput than the average in the rest of LAC sub-regions. Nevertheless, this average masks intra-regional variations. The smallest Caribbean port in the sample, Vieux Fort, has an annual average movement of about 33,000 TEUs, which drastically contrasts with Kingston, the second-largest transshipment hub of the continent, which moved roughly 2 million TEUs in 2008 and 2009. Similarly, ports in Central and South America show enormous contrasts and disparities in traffic patterns (see Annex 1 for details).

In terms of infrastructure assets, South American ports possess on average longer total berth lengths and larger terminals, averaging 1,262m and 299,502m^2 respectively. Nevertheless, the number of gantry cranes in Central America and the Caribbean is higher due to the transshipment activity, mainly in Panama and in Caribbean islands.

Table 3: Descriptive Statistics, Averages by Sub-region over the Period 1999–2009

Region	**Number of Ports**		**Annual Throughput (TEU)**	**Berth Length (m)**	**Area (m^2)**	**Mobile Cranes with Capacity>14t (units)**	**STS Gantry Cranes (units)**
Central America and Mexico	18	Average	403,069	722	174,083	0.8	2.6
		Minimum	31,527	150	15,000	0	0
		Maximum	1,235,869	2,205	431,818	5	11
Caribbean	14	Average	455,102	837	268,405	1.3	3.4
		Minimum	32,969	250	32,400	0	0
		Maximum	1,731,039	3,180	1,037,67	5	13
South America	35	Average	348,328	1,262	299,502	3.0	1.7
		Minimum	27,933	250	15,000	0	0
		Maximum	1,847,604	4,485	933,000	37	12
Total	67	Average	385,345	1,029	259,309	2.0	2.3
		Minimum	27,933	150	15,000	0	0
		Maximum	1,847,604	4,485	1,037,67	37	13

Source: Containerization International Yearbook, various years. See Annex 1 for port-specific data.

As shown in Table 4, in our sample, total container throughput increased 210% in the LAC region at a compound annual growth rate of 12%, despite the fall during the economic international crisis in 2008–2009. The data also show that the sub-region most affected by the crisis was Central America, with an 18% decrease in container throughput from 2008 to 2009, followed by the Caribbean. In turn, South America has been the region with the fastest growth.

Table 4: Throughput Growth by Sub-Region

	Growth 1999–2009	**Compound annual growth rate**	**Throughput decrease 2008–2009**
Central America and Mexico	205%	12%	-18%
Caribbean	89%	7%	-12%
South America	328%	16%	-8%
Grand Total	210%	12%	-12%

Source: Own calculation based on Containerization International Yearbook (1999–20009)

In addition to the container port database, we also collected other variables that are important to explain port throughput and technical efficiency. First, we identified which ports have landlord models, that is, have at least one terminal under concession to the private sector (these data were collected using the Containerization International Yearbook). The data show that, in 2009, 61% of the sampled ports have terminals with private operations; this percentage is the largest in the Caribbean (72%) and the lowest in Central America/Mexico (45%). Second, we collected information on whether a port is specialized in container traffic or serves as a multi-purpose facility, that is, also operates general cargo or bulk (collected using the Containerization International Yearbook). The data show that 40% of the ports in the sample mainly operate containers; this percentage is the largest in the Caribbean (57%) where most of the transshipment ports are located and is the lowest in South America (28%).

Regarding variables at the country level, per capita income (in constant US$) from the World Development Indicators (WDI) was collected, it measures average income levels. In addition, liner shipping connectivity (produced by UNCTAD), an index number in which the highest index in 2004 is equal to 100, measures how well countries are connected to the global shipping network. GDP (in constant US$), extracted from the WDI, measures the size of the economies. Trade openness (in GDP percentage), also collected in the WDI, measures the degree to which countries import and export merchandise with the rest of the world. Finally, as a measure of the perception of corruption in the public sector, we collected a corruption index from Transparency International, ranging from 0 (highly corrupt) to 10 (highly clean).

4. Model

A starting point to assess port efficiency in LAC using an SFA methodology is the specification of a translog stochastic production frontier, such as in Liu (1995), Cullilane (2006b), and Trujillo et al. (2013), and described in Equation 1.

$$ln(Q_{it}) = \alpha + \beta_1 ln(A_{it}) + \beta_2 ln(B_{it}) + \beta_3 ln(C_{it}) + \beta_4 T_t + v_{it} + u_{it} \quad (1)$$

These variables are defined as follows:

$\forall \mathrm{i} = 1, \dots, \mathrm{N}$ and $\mathrm{t} = 1, \dots, \mathrm{T}$

Q_{it} is the container throughput (in TEUs) handled by port i in period t; A_{it} is the total area (in squared meters) of the container terminals in port i in period t; B_{it} is the total length (in meters) of berths used for container handling in port i in period t; C_{it} is the number of container cranes owned by port i in period t; and T_t is a time trend that captures overall changes in productivity through time[4]. In the model, v_{it} is a random error term assumed to be independent from u_{it}, which is assumed to be a truncated-normal random variable associated with technical inefficiency, as detailed in Section 2.

Other noteworthy input variables not contemplated in this model are labor and energy consumption. In container terminals, nevertheless, these variables play smaller roles, since container handling is highly infrastructure intensive and, as a result, the throughput elasticities of inputs such as workforce and energy consumption are expected to be relatively low. In this regard, our production function assumes implicitly that workforce and energy consumption are fixed for each unit of

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[4] In the original specifications by Cullilane (2006b), and Trujillo et al. (2013), the model also included interaction terms between all independent variables. We have also estimated such specifications, but the interaction terms were not significantly different from zero, therefore we omit the presentation and discussion of such results.

infrastructure (*e.g.* that the labor and energy required for operating a STS gantry crane is the same across ports in LAC).

On a different note, working hours of ports in the region could also play a role in the identification of model parameters. If the number of weekly hours of port operations varied, it would be necessary to normalize the use of port infrastructure per working hours. However, according to the figures from Containerization International, all terminals in the sample were open to business 24 hours a day, seven days a week. As a result, working hours do not impact the estimations: occasional idle infrastructure is part of the technical inefficiency once the port can be continuously open for business.

