Measuring the economic efficiency performance in Latin American and Caribbean countries: An empirical evidence from Stochastic Production Frontier and Data Envelopment Analysis

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Abstract: The development of the global economy has raised concerns about economic efficiency and productivity. In this context, understanding the concepts of economic efficiency and productivity and the knowledge of the techniques available for their measurement are also of fundamental importance. Thus, the objective of the present study is to measure the economic efficiency performance of 14 countries from the Latin America and the Caribbean (LAC) region in the period from 1990 to 2017. Analysing the economic performance of these countries with linear Cobb-Douglas production function, two methods were used: the parametric stochastic frontier analysis (SFA) and non-parametric data envelopment analysis (DEA). Both approaches (SFA and DEA) show that Panama is the most economically efficient country in the LAC region, followed by Chile. Concerning other countries, the choice between the SFA and DEA models affects the ratings. Results indicate that Brazil (SFA) and Nicaragua (DAE) are the least economically efficient LAC countries.

Keywords: Stochastic frontier analysis, Economic performance, Latin American and Caribbean countries.

1.Introduction

With the development of the global economy and the impressive growth of increasing demand for resources, the efficient use and saving of scarce resources, especially energy, is a major challenge for economic researchers and policymakers. Given that 0.7% of world GDP and 8.5% of the world population are located in Latin America and the Caribbean (LAC) region, the LAC region's energy consumption per capita is high. Therefore, this global challenge has also affected the LAC region (World Population Prospects, 2019).

According to World Bank Development Indicators, the GDP growth in the LAC region in 1990 was about 0.347 and in 2017 reached about 1.792. On the other hand, such high economic growth requires considerably higher energy consumption, reducing

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efficiency (e.g., Ozturk, 2010; Setyawan, 2020). As a result, energy consumption in the LAC region has accelerated in recent decades. One of the reasons for the growth of energy consumption is the region's economic growth. Energy consumption follows the trend of per capita GDP growth in this region (e.g., Koengkan, 2017; and Koengkan & Fuinhas, 2020). The growth of energy consumption in the LAC region is faster than the growth of energy consumption in most countries in the world (Chang & Soruco-Carballo, 2011).

Additionally, economic efficiency is reduced due to climate changes. Some authors refer that the LAC region is more affected by climate change than any other World region (e.g., Chang & Soruco-Carballo, 2011; and Arshad et al., 2018). Therefore, economic efficiency, which relates to the optimal allocation of scarce resources, is a topic of interest for researchers and policymakers because improving economic efficiency leads to resource security and sustainable economic development. Therefore, economic efficiency is an essential step towards sustainable development (e.g., Ma et al., 2019).

The main point of all efficiency theories is how to deal with resource scarcity (Deilmann et al., 2016). Economic efficiency conveys the same concept as the production function. The production function is used to define the relationship between inputs and outputs by demonstrating the maximum output obtained from the inputs used (Hadad et al., 2012). The growth theory of Solow (1957) states that the production function is a function of labour and capital inputs (e.g., Halkos & Tzeremes, 2011). Therefore, economic efficiency is the efficiency of labour and capital and other factors of production. Some researchers also consider energy consumption as one factor of production (e.g., Thompson, 2006; and Ma et al., 2019). In this study, energy consumption is also considered as one of the factors of production.

A country achieves efficiency when maximising output from a given set of inputs (Alem et al., 2018). Therefore, increasing the country's economic efficiency can increase competitiveness and increase the share of the economy in international markets and improve the country's position in using resources among other countries. The result of this is to achieve sustainable growth. When a country operates using low-efficiency factors of production, it will generate waste of economic resources. If the unit continues to operate under the same conditions, it will ultimately lead to higher costs.

There are two main methods for calculating efficiency: parametric and non-parametric. Data Envelopment Analysis (DEA) is widely used as a non-parametric method to evaluate the efficiency of decision-making units (Luo et al., 2021). This approach is based on input and output. DEA does not deviate from the estimated values because the approach has a specific functional shape that is not considered in advance (e.g., Zhou et al., 2012; and Wang et al., 2017). This feature has caused many researchers in various fields to use the DEA approach (e.g., Singpai & Wu, 2021; Fathi et al., 2021; Zhong et al., 2020; Zhang et al., 2019; Carboni & Russu, 2018; Deilmann et al., 2016; Hadad et al., 2012; Halkos & Tzeremes, 2011; Assaf & Agbola, 2011; and Byrnes et al., 2010). Although data envelopment analysis is a powerful approach, it does not examine statistical noises. To solve this problem, was propose a parametric frontier analysis method to measure economic efficiency. Stochastic Frontier Analysis (SFA) is an econometric approach that differs from ordinary regression analysis. The ordinary regression analysis considers mean points in function estimation, while the SFA approach frontier points for countering best performance are considered. In the parametric method, production functions (e.g., Cobb-Douglas function) are used to estimate the available parameters (Zhou et al., 2012). Some researchers have used the SFA approach to calculate economic performance in various contexts (e.g., Li et al., 2020; Tateishi et al., 2020; Osborne & Trueblood, 2006; and Zhou et al., 2012).

Since increasing economic efficiency leads to efficient use of resources, increasing the level of potential production and thus increasing economic growth and improving the level of welfare, the question arises whether the countries of the LAC region are efficient in using their resources? Economic efficiency was measured using data from 14 LAC countries by applying the stochastic border analysis estimation to answer this question. For further analysis, the DEA approach is used to answer the following question "Does the proposed parametric SFA method has more differentiation power in measuring the economic efficiency of LAC countries compared to non-parametric samples? The results allow us to have a ranking of LAC countries with the best resource savings. Measuring economic efficiency and identifying its determinants can be helpful for managers, policymakers and planners to improve economic performance.

In previous studies, measuring macroeconomic efficiency and proposing a parametric boundary method for estimating economic performance from a production point of view have not been analysed in LAC countries. So to create effective policies to save resources, a study in this area is important and necessary. The empirical findings of this study contribute to the advancement of the existing literature and have significant implications for LAC policy. It can also help develop new policies that lead to efficient use of resources and sustainable development.

The article is organised as follows. **Section 2** provides a literature review. **Section 3** describes an overview of production theory. **Section 4** presents the data and methodology. **Section 5** contains the empirical results of the model (different models). **Section 6** discusses the results obtained. Finally, **Section 7** contains conclusions and implications.

2. Literature review

Economic efficiency usually means how much economic production can be achieved with less economic input. In general, economic efficiency assessment methods can be divided into parametric and non-parametric approaches. One of the most common non-parametric methods is the Data Envelopment Analysis (DEA) approach, first developed by Charnes et al. (1978). On the other hand, stochastic frontier analysis (SFA) is the most common parametric border-based method for performance analysis (e.g., Aigner et al., 1977; and Meeusen & van Den Broeck, 1977). In the following section, we will review the studies conducted in the field of economic efficiency.

Some of these studies measured economic efficiency using DEA models. Singpai & Wu (2021) evaluated the economic productivity of the environment from 1992 to 2017 using an integrated two-stage model using LMDI analysis and the DEA model. The results showed that the labour market, labour productivity and energy intensity are the main energy consumption factors. Higher-income countries perform better both in terms of energy and economic efficiency. Hababou et al. (2016) measured economic productivity in the film industry, and its determinants using a DEA approach showed that the most important factors influencing the economic productivity of the film industry are academy awards, sequences, genres, the volume of user reviews and the studios. Halkos & Tzeremes (2010) showed a significant inefficiency of regional policies among the Greek provinces in a study to measure the regional economic efficiency of the Greek provinces using the DEA model for the period 2003-2006. In addition, growth inefficiencies have been reported in 13 regions. Hadad et al. (2012) stated that globalisation and the ability to achieve tourism sector productivity in developing countries is crucial in a study to evaluate the efficiency of the tourism sector in 105 countries, including 34 developed and 71 developing countries, using data envelopment analysis.

The study of Carboni & Russu (2018) measures and forecasts the economic and environmental productivity of 20 regions of Italy, using data analysis and Malmquist productivity index during the period 2004 to 2011, showing that the northern regions are more efficient than the south has it. Zhao et al. (2020), in a study for 30 Chinese provinces from 2008 to 2017 based on the super-SBM model with undesirable outputs and the Dubin space model, showed that China's overall green economic productivity during the study period was low with remarkable regional differences. The trend of national green economic productivity initially decreased and then gradually stabilised during the study period. Fathi et al. (2021) measured energy, environmental and economic efficiency in fossil fuel exporting countries with a DEA model approach during 2015-2017. According to the results, the average energy, economic, and environmental efficiencies are 0.77, 0.8 and 0.26. The results of the DEA approach showed that efficiency performance is different in each country. Tao et al. (2016), in a study for Chinese provinces using the SBM approach of inseparable inputs and outputs from 1995 to 2012, showed a larger interregional difference in green economic efficiency. The highest yields of 0.7339 were recorded in the southern coastal region, followed by the eastern and northern coastal regions. The lowest returns are just 0.3049 in the Northwest region, and energy and CO_2 emissions are critical to green economic productivity.