Representing a departure from the standard port production function usually employed in the literature, our database allows us to breakdown the type of cranes owned by a port between mobile/quay cranes (with container handling capacity) and STS gantry cranes. Clearly, these two inputs are expected to have different impacts on throughput[5], since a typical STS gantry crane in LAC can move at least 50% more containers per hours than a typical mobile crane (Kent, 2011). In the model, we identified these two variables as MQC_{it} and GC_{it}, respectively.

A challenge related to the use of these inputs is that a Cobb-Douglas production function fails to capture the effects of variables when their values are zeros. In our model, MQC_{it} and GC_{it} are non-essential inputs, since container terminals might use, alternatively, mobile cranes, STS gantry cranes or even ships' cranes to move containers. As a result, in a translog model, observations with zero non-essential inputs would drop out of the sample because the log of zero is unidentified. In our sample, a total of 42 ports doesn't have either mobile/quay cranes or STS gantry cranes in 2009, and 8 of these ports had no cranes whatsoever. In the literature, different solutions have been assessed, such as using quadratic functional forms, resampling techniques, or substituting a small value for the zero observations (Moss, 2000). According to Soloaga (2000), adding a constant to the variable for every observation in the sample can be a solution with little impact to the parameter estimation, depending on the degree of essentiality of the variable. Therefore, in order to maintain the original sample with ports that have zero non-essential inputs, we added one unit to MQC_{it} and GC_{it}. Equation 2 shows the translog model after modifications.

$$ln(Q_{it}) = \alpha + \beta_1 ln(A_{it}) + \beta_2 ln(B_{it}) + \beta_3 ln(MQC_{it}) + \beta_4 ln(GC_{it}) + \beta_5 T_t + v_{it} + u_{it} \qquad (2)$$

a. Use of Ships' Cranes

There are two possible ways to offload containers from ships to terminals: using cranes in the terminal or cranes mounted directly on ships. Therefore, the use of ships' cranes has to be taken into account when estimating port efficiency because they represent a port-exogenous asset that is fundamental for the productivity of terminals with modest infrastructure (*i.e.* container ports that do not have any crane, or have just a few, but have a relatively high level of throughput). As a result, disregarding the use of these "shared" assets would benefit the technical efficiency of ports that often rely on ships' cranes to handle containers whenever this input is omitted as an explanatory variable in the estimation.

In order to account for this heterogeneity, we created a dummy variable that takes the value of 1 when ports are likely to make an intense use of ships' cranes to handle containers. Thus, this

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[5] Further disaggregation of crane information, for example, by equipment age or crane reliability, is not possible due to data limitations, although these characteristics also play a role in the explanation of crane productivity.

dummy attempts to offset the artificial efficiency advantage generated from the absence of this variable as an input in the regression. The criteria we used to classify ports as likely to use ships' cranes are:

1) As a rule-of-thumb, we considered that the productivity of a quay or mobile crane does not exceed 130,000 TEUs per year,[6] and that the productivity of a STS gantry crane does not exceed 390,000 TEUs per year[7]. Therefore, ports in 2009 with throughput in excess of that predicted by the use of all own cranes combined, under the above criteria, are considered to be using ships' cranes intensively for handling cargo.

2) Ports that had no mobile, quay or STS gantry cranes for loading or unloading containers in 2009[8].

The ports meeting these two criteria are shown in *Table 5*. It is important to highlight that this list does not include all ports that make use of ships' cranes, but only those that use are likely to use ships' cranes more often according to the criteria.

Table 5: Proxy for Ports Using Ships' Cranes Often

Ports That Meet the First Criteria	Ports That Meet the Second Criteria
Puerto Cortés-HON	Arica-CHL
Buenaventura-COL	Callao-PER
San Vicente-CHL	Paita-PER
Puerto Quetzal-GUA	Puerto Barrios-GUA
Puerto Limón-CRI	Puerto Caldera-CRI
Manaus-BRA	Puerto Castilla-HON
Santo Tomás de Castilla-GUA	Rosario-ARG
Acajutla-SLV	Santa Marta-COL

Source: own calculations

Consequently, the modified equation becomes:

$$ln(Q_{it}) = \alpha + \beta_1 ln(A_{it}) + \beta_2 ln(B_{it}) + \beta_3 ln(MQC_{it}) + \beta_4 ln(GC_{it}) + \beta_5 T_t + \gamma_1 Ships'Cranes_i + v_{it} + u_{it} \quad (3)$$

where *Ships'Cranes*$_i$ is a dummy for ports that utilize ships' cranes more intensively for container handling.

b. Container Transshipment

Another form of productivity boost that is not captured directly by the model is transshipment traffic. Transshipment ports use their available infrastructure differently because most of the containers are in transit. In transshipment ports, containers have to be offloaded and loaded at higher speeds to optimize transit times without much use of port resources such as storage, yard infrastructure and customs. To capture this port characteristic, we introduce a binary variable that takes the value of 1

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[6] A crane operating 24 hours a day and 365 days per year and moving 15 TEUs per hour would move 130,000 TEUs annually. We consider this is a sufficiently high upper-bound for the annual productivity of an average crane. Kent (2011) finds that in its sample of ports, the average productivity of a mobile crane is under 15 moves per hour.

[7] Considering that modern STS gantry cranes can perform up to 45 moves per hour.

[8] We applied these criteria for the year 2009.

when a port specializes in transshipment. The inclusion of this dummy allows accounting for the advantage that these ports may have in overall efficiency calculations. The list of ports whose cargo is composed mostly of transshipment is given below, as identified by Frankel (2009):

Table 6: List of Transshipment Ports

Transshipment Ports
San Juan-PRI
Kingston-JAM
Freeport-BAH
Caucedo-DOM
Balboa-PAN
Puerto Manzanillo-PAN
Colon Container-PAN
Cartagena-COL
Puerto Cabello-VEN

Equation (4) accounts for the use of ships' cranes and the transshipment status of ports:

$$\begin{aligned} ln(Q_{it}) = \alpha + \beta_1 ln(A_{it}) + \beta_2 ln(B_{it}) + \beta_3 ln(MQC_{it}) + \beta_4 ln(GC_{it}) + \beta_5 T_t \\ + \gamma_1 Ships'Cranes_i + \gamma_2 Transship_i + v_{it} + u_{it} \end{aligned} \tag{4}$$

where *Transship*$_i$ is a dummy for ports that specialize in transshipment.