Chiu et al. (2011), in a study evaluating transit and economic efficiency in 30 regions of China using a modified DEA model with a value chain, showed that large-scale transit development in the coastal region of China does not necessarily indicate higher transport efficiency. Because in the coastal region, there is no significant positive relationship between transportation and economic productivity. The finding also showed that economic and transportation productivity had improved significantly in many parts of China as passenger and freight transport volume has declined simultaneously. Halkos &Tzeremes (2011) studied economic efficiency and oil consumption in 42 countries (advanced economies and emerging economies) using DEA window analysis from 1986 to 2006. They showed that the economies of advanced countries have much higher milestones compared to emerging and developing economies.

Furthermore, that oil consumption increases the economic efficiency of countries. Byrnes et al. (2010), in a study of the relative economic efficiency of urban water and electricity in New South Wales and Victoria, using the DEA model, found that global water restriction policies are likely to reduce relative efficiency. They also identified that those larger companies, based in Victoria, have higher degrees of managerial efficiency. Nie & Wen (2015) using the SBM model, a non-radial and non-axial model in DEA performance models, to achieve the green economic productivity of 286 Chinese cities in the province over seven years (2005 to 2011). Experimental results showed that green economic efficiency in cities in the province has a "U" relationship with GDP per capita.

Zhao et al. (2019), in a study of urban construction land in 31 provinces of China using high-yield EBM during the period 2008 to 2017, stated that the economic efficiency of land in the eastern region is higher than the central and western regions, and the coastal area has higher efficiency than the inland. Zhang et al. (2019) measured the efficiency performance of the low carbon economy from a global perspective using the Super-slack model from 1993-1993. The results showed that the overall performance of the low-carbon economy is globally low, and the difference in the efficiency of the low-carbon economy among the 115 sample countries is significant. It also showed that the efficiency performance of the low carbon economy is generally better in developed countries. Zhong et al. (2020), in a study for the Yangtze River metropolitan area using the Slack-based model (SBM) from 2008 to 2017, showed that YRUA energy efficiency first decreased and then increased overall. In particular, the economic productivity of Suzhou and Wuxi has been in the effective position of the evaluation unit. At the same time, the energy efficiency of Yangzhou, Taizhou and Zhenjiang is relatively low. Yuan et al. (2020) investigated the effect of productive agglomeration on green economy efficiency using panel data from 287 cities in China using the super-slack model between 2003 and 2016. The results indicate a positive "U-shaped" relationship between productive consensus and green economy productivity in the short and long term. Du & O'Connor (2018), in a study to examine entrepreneurship and the development of economic efficiency at the national level, found that new product entrepreneurship and, to some extent, entrepreneurship based on improvement significantly contribute to improving economic efficiency at the national level.

Several other studies have used stochastic frontier analysis to evaluate economic efficiency. Kolawole & Ojo (2007) showed that the average technical, allocative and economic efficiency 0.733, 0.872 and 0.684, respectively, in a study to measure the economic productivity of small-scale food production in Nigeria using a stochastic frontier analysis. The analysis of economic efficiency showed that the existence of technical inefficiency and allocation inefficiency in food production has been effective. Wadud (2003), in a study for rice farmers using SFA and DEA techniques, showed that there is a significant technical and economic inefficiency in allocation production and policies to reduce land fragmentation and improve irrigation infrastructure. Environmental factors can improve technical, allocative and economic efficiency. Using a stochastic frontier cost function, Coto-Millan et al. (2000) estimated the economic efficiency of Spanish ports through panel data from 27 Spanish ports during 1985-1989. The results show that relatively large seaports are more economically inefficient. Tateishi et al. (2020) showed that for countries with very high institutional quality, their economic and technical efficiency was close to efficient boundaries in a study to evaluate the role of individual institutions in economic efficiency, using stochastic frontier analysis, with a production approach in 116 countries during 1993-2012. Kuboja et al. (2017), in a study among small-scale beekeepers in the Tabora and Katavi regions of Tanzania, using a stochastic profit frontier analysis, showed that small-scale beekeepers are economically efficient and have an average efficiency of 92%. This finding means that there is a possibility of improvement of about 8% without a change in the profit margin.