c. Other Explanatory Variables

In our model specification we also take into account specific variables (other than inputs) affecting port output and efficiency by controlling for factors that are exogenous to ports. To this end, we have selected variables that are likely to play a role in the determination of port container throughput. These variables are incorporated into equation (5):

$$\begin{aligned} ln(Q_{it}) = \alpha + \beta_1 ln(A_{it}) + \beta_2 ln(B_{it}) + \beta_3 ln(MQC_{it}) + \beta_4 ln(GC_{it}) + \beta_5 T_t \\ + \gamma_1 Ships'Cranes_i + \gamma_2 Transship_i + \gamma_3 TerminalType_{it} \\ + \gamma_4 ln(GDP_{it}) + \gamma_5 ln(Connectivity_{it}) + \gamma_6 ln(Trade_{it}) + \gamma_7 Crisis_t \\ + v_{it} + u_{it} \end{aligned} \tag{5}$$

where $TerminalType_{it}$ is a binary variable that assumes the value of 1 when all terminals in port i and period t are specialized in container handling and 0 if the port has multipurpose terminals; GDP_{it} is the output in period t of the country in which port i is located (in constant US dollars); $Connectivity_{it}$ is the liner shipping connectivity index in period t of the country in which port i is located; $Trade_{it}$ is the trade openness (as a share of GDP) in period t of the country in which port i is located. In addition, due to the international financial crisis that impacted worldwide container throughput, we also introduced a binary variable that takes the value 1 in the year 2009.

Moreover, following the model specification in Battese and Coelli (1995), discussed in Section 2, we introduced independent explanatory variables for the inefficiency term. Along these lines, the model for the technical inefficiency effects in the stochastic frontier is defined by:

$$\begin{aligned} u_{it} = \delta_1 + \delta_2 Landlord_{it} + \delta_3 Corruption_i + \delta_4 TerminalType_{it} + \delta_5 \ln(GDPpc_{it}) + \\ \delta_6 SouthAmerica_i + \delta_7 Transship_i + \delta_8 T_t + w_{it} \end{aligned} \tag{6}$$

where $Landlord_{it}$ is a dummy that takes the value 1 if port i had a landlord model in period t; $Corruption_{i}$ is the corruption index in period t=T in the country in which port i is located[9]; $SouthAmerica_{i}$ is a dummy that takes the value 1 if port i is located in that sub-region; and $GDPpc_{it}$ is the income per capita in period t of the country in which port i is located (in constant US dollars). Three other variables ($TerminalType_{it}$, $Tranship_{i}$ and a linear trend) are used as explanatory factors for both output and efficiency. The distributional assumptions of the efficiency term allow the set of explanatory variables in the efficiency model to include variables from the stochastic frontier, provided the inefficiency effects are stochastic (Battese and Coelli, 1995).

5. Estimation Results

Table 7 summarizes the maximum-likelihood estimation results of the production function and technical efficiency parameters in a time-variant frontier model. We first estimate a model as specified in equation 2; its results are presented in column 1. Specifications (2) to (4) incorporate other inputs and explanatory variables into the basic model. Finally, columns 5 to 8 provide the results for the parameters of the stochastic frontier and inefficiency model.

All specifications show that port area, berth length and the number of mobile cranes and STS gantry cranes have a positive and significant impact on throughput levels, an intuitive result for inputs in production functions. Moreover, there is a significant difference between the elasticities for mobile cranes and for STS gantry cranes, confirming the need to consider these two types of crane separately in the estimations. In all eight alternative specifications presented in *Table 7*, the STS gantry crane elasticity is at least twice as the mobile crane elasticity. On another note, the results show that the coefficient associated with berth length is larger than the one associated with port area, providing evidence of the importance of ample space for the mooring of vessels.

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[9] Time series not available for this variable, therefore we used the observation in 2009 for every period.

Table 7: Maximum Likelihood Estimates of the Stochastic Frontier

	Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
β_1	Area	0.12**	0.19**	0.21**	0.24**	0.21**	0.23**	0.20**	0.23**
		(0.03)	(0.03)	(0.02)	(0.02)	(0.01)	(0.02)	(0.03)	(0.02)
β_2	Berth Length	0.51**	0.38**	0.41**	0.43**	0.42**	0.46**	0.39**	0.44**
		(0.04)	(0.04)	(0.03)	(0.02)	(0.02)	(0.03)	(0.05)	(0.01)
β_3	Mobile/Quay Cranes	0.13**	0.25**	0.22**	0.19**	0.21**	0.23**	0.18**	0.22**
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)
β_4	STS Gantry Cranes	0.56**	0.68**	0.58**	0.49**	0.52**	0.48**	0.54**	0.49**
		(0.04)	(0.04)	(0.03)	(0.05)	(0.04)	(0.02)	(0.03)	(0.02)
β_5	Linear Trend	0.04**	0.02*	0.03**	0.01	-0.02**	-0.02**	-0.03**	-0.02**
		(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)
γ_1	Ships' Cranes		0.75**	0.63**	0.60**	0.79**	0.70**	0.86**	0.67**
			(0.08)	(0.06)	(0.05)	(0.05)	(0.12)	(0.06)	(0.04)
γ_2	Transshipment		0.49**	0.40**	0.38**	0.39**	0.31**	0.45**	0.31**
			(0.07)	(0.07)	(0.06)	(0.06)	(0.10)	(0.09)	(0.02)
γ_3	Terminal Type			0.38**	0.39**	0.17**	0.31**	0.10	0.29**
				(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)
γ_4	GDP				-0.05*	-0.08**	-0.06	-0.10**	-0.05**
					(0.02)	(0.01)	(0.05)	(0.02)	(0.01)
γ_5	Connectivity				0.58**	0.59**	0.74**	0.55**	0.69**
					(0.11)	(0.03)	(0.10)	(0.04)	(0.07)
γ_6	Trade				0.13	0.12**	0.20	0.05	0.24**
					(0.09)	(0.04)	(0.16)	(0.08)	(0.05)
γ_7	Crisis	-0.14	-0.10	-0.13	-0.06*	-0.07**	-0.04*	-0.08**	-0.01
		(0.11)	(0.10)	(0.08)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
α	Constant	7.55**	6.95**	6.95**	5.00**	6.04**	4.63**	7.08**	4.61**
		(0.41)	(0.37)	(0.27)	(0.54)	(0.63)	(1.16)	(0.97)	(0.30)
δ_1	Constant	0.07	-8.24	0.78**	0.70**	1.65**	1.35	4.55**	1.21**
		(0.75)	(23.27)	(0.13)	(0.09)	(0.22)	(1.84)	(1.30)	(0.14)
δ_2	Landlord					-0.22	-0.11		
						(0.13)	(0.14)		
δ_3	Corruption					-0.11	-0.30		
						(0.16)	(0.25)		
δ_4	Terminal Type					-0.35*		-0.58**	
						(0.14)		(0.21)	
δ_5	GDP per capita						0.03	-0.32*	
							(0.22)	(0.14)	
δ_6	South America						0.06	-0.22	-0.11
							(0.14)	(0.17)	(0.12)
δ_7	Transshipment						-0.23		-0.34*
							(0.29)		(0.15)
δ_8	Trend					-0.08**	-0.06*	-0.09**	-0.05**
						(0.02)	(0.02)	(0.03)	(0.02)
	σ^2_u	1.02**	2.38	0.89**	0.90**	0.88**	0.86**	0.92**	0.87**
		(0.19)	(2.73)	(0.06)	(0.06)	(0.05)	(0.05)	(0.07)	(0.05)
	σ^2_v	0.44**	0.44**	0.11**	0.00	0.00	0.00	0.00	0.00
		(0.07)	(0.06)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	λ	2.31**	5.42*	8.49**	11833**	8527**	10448**	6467**	5176**
		(0.18)	(2.69)	(0.06)	(0.06)	(0.05)	(0.05)	(0.07)	(0.05)
Observations		**599**	**599**	**599**	**566**	**566**	**566**	**566**	**566**
Number of Ports		**67**	**67**	**67**	**63**	**63**	**63**	**63**	**63**

Standard Errors in Parentheses. *p<0.05, **p<0.01.
Source: Authors' calculations.

Specifications (2) to (8) include a proxy for the use of ships' cranes. This binary variable is highly significant and positive, confirming the intuition that the use of cranes mounted on vessels is a determinant of port throughput in Latin America. Disregarding this dummy would cause a potential omitted variable bias in the model, affecting the estimated parameters and the efficiency results, especially in ports that rely heavily on the use of ships' cranes. The interpretation of this binary parameter in terms of the log-transformed dependent variable is that throughput is, on average, 105% higher in ports using ships' crane intensively, what is expected in small ports with limited number of cranes. Another interpretation is that, in ports using ships' cranes, on average over half of their throughput is handled with ship gear.

Specification (2) also adds a binary variable that identifies the ports specialized in transshipment traffic. The estimated effect is highly positive and significant, showing that these ports experience a boost in productivity due to the expedited nature of their container handling. In this case, the interpretation of the parameter in terms of the log dependent variable is that transshipment traffic translates into an expected average increase of 47% in container throughput.

The next specification incorporates into the model the binary variable that indicates the ports that are specialized in container handling. This control variable in the production function shows that specialized ports tend to have more container traffic. On average, container ports, compared with multipurpose ports (that also handle bulk or general cargo), have 31% more container throughput.

Among the control variables incorporated into equation (4), GDP accounts for the size of the domestic market as a determinant of container throughput in each port. In specifications (4), (5), (7) and (8) this variable is negative and significantly different from zero, despite a relatively low elasticity (between -0.05 and -0.10). A plausible interpretation for this finding is that smaller economies concentrate their maritime container traffic in one or few large ports (such as Uruguay, Costa Rica and Ecuador), while larger economies distribute their container traffic through a network of large, medium and small ports (such as Brazil, Colombia and Mexico). A second control variable measuring national liner shipping connectivity has a positive and significant relationship with port throughput. Finally, specifications (5) and (8) point out that merchandise trade as a share of GDP (trade openness) is a driver of port throughput, while the remaining estimations in specifications (4), (5) and (7) indicate that the same elasticity is positive but not significantly different from zero.

To provide an analysis of the relationship between port technical inefficiency and its potential determinants, specifications (5) to (8) estimate the inefficiency frontier model involving a set of explanatory factors. The results show interesting aspects. First of all, the Landlord coefficient is negative, which indicates that ports that have privately operated terminals tend to be less inefficient. The negative estimate for Corruption implies that ports located in countries perceived to be less corrupt are less inefficient. The sign of this association is intuitive, providing evidence that privately operated ports in countries with stronger institutions (*i.e.* lower corruption levels) are closer to the efficiency frontier. However, these relationships are weak (not statistically different from zero), because the coefficients are small relative to their estimated standard errors.

The next coefficient (for Terminal Type) indicates that ports specialized in container traffic are significantly less inefficient than those that also operate bulk and general cargo, as they are able to focus their systems and operation in a single type of shipment (besides inefficiency, this variable also predicted more container throughput in the stochastic frontier). On a different note, the relationship between inefficiency and income per capita is significant in specification (7), providing empirical evidence that there is a significant association between the income level of a country and port efficiency.

Regarding port location, the binary variable that indicates if a port is located in South America is not significant and does not have a consistent sign patter across specifications. Therefore, technical efficiencies in ports located in that sub-region are not different from that in ports located in Central America, Mexico or the Caribbean. A plausible interpretation is that technically efficient and inefficient ports can be found across all sub-regions in LAC, after controlling for other effects. The next variable assessed in the inefficiency model is the binary variable that controls for transshipment traffic, which has a negative and significant coefficient in specification (8), implying that transshipment ports are less inefficient than import/export ports (this variable also predicted higher output in the production function). Finally, the time trend is significant and negative across all specifications, suggesting that port inefficiencies of production tended to decline throughout the ten-year period.

In respect to the parameters associated with the disturbance terms, the model shows a desirable higher variance of the inefficiency term u_{it} than of the random error v_{it} [σ^2_u=1.02 and σ^2_v=0.44 in specification (1) and σ^2_u=0.87 and σ^2_v=0.0001 in specification (8), for example]. These results imply that γ (the ratio between the variance of the inefficiency term σ^2_u to the total disturbance in the model σ^2) ranges between 0.70 and 0.99 and is significantly different from zero. As a result, most of the differential between observed and best-practice output is due to the existing difference in efficiency among ports. Therefore, it becomes evident that a traditional average production function approach (without an inefficiency term) would not be an adequate representation of the data. As a result, the proposed approach is deemed appropriate to model technical efficiency in the sample.