Arshad et al. (2018) found that final heat above 34°C has a significant negative effect on the economic efficiency of wheat production in a study to investigate the effects of climate diversity and heat tension on the economic efficiency of Pakistani rice and wheat using SFA. Heat tension greater than 35.5°C during the flowering of rice also had a significant and negative effect. Zaimova (2011) measured the economic productivity of Italian agricultural enterprises using stochastic frontier analysis during the period 2003-2007. The results showed that the balanced growth of productivity in 21 regions of Italy is supported by the change in efficiency in total factor productivity. Li et al. (2020) found that the opening of high-speed rail has a significant positive effect on urban economic efficiency in a study to investigate the impact of high-speed rail on urban economic efficiency in China. More service works have a positive impact also. Mburu et al. (2014) showed that the average technical, allocative and economic efficiency indicators of small-scale wheat farmers were 85%, 96%, and 84%, respectively, in a study to investigate the effect of farm size on economic efficiency among 130 large and small wheat producers in Nakuru, Kenya. At the same time, for large-scale farmers, these indicators were 91%, 94%, and 88%, respectively. Osborne & Trueblood (2006) examined the economic efficiency of Russian crop production in the reform period years using the DEA and SFA models during 1993-1998. The results showed that due to the decrease in technical efficiency and allocation, economic efficiency decreased during the period. The results of economic efficiency also showed that Russian corporate farms could increase efficiency by reducing all inputs, especially fertiliser and fuel. Zhou et al. (2012) measured energy efficiency performance in the whole economy for OECD countries with a parametric frontier approach. They showed that the proposed parametric frontier method has a higher differentiation power in measuring energy efficiency than its non-parametric frontier counterparts.

The results of previous studies showed that although different studies have been conducted in different countries and regions in the field of efficiency, no comprehensive study on measuring economic efficiency has been conducted in Latin American countries. Also, most of the studies have used one of the DEA or SFA methods to measure economic efficiency, while both models have been used for us in this study. In the next section, the methodology and data used in this research will be presented.

3. Production theory

The theoretical framework of the production function builds on the neoclassical production theory. Central to it is the production function showing how maximum output (goods and services) can be obtained by utilising different combinations of input factors of production, assuming perfectly competitive markets and profit-maximising firms (Miller, 2008). The maximum output can then be used for comparison with the actual output to calculate economic efficiency.

The model of production includes capital (K), labour (L) and energy (E) as different factors of production, which can produce maximum output (Y) for a given set of inputs and technology (see **Equation 1**, below).

$$Y = f\,(K, L, E) \qquad \textbf{(1)}$$

where output is strictly non-negative and convex.

The section uses a methodological approach that is not time-relevant, contrary to most production theories that model this as the technology available at a particular time. All inputs are strongly disposable, and the model does not account for weakly disposable "bad" outputs, as it compares efficiency only from an output orientation standpoint. Materials balance condition is not strictly implied, and therefore, it is free of charge to dispose of unwanted inputs or outputs (Coelli et al., 2005). Here, technical change, or production technology, is assumed as exogeneous and neutral, i.e., determined outside the scope of the economy. Production functions are assumed to be positive, twice differentiable and quasi-concave, taking Cobb-Douglas form (see **Equation 2**, below).

$$Y = K^{\alpha}\, L^{1-\alpha-\theta}\, E^{\theta}, \qquad \textbf{(2)}$$

where parameters α and θ are constant physical capital and energy elasticities, respectively, and are not restricted.

Contrary to the early aggregate production models (i.e., Solow, 1957), the one-sector production model includes energy not as an intermediate but as a separate primary production input to analyse its role in achieving country-wide economic efficiency.

Perfect markets and profit-maximising firms assumptions apply so that factors are paid their marginal returns. With changing input prices, there may be changes in inputs, that is, the substitution of input with another.

When there are more than two inputs, the issue of input nesting and substitutability arises. Using inputs as substitutes are restrictive, as it excludes the possibility of complementarity; therefore, nesting is sometimes practised (Brockway et al., 2017). However, in this framework, none of the inputs being designed as complements, and they can increase the level, but not the growth of production.

In this model, returns to scale are assumed to be constant. Consequently, the change in total factor productivity equals the change in costs of inputs, and comparatively higher efficiency can be achieved only by substitution by other inputs, not technical change, which is modelled equally to all countries.