In summary, the production function presents elasticities significantly different from zero, indicating that the returns in terms of throughput are the largest for STS gantry cranes and the length of berths, but they are also positive for mobile cranes and terminal area. The findings also show that ships' cranes and transshipment activities are important components of a LAC port production function. In addition, the control variables specified in the model captured the significant effect of country size, maritime connectivity and trade flows in container throughput. These robust results associated with the estimation of the production function allow a more accurate estimation of technical inefficiency across ports in the region. Accordingly, the inefficiency frontier model was estimated conditionally on variables such as terminal type, income per capita, and transshipment activities, resulting in significant association; other variables employed in this model are type of ownership, corruption and location, whose coefficients showed weaker relationships.

6. Port Efficiency

The results derived from the stochastic frontier model reveal that, between 1999 and 2009, port technical efficiencies in LAC ranged between 5% in Rosario to 93% in San Juan (Table 8). The overall average is 41.7% and the standard deviation is 21.4%. This result shows that even the most technical efficient port in the region still has room for improvement and, on the other hand, the least technical efficient port has a very large gap to close with respect to the frontier.

Table 8 divides technical efficiency in quartiles; the fourth quartile (most efficient) shows 16 container ports with efficiencies between 59% and 93%; 10 of which are located in South America (5 in Brazil), 4 in Central America and Mexico, and other 2 in the Caribbean. The first quartile (grouping the less efficient ports) is composed of container ports with technical efficiencies between 5% and 24%, 8 of which are located in South America, 3 in Central America and Mexico and 4 in the Caribbean. Overall, the results reveal significant differences and indicate that high and low technically efficient ports are found across all sub-regions. It is important to highlight that many ports in the bottom part of the distribution are not specialized in handling containers (such as Rosario, Arica, Zárate or Corinto) but rather in bulk or general cargo, a characteristic that has been accounted for in the production function and in the efficiency estimations, leading to the conclusion that multipurpose terminals are, in general, more inefficient than container terminals.

The 41.3% average technical efficiency in the LAC region during our ten-year sample compares fairly well against 30% in African ports for the period 1998–2007 (Trujillo et al, 2013), but is significantly lower than ports' technical efficiency in Europe, which for the year 2002 was estimated at 60% of its potential (Cullinane et al., 2006b).

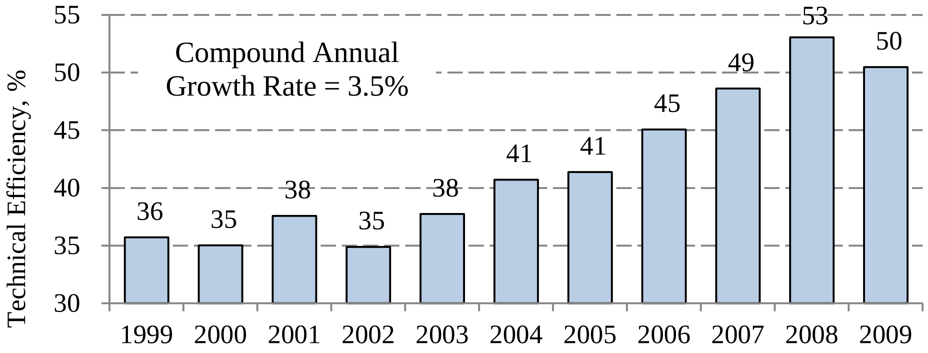
Table 8: Efficiency Ranking of Container Ports, 1999–2009

	Ranking	**Port**	**Efficiency Score**		**Ranking**	**Port**	**Efficiency Score**
Quartile 4	1	San Juan	93%	**Quartile 2**	37	Progreso	38%
	2	Guayaquil	83%		38	Valparaiso	37%
	3	Santos	81%		39	Lázaro Cárdenas	36%
	4	Puerto Limón	80%		40	Pecém	35%
	5	Sao Francisco Do Sul	77%		41	Altamira	32%
	6	Manzanillo	77%		42	Suape	31%
	7	Salvador	73%		43	Puerto Castilla	31%
	8	Montevideo	73%		44	Sepetiba	30%
	9	Veracruz	71%		45	Puerto Caldera	30%
	10	Lirquén	69%		46	Manaus	30%
	11	Paranaguá	67%		47	Rio Haina	30%
	12	San Antonio	65%		48	Puerto Manzanillo	28%
	13	La Guaira	62%		49	Caucedo	28%
	14	Itajaí	62%		50	Santo Tomás de Castilla	27%
	15	Puerto Barrios	59%		51	Fortaleza	27%
	16	Freeport	59%		52	Antofagasta	27%
Quartile 3	17	Callao	58%	**Quartile 1**	53	Bridgetown	24%
	18	Iquique	53%		54	Acajutla	23%
	19	Exolgan	49%		55	Buenos Aires (excl. Exolgan)	23%
	20	Buenaventura	48%		56	Oranjestad	23%
	21	Balboa	47%		57	Paita	23%
	22	Cartagena	47%		58	Belem	19%
	23	Colon CT	47%		59	Ensenada	19%
	24	Puerto Cabello	46%		60	Kingston	18%
	25	Port of Spain	46%		61	Barranquilla	18%
	26	Rio Grande	46%		62	Vieux Fort	15%
	27	Puerto Quetzal	45%		63	Santa Marta	13%
	28	Vitoria	42%		64	Corinto	11%
	29	Point Lisas	39%		65	Zárate	10%
	30	San Vicente	38%		66	Arica	9%
	31	Puerto Cortés	38%		67	Rosario	5%
	32	Rio De Janeiro	38%				

Source: Own Calculations

The evolution of technical efficiency over time as an aggregate average is quite positive in the region. *Figure 1* shows an overall improvement in the LAC region as a whole, rising from 36% in 1999 to 51% in 2009. The average compound technical efficiency rate of growth per year is 3.5%, i.e. the region is slowly closing the gap with respect to the production frontier. Moreover, the graph reveals a fall in average efficiency in the region in the year 2009 as a result of the international financial crisis, a similar result to that found by Wilmsmeier (2013). With respect to sub-regions (*Table 9*), the estimations reveal that South America has the highest average efficiency (44%), having experienced the highest improvement in the period. Central America and Mexico has a 41% average efficiency and, finally, the Caribbean has 39%. In fact, the Caribbean is the only sub-region that has not been able to close the gap with respect to the efficiency frontier during the ten-year period.