4. Data and methodology

This section is organised into two parts. The first one describes the data/variables, while the second part describes the methods used in this empirical investigation.

4.1. Data

This subsection will present the data/variables that will be utilised in this empirical analysis. Therefore, fourteen countries from the LAC region were selected to realise this investigation (e.g., **Argentina**, **Bolivia**, **Brazil**, **Chile**, **Colombia**, **Dominican Republic**, **Ecuador**, **El Salvador**, **Guatemala**, **Mexico**, **Nicaragua**, **Panama**, **Peru**, and **Venezuela**). Furthermore, this study opted to use the period of data from 1990 to 2017 due to data availability for all variables. Therefore, the variables used to identify the economic efficiency performance in LAC' countries is shown in **Table 1** below.

Table 1. Variables' description and summary statistics

Variables' description	
Variable	**Source**
Natural logarithms of *per capita* Gross Domestic Production (GDP) in Constant 201 US$. In this investigation, we called this variable **Y**.	World Bank Open Data (2021)
Natural logarithms of energy consumption (kWh *per capita*). In this investigation, we called this variable **E**.	World Bank Open Data (2021)
Natural logarithms of Labour force total. In this investigation, we called this variable **L**.	World Bank Open Data (2021)
Natural logarithms of *per capita* of total capital stock (constructed based on the sum of public, private, and PPP capital stock) in billions of constant 2011 international dollars. In this investigation, we called this variable **K**.	IMF (2017)

Summary statistics					
Variables	**Obs.**	**Mean**	**Std. Dev**	**Min**	**Max**
Y	392	8.4895	0.6904	6.9659	9.6138
E	392	6.9799	0.7174	5.3006	8.3850
L	392	15.8684	1.1489	13.7413	18.5157
K	392	-11.0351	0.5484	-12.1040	-10.0205

Notes: Obs. denotes the number of observations; Std. Dev. is the Standard Deviation; Min. and Max. are the minimum and maximum values.

In this empirical investigation, we used the variables, energy consumption (**E**), the labour force (**L**), and capital (**K**), because, in the neoclassical one-section aggregate production framework, these variables are treated as inputs and the variable gross domestic product (**Y**) as outputs (Zhou et al., 2012). Indeed, conceptually the production technology can be described as follows (see **Equation 3**, below).

$$T = \{(Y, E, L, K) : (E, L, K)\ can\ produce\ Y\} \quad \textbf{(3)}$$

where T consists of all the feasible input-output vectors.

Indeed, T is often referred to as the graph of production technology, which can also be represented by this equivalent input or output set (e.g., Fare et al., 1994; and Zhou et al., 2012). Moreover, production theory T is often assumed to be a closed and bounded set, where the inputs and output are often assumed to be strongly disposable (e.g., Zhou et al., 2012).

4.2. Method

As mentioned before, this subsection will expose the methods approach used in this empirical investigation. Therefore, this investigation opted to use the stochastic production frontier model (SFA) and Data Envelopment Analysis (DEA) to measure the economic efficiency performance in LAC countries. The relative advantages of SFA and DEA have been extensively debated in the literature (e.g., Parman & Featherstone, 2019). Nevertheless, it is worthwhile to remember the essential characteristics of SFA and DEA approaches. SFA is a parametric approach of statistical analysis to estimate production/cost frontiers in as context of explicit producer inefficiency. Central to SFA is the inefficiency of producers. This characteristic means that the decisions of maximizing/minimizing can materialize can be sub-optimal. DEA is a nonparametric approach used in economics to estimate production frontiers (or their dual cost function). DEA is used to assesses the efficiency of decision-making units (DMUs), and the economic theory of production supports it. DEA has the advantage that it does not be conditional on a function or a technology specification. DEA also not be constrained by the imposition of curvature for the production function (or the "best-practice frontier"). The shortcomings of DEA relatively to SFA is related to hypothesis testing and small sample bias.