Figure 1: Evolution of the Average Technical Efficiency of Container Terminals in LAC



Source: Own Calculations

Table 9: Average Technical Efficiency of Container Ports by sub-region

	1999	2004	2009
Central America	30.8%	38.8%	38.7%
South America	37.2%	41.4%	43.9%
Caribbean	42.1%	42.0%	40.6%

Source: Own Calculations

7. Conclusions

In an effort to assess port technical efficiency in Latin America and the Caribbean, we developed a Stochastic Frontier Analysis using a panel of 67 container ports for the period 1999–2009. The output variable in the production function is annual container throughput, whereas the input variables are total area, berth length, and number of cranes in container terminals. Our model also evaluates three other port productivity sources: (i) we consider ship-to-shore gantry cranes and mobile container cranes as separate variables, in order to account for the higher productivity of the former; (ii) we use a binary variable indicating ports that take advantage of cranes mounted on vessels for container handling; and (iii) we use a binary variable indicating ports whose main form of container traffic is transshipment. We also control for other exogenous effects such as terminal purpose, national trade flows, maritime connectivity and GDP. Moreover, following the Battese and Coelli (1995), in a one-step estimation we determine inefficiency as a linear function of independent variables, such as port ownership, terminal purpose, corruption and income. To our knowledge, this is the first estimation of technical efficiency using Stochastic Frontier Analysis in a large sample of ports in the LAC region.

The estimations indicate that the gains in productivity from the use of ship-to-shore gantry cranes are the largest among the inputs considered followed by berth length, which has the second largest elasticity. Moreover, the effect of the binary variables in the model is positive and significant, confirming the premise that ships' cranes and transshipment traffic are significant sources of productivity in the region and that these variables improve the accuracy of parameter estimation. The inclusion of the control variables terminal purpose (either container or multi-purpose), country's GDP, shipping liner connectivity and trade openness, also help explain output in the production function and disentangle technical efficiency.

In order to associate technical efficiency with its potential explanatory factors, we have incorporated a conditional mean structure to the model's inefficiency term. The results revealed that technical efficiencies in our sample are significant and time-varying. First of all, the findings show that there are efficiency gains in specialized container terminals with respect to multi-purpose terminals. Moreover, there is evidence that ports in higher per capita income countries are more technically efficient, and that transshipment traffic is another variable significantly associated with efficiency. In addition, the model reveals that landlord ports (those with privately operated terminals) and the perception of transparency in the public sector are associated with technical efficiency, although with weaker estimates.

The technical efficiency results show that the average port efficiency in the ten-year period was 41% in Latin America and the Caribbean, higher than the 30% estimate found in Africa (Trujillo et al, 2013) but lower than 60% for Europe (Cullinane et al., 2006b) in relatively similar periods. The analysis shows an improvement in average technical efficiency over time in LAC: from 36% to 50% between 1999 and 2009. On average, ports in South America (44%) are closer to the frontier than ports in Central America and Mexico (39%) and the Caribbean (41%) although the differences are not significant; moreover, one can find technical efficient and inefficient ports in all sub-regions. The estimations revealed that the Port of San Juan (93%) is on average the closest to the efficiency frontier, followed by Guayaquil (83%) and Santos (81%).

In further research, other types of analyses might take into account alternative dimensions of port efficiency, such as dwell times and crane productivity, which are particularly important when assessing ports individually or in smaller groups, and associate these variables with technical efficiency.

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9. Annexes

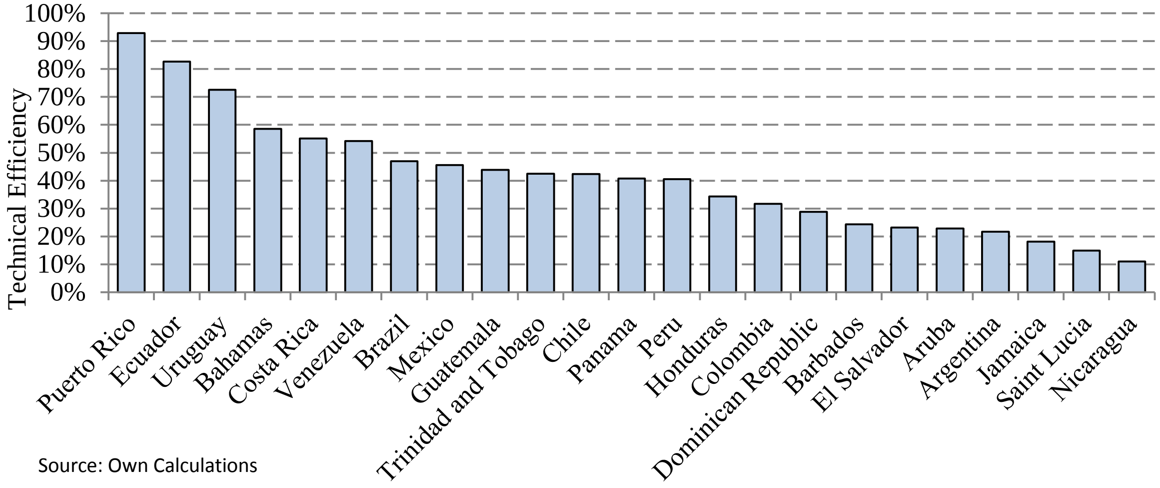
Annex 1: Port Characteristics. Average between 1999–2009