4.2.1. Stochastic Frontier Analysis (SFA)

This model was introduced by Aigner, Lovell, & Schmidt (1977) and improved in the same year by Meeusen & Broeck (1977). The SFA models have become a popular model subfield in econometrics. They fit into two stochastic frontier models with distinct specifications of the inefficiency term and can fit both production- and cost-frontier models (e.g., Alem, 2018; and Greene, 2008). A key feature of an SFA model is its error structure, which separates the effects of over-production beyond the manufacturer's control (e.g., strikes, material un suction, or bad weather) from technical efficiency. A linear Cobb-Douglas log function is taken for the production frontier for the SFA model in this work. The main advantage of SFA models is that the share of random effects in changes in technical efficiency can be separated. Assuming N input to produce a single output unit, the following Cap Douglas linear equation is applied (see **Equation 4**, below) (Kumbhakar & Lovell, 2000).

$$lny_i = \beta_0 + \sum_n \beta_n lnx_{ni} + v_i - u_i \quad \textbf{(4)}$$

where y_i is the output of the i^{th}, β_0 is constant, x_{ni} are the inputs of the i^{th}, β_n the technological parameters, v_i is the effect of random (statistical) noise in production, and u_i is the inefficiency of the unit.

Therefore, to our neoclassical one-sector aggregate production framework, where energy consumption (**E**), the labour force (**L**), and capital **(K)** are treated as inputs and gross domestic product (**Y**) is taken as the output, follows the time-invariant model production equation (see **Equation 5**, below).

$$ln(Y_{it}) = \beta_0 + \sum_{j=1}^{k} \beta_j \, ln(E_{it}) + \sum_{j=1}^{k} \beta_j \, ln(L_{it}) + \sum_{j=1}^{k} \beta_j \, ln(K_{it}) + v_{it} - u_{it} \quad \textbf{(5)}$$

where u_{it} is subtracted from $ln(Y_{it})$, restricting $u_{it} > 0$ implies that $\varepsilon_{it} \leq 1$.

Unlike conventional regression models, the Cobb-Douglas SFA model contains a compound error term $\varepsilon_i = v_i - u_i$. The term v_i reflects random fluctuations and is symmetric and is assumed to be independently distributed uniformly as a natural distribution with mean zero: $v_i \sim$ i.i.d. N (0, σ^2_v), independently u_i. The term u_i corresponds to the best method deviation, in other words, the degree of inefficiency of each unit. Since $u_i \geq 0$, u_i assumes a positive one-way distribution such as semi-normal, exponential, truncated normal or gamma.

Ordinary least squares (OLS) are not suitable for estimating the parameters in (1) for two reasons: First, the residual mean of the error is assumed to be zero, which is positive in the current situation where $\varepsilon_i = v_i - u_i$ is not always usable. Second: OLS does not provide a unit-specific technical efficiency estimate. This limitation can be overcome with Maximum Likelihood Estimation (MLE). By adopting the Cobb-Douglas model and assuming a semi-normal distribution for the term u_i, the log-likelihood function of the model (1) has been parameterised again in terms of $\sigma^2 = \sigma^2_u + \sigma^2_v$ and $\lambda = \sigma_u / \sigma_v \geqslant 0$ (Aigner et al., 1977). The log-likelihood function, using this parameter, is:(see **Equation 6**, below)

$$lnL = constant - Iln\sigma - \frac{1}{2\sigma^2}\sum \varepsilon_l^2 + \sum_i \Phi(-\frac{\varepsilon_l \lambda}{\sigma}) \quad \textbf{(6)}$$

where Φ (x) is the cumulative distribution function of the standard normal distribution.

The parameter λ is used to test the hypothesis, where $\lambda \rightarrow 0$ is the result of $\sigma^2_v \rightarrow \propto$ or $\sigma^2_u \rightarrow 0$, stating that the symmetric term "random" v_i prevails over the determination of ε_i. It shows that there is no technical inefficiency among the producer, and all deviations from the boundaries of the best method are due to random effects. Using MLE, lnL in **Equation 6** can be maximised according to the parameters to obtain the MLE estimate of all parameters. The equation provides the estimate of the technical inefficiency of each unit (see **Equation 7**, below):

$$TE_i = \exp\{-\widehat{u_i}\} \quad \textbf{(7)}$$

MLE gives us an estimate of the compound term $\varepsilon_i = v_i - u_i$, which contains information about u_i and v_i. To extract technical efficiency information from u using technical **Equation 7** can be obtained by adopting the conditional distribution u_i concerning ε_i: f (u_i | ε_i), using a method of providing a point estimator and $\hat{u_i}$= E (u_i | ε_i). It can be substituted in **(7)** to calculate the technical efficiency of each unit (Jondrow et al., 1982).

However, before the realisation of model regression, it is needed to detect the proprieties of variables used in this empirical investigation. To this end, some preliminary tests will be applied, namely, **(i)** Kendall's correlation coefficient (Kendall & Gibbonsm, 1990). This test will be used to identify the correlation between the variables of our model; **(ii)** Variance inflation factor (VIF) (Belsley et al., 1980). This test will be carried to check for the existence of multicollinearity between the variables; **(iii)** Panel unit root test (CIPS) (Pesaran, 2007). This test will identify the presence of unit roots; and **(iv)** Bias-corrected LM-based test (Born & Breitung, 2016). This test will check the presence of serial correlation in the fixed-effects panel model.

After the time-invariant model production regression, it is necessary to carry out the post-estimation test. In this case, this investigation opted to carry the test for constant returns to scale. A production function exhibits constant returns to scale if doubling the amount of each input results in a doubling in quantity produced. When the production function is linear in logs, constant returns to scale implies that the sum of the coefficients on the inputs is one. In this test, the null hypothesis is the presence of constant returns to scale. Moreover, if our Wald x^2 of constant returns to scale test indicates that the sum of the coefficients does not equal one, then it is necessary to carry the Lincom test to compute the sum explicitly.

4.2.2. Data Envelopment Analysis (DEA)

The DEA also was used in our investigation. Indeed, the DEA approach uses mathematical programming techniques to estimate the best practice frontier and defines the relative efficiency of the studied DMU through its distance from the performance frontier. Conventional DEA models are built on the Shepard distance function (e.g., Chen & Golley, 2014; and Lin & Du, 2015). Because the DEA approach is easily used for multiple inputs and outputs, it is more generalisable and extensible than other methods (Jia & Li, 2015). In addition, the DEA approach compares the units and provides the rank of the DMUs under study. The efficiency score of each DMU indicates the ability to obtain the maximum output from a given input or to reduce the input without reducing the output level, which is measured by the relative distance from the frontier of the best performance (e.g., Jia & Li, 2015; and Lin & Du, 2015).

Farrell first proposed non-parametric efficiency estimation in 1957. Instead of estimating the production function, he set a limit for decision-making units, which used this limit to measure efficiency. After him, the DEA approach was developed by Charnes et al. (1978).

For comparison, we also calculated economic efficiency in the non-parametric DEA framework. Here we calculate economic efficiency using the DEA-CRS model. In this study, 14 selected LAC countries are introduced as DMUs. Economic efficiency is calculated by solving the following linear programming problem (see **Equation 8**, below):

$$
\begin{aligned}
&\text{Min } \theta \\
&\text{s.t:} \\
&\sum_{j=1}^{n} \lambda_j L_j \leq \theta L_i \\
&\sum_{j=1}^{n} \lambda_j K_j \leq \theta K_i \\
&\sum_{j=1}^{n} \lambda_j E_j \leq \theta E_i \\
&\sum_{j=1}^{n} \lambda_j Y_j \geq Y_i \\
&\lambda_{j \geq 0} \\
&j=1, 2, \ldots, n
\end{aligned}
\qquad \textbf{(8)}
$$

The following section will show the empirical results from the time-invariant model production estimation and the post-estimation tests.

5. Empirical results

Table 2 shows Kendall's rank correlation coefficients between the variables. This approach is intended for use on small- and moderate-sized datasets, as is the case of our study. The correlations between explanatory variables are below the values that raise concerns of potential variables' multicollinearity.

Table 2. Kendall's correlations

Variables	Y		E		L		K
Y	1.0000						
E	0.8347	***	1.0000				
L	0.4701	***	0.3284	***	1.0000		
K	0.7780	***	0.4878	***	0.4866	***	1.0000

Notes: The Stata command *ktau* was used; *** denotes statistically significant at 1% level.

The VIF-test confirmed the absence of worrying multicollinearity (see **Table 3**). Indeed, all individual VIF statistics are below the benchmark (10), and the mean VIF also is below the referential (6), commonly accepted as the threshold of stressful collinearity.

Table 3. VIF-test

	Dependent variable (Y)		
Variables	VIF	1/VIF	Thumb's rule
E	3.86	0.2587	<10
L	1.69	0.5918	<10
K	4.65	0.2150	<10
Mean VIF	3.40		<6

Notes: The Stata command *estat vif* was used.