	Average Annual Throughput (TEU)	Average Berth Length (m)	Average Area (m2)	Average Mobile Cranes	Average STS Cranes
Argentina					
Buenos Aires (excl. Exolgan)	870,314	3,673	788,250	8	12
Exolgan	409,203	750	450,000	0	4
Rosario	27,933	1,000	66,000	0	0
Zárate	28,575	250	500,000	0	1
Aruba					
Oranjestad	60,425	250	130,000	1	1
Bahamas					
Freeport	1,115,910	990	320,125	1	6
Barbados					
Bridgetown	77,762	455	70,909	1	1
Brazil					
Belem	50,856	1,624	19,620	2	0
Fortaleza	63,010	929	24,000	1	0
Itajaí	462,963	800	83,909	3	0
Manaus	126,075	620	30,000	1	0
Paranaguá	402,774	647	236,091	1	3
Pecém	135,876	700	380,000	0	1
Rio De Janeiro	345,644	1,078	322,500	0	7
Rio Grande	536,023	2,408	550,227	3	2
Salvador	177,233	272	40,000	3	1
Santos	1,847,604	2,123	756,600	3	10
Sao Francisco Do Sul	247,947	473	800,000	1	0
Sepetiba	218,584	810	400,000	2	2
Suape	147,582	765	223,636	0	2
Vitoria	178,663	692	110,727	1	1
Chile					
Antofagasta	57,022	1,230	15,000	2	0
Arica	63,000	1,050	193,000	1	0
Iquique	179,366	1,102	88,218	5	0
Lirquén	185,254	400	424,000	3	0
San Antonio	668,296	1,155	466,715	4	4
San Vicente	268,015	603	405,383	2	0
Valparaiso	479,471	2,381	280,710	5	3
Colombia					
Barranquilla	78,914	1,057	933,000	1	0
Buenaventura	485,173	742	271,821	2	1
Cartagena	655,440	1,558	410,909	2	2
Santa Marta	65,924	1,085	133,000	1	0
Costa Rica					
Puerto Caldera	102,978	490	30,000	0	0
Puerto Limón	677,276	494	94,091	1	1
Cuba					
Havana	269,314	358	187,314	1	2
Curacao					
Willemstad	85,234	500	160,000	1	2

Dominican Republic					
Caucedo	377,005	600	500,000	0	5
Rio Haina	342,210	1,216	307,975	1	2
Ecuador					
Guayaquil	536,071	1,320	228,273	2	2
El Salvador					
Acajutla	81,498	520	105,000	0	0
Guadeloupe					
Pointe-A-Pitre	133,168	600	275,000	0	3
Guatemala					
Puerto Barrios	245,676	610	15,000	1	0
Puerto Quetzal	192,930	560	68,578	1	0
Santo Tomás de Castilla	296,787	915	283,000	5	0
Honduras					
Puerto Castilla	75,519	150	80,000	0	0
Puerto Cortés	449,795	998	144,300	1	2
Jamaica					
Kingston	1,558,870	3,180	1,037,671	5	13
Martinique					
Fort-De-France	142,135	385	230,000	0	3
Mexico					
Altamira	295,366	973	396,570	1	4
Ensenada	66,710	300	70,000	1	2
Lázaro Cárdenas	335,934	589	387,766	1	6
Manzanillo	838,872	2,205	316,333	1	4
Progreso	63,687	291	81,636	0	1
Veracruz	603,723	464	402,909	1	5
Nicaragua					
Corinto	31,527	240	20,000	0	1
Panama					
Balboa	1,115,371	1,124	181,500	0	5
Colon CT	545,725	612	25,000	0	5
Puerto Manzanillo	1,235,869	1,469	431,818	0	11
Peru					
Callao	744,955	4,000	441,080	0	0
Paita	90,494	730	37,123	0	0
Puerto Rico					
San Juan	1,731,039	1,688	287,273	0	6
Saint Lucia					
Vieux Fort	32,969	370	50,000	1	0
Trinidad and Tobago					
Point Lisas	120,737	362	32,400	3	1
Port of Spain	324,643	769	169,000	5	3
Uruguay					
Montevideo	429,377	580	187,273	2	2
Venezuela					
La Guaira	276,859	1,093	24,000	7	0
Puerto Cabello	650,982	4,485	161,491	37	0

Source: Own elaboration based on Containerization International Yearbook (1999–2009)

Annex 2: Technical Efficiency by Country (1999–2009)



Source: Own Calculations

Annex 3: Comparison between Data Envelopment Analysis and Stochastic Frontier Analysis Results

We calculated the technical efficiency frontier for 2009 using Data Envelopment Analysis (DEA) under two different specifications, constant returns to scale (CRS) and variable returns to scale (VRS). In DEA, the output variable is annual container throughput and the input variables are (i) length of berths (in meters), (ii) terminal area (in square meters), and (iii) crane capacity equivalent. The latter variable is a combination of the number of ship-to-shore (STS) gantry cranes and mobile cranes, in which the number of STS gantries is estimated as a mobile crane equivalent. This approach allows maximizing the number of observations included in the estimations; since many ports would drop from the sample due to nil values in the variables STS cranes or mobile cranes. Overall, 62 container terminals were included in the estimations, compared to 67 in the SFA. Moreover, it’s important to highlight that under the DEA specification it’s not possible to account for the use of ships’ cranes and transshipment as binary variables as in the SFA.

a) Constant Returns to Scale

Under constant returns to scale, DEA produces the results showed in the table below. The distribution of technical efficiency according to these results has an average of 40% and a standard deviation of 27%, similar to the statistics obtained with SFA (41% and 21%, respectively).

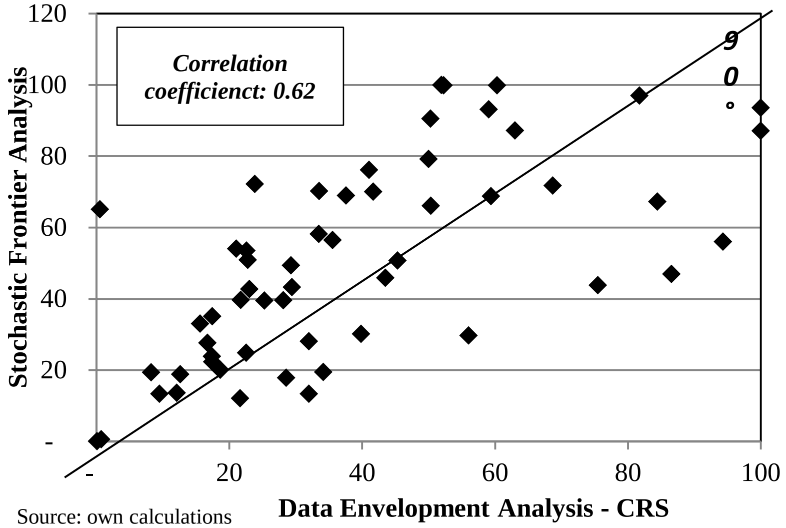
We found a positive correlation of 0.62 when comparing the technical efficiency rankings obtained with the SFA and DEA-CRS. Culinnane et al. (2006a) have already provided evidence that the two methodological approaches produce analogous results: the authors found a correlation of 0.79 when applying similar input/output specifications for SFA (truncated normal distribution) and DEA-CRS. Among the sources of difference from our estimations, it’s important to highlight that the estimation strategy we used for SFA is different, by controlling for transshipment and ships’ cranes use, on top of other control variables used in the production function estimation. In spite of this, only six out of fifty-four ports had a difference larger than 30 efficiency points between the results obtained through both approaches, as shown in the scatter plot below.

Table A3-10: Container Terminal Technical Efficiency Ranking, Constant Returns to Scale DEA, 2009

	Ranking	Port	Technical Efficiency		Ranking	Port	Technical Efficiency
Group 1	1	Puerto Barrios	100%	**Group 3**	32	Belize City	31%
	2	Puerto Limón	100%		33	Valparaiso	29%
	3	Freeport	94%		34	Port of Spain	29%
	4	Colon CT	87%		35	Barranquilla	29%
	5	Veracruz	84%		36	Pecém	28%
	6	San Juan	82%		37	Santo Tomás de Castilla	25%
	7	Buenaventura	75%		38	Iquique	24%
	8	Balboa	69%		39	Antofagasta	23%
	9	Santos	63%		40	Vitoria	23%
	10	Paranaguá	60%		41	Rio De Janeiro	23%
	11	Itajaí	59%		42	Fortaleza	23%
	12	Guayaquil	59%		43	Altamira	22%
	13	Puerto Manzanillo	56%		44	Arica	22%
	14	Montevideo	52%		45	Lázaro Cárdenas	21%
	15	Havana	52%		46	Belem	19%
Group 2	16	Salvador	52%	**Group 4**	47	Suape	17%
	17	San Vicente	50%		48	Bridgetown	17%
	18	Cartagena	50%		49	Buenos Aires (excl. Exolgan)	17%
	19	La Guaira	50%		50	Ensenada	17%
	20	Puerto Quetzal	45%		51	Pointe-A-Pitre	16%
	21	Puerto Cortés	44%		52	Sepetiba	16%
	22	MIT - Manzanillo	42%		53	Corinto	13%
	23	San Antonio	41%		54	Vieux Fort	12%
	24	Caucedo	40%		55	Willemstad	12%
	25	Exolgan	38%		56	Boca Chica	10%
	26	Puerto Cabello	36%		57	Progreso	10%
	27	Kingston	34%		58	Castries	8%
	28	Lirquén	34%		59	Zárate	8%
	29	Rio Grande	34%		60	St John's	7%
	30	Point Lisas	32%		61	Tampico	2%
	31	Rio Haina	32%		62	Salina Cruz	1%

Source: own calculations

Figure A3-1: Scatter Plot of Technical Efficiency Indices, Comparing SFA and DEA-CRS Results



Source: own calculations

b) Variable Returns to Scale

The results from the VRS-DEA are different from the CRS-DEA and the SFA. Under a Variable Returns to Scale specification, the number of ports on the frontier tends to increase with the number of input variables. Therefore, the use of 3 production inputs places 18 container ports on the frontier, and only 7 of these ports also rank in the top quartile of the SFA technical efficiency distribution. By construction, the smallest ports in the sample, such as Boca Chica (Dominican Republic) and Vieux Fort (St. Lucia), are also on the frontier. The average efficiency is relatively high (67%) and the standard deviation is 27%. Moreover, the results point out that most ports in LAC are operating with increasing returns to scale, *i.e.* additional throughput would allow ports to achieve higher levels of efficiency, as was confirmed in the estimation of the parameters of the Stochastic Frontier Analysis. On the other hand, according to the result, there are 5 ports operating with decreasing returns to scale: Cartagena (Colombia), San Juan (Puerto Rico), Santos (Brazil), Kingston (Jamaica) and Puerto Cabello (Venezuela).

Table A3-2: Container Terminal Technical Efficiency Ranking, Variable Returns to Scale DEA, 2009

	Ranking	Port	Technical Efficiency		Ranking	Port	Technical Efficiency
Group 1	1	Arica	100%	**Group 3**	32	Havana	66%
	2	Barranquilla	100%		33	Lirquén	64%
	3	Belize City	100%		34	Montevideo	62%
	4	Boca Chica	100%		35	Zárate	62%
	5	Puerto Barrios	100%		36	Guayaquil	61%
	6	Puerto Limón	100%		37	Itajaí	61%
	7	San Juan	100%		38	Cartagena	55%
	8	Vieux Fort	100%		39	Lázaro Cárdenas	53%
	9	Freeport	100%		40	Puerto Cortés	49%
	10	Corinto	99%		41	Caucedo	49%
	11	Colon CT	95%		42	Manzanillo	48%
	12	Salvador	91%		43	Progreso	46%
	13	Santos	90%		44	Willemstad	44%
	14	Castries	90%		45	Exolgan	44%
	15	Fortaleza	89%		46	Kingston	44%
Group 2	16	Veracruz	86%	**Group 4**	47	Vitória	43%
	17	Antofagasta	84%		48	San Antonio	43%
	18	Salina Cruz	82%		49	Rio Haina	42%
	19	Puerto Quetzal	80%		50	Port of Spain	42%
	20	Point Lisas	80%		51	Pointe-A-Pitre	41%
	21	Buenaventura	78%		52	Iquique	40%
	22	Balboa	74%		53	Puerto Cabello	39%
	23	San Vicente	74%		54	Suape	37%
	24	Bridgetown	70%		55	Santo Tomás de Castilla	37%
	25	Paranaguá	68%		56	Rio Grande	35%
	26	Pecém	67%		57	Sepetiba	34%
	27	Puerto Manzanillo	67%		58	Valparaiso	32%
	28	La Guaira	67%		59	Altamira	31%
	29	Belem	66%		60	Rio De Janeiro	30%
	30	St John's	66%		61	Buenos Aires (excl. Exolgan)	18%
	31	Ensenada	66%		62	Tampico	13%

Source: own calculations