Given that LAC countries share several common features, the presence of contemporaneous correlation between the crosses (i.e., cross-sectional dependence) is probable. If cross-sectional dependence is present, ought to be used unit root tests of the second generation. The second-generation unit root CIPS-test (without trend) support that variables Y, E, and L are stationary (see **Table 4**). Nevertheless, the same test appoints variable K to be nonstationary, i.e., integrated of order one (see **Table 4**). The presence of one unit root is more often than not due to variables incorporate a stochastic trend. This trend can be removed taken the variable's first differences. However, stationarity was achieved by removing the information of the long-run in the variable. Provided that only one of the explanatory variables (K) is nonstationary, the trap of spurious regression is away.

Table 4. Panel Unit Root test (CIPS-test)

Variables	Panel Unit Root test (CIPS) (Zt-bar)		
	Without trend		With trend
	Lags	Zt-bar	Zt-bar
Y	1	-4.233 ***	-2.319 **
E	1	-2.232 **	-0.284
L	1	-2.733 ***	-0.830
K	1	1.324	0.372

Notes: The Stata command *multipurt* was used; the null for CIPS test is: series have unit root; the lag length (1) and trend were used in this test; ***, ** denotes statistically significant at the 1% and 5% levels, respectively.

The LM (k) statistic is a robust t-test of heteroscedasticity and autocorrelation. The test strongly rejects the null hypothesis, indicating the variables are serially correlated (see **Table 5**). The LM (k) test is generally used to assess residuals' autocorrelation and can be used to assess the persistence in a series, as is the case here.

Table 5. Bias-corrected LM-based test

Variables	**LM(k)-stat**
Y	4.89 ***
E	6.24 ***
L	8.76 ***
K	2.74 ***

Notes: The Stata command *xtqptest* (Wursten, 2018) was used; *** denotes statistical significance at 1% level; Under H0, LM(k) ~ N(0,1).

Table 6 shows the results for the time-invariant model production estimation and the post-estimation tests. The test statistic for constant returns to scale is statistically significant in rejecting the null hypothesis (H_0: production function exhibit constant returns to scale). Therefore, one can conclude that this production function does not exhibit constant returns to scale.

Given the previous Wald χ^2 test rejected that the sum of the coefficients is an equal one, we use the Lincom approach to compute the sum explicitly and test its statistical significance. The sum of the coefficients is less than one and statistically significantly (see **Table 6**), so this production function exhibits decreasing returns to scale. In other words, if we doubled the production factors (E, K, and L), we would get less than twice as much output (Y).

Table 6. Time-invariant model production estimation and post-estimation tests

Inputs	**Time-invariant model production estimation**	
	Outputs (Y)	
Constant	7.5065	***
E	0.1971	***
L	0.3088	***
K	0.4158	***
/MU	0.6851	***
/LNSIGMA2	-2.0949	***
/LGTGAMMA	3.4707	***
Statistics	**Post estimation tools**	
	Test for constant returns to scale	
	chi2(1) = 10.62	***
	Lincom test to compute the sum explicitly	
	0.9217	***

Notes: ***, ** denote statistically significant at 1% level; the Stata command *xtfrontier* was used; H_0 of constant returns to scale test is that this production function exhibit constant returns to scale; the Stata command *test* was used. The Stata command *lincom* was used in the Lincom test.

The output elasticities of energy, labour and capital are all statistically significant and below 1% level. These elasticities are conditional on the available technology and measure output response to changes in energy levels, labour and capital, *ceteris paribus*. The values align with what is expected for LAC countries, i.e., a capital increase has more impact on the output (an increase of 1% in capital leads to approximately 0.42% increase in output) than labour (about 31%). Energy increases have the lowest impact on output but still not negligible (almost 20%).

Economic efficiency by country is revealed in **Table 7**. Two approaches were used to identify the countries' economic efficiency, the stochastic frontier analysis (SFA) and the data envelop analysis (DEA).

Table 7. Economic efficiency and ranks from the SFA and DEA models by country

Country	Economic efficiency			
	SFA	**Rank**	**DEA(CRS)**	**Rank**
Argentina	0.5124	6	0.7357	12
Bolivia	0.3624	11	0.5999	13
Brazil	0.3200	14	0.8122	8
Chile	0.8788	**2**	**1**	**1**
Colombia	0.4261	9	0.9404	4
Dominican Republic	0.5612	5	0.806	9
Ecuador	0.4498	8	0.8587	7
El Salvador	0.5604	4	0.7895	10
Guatemala	0.4652	7	0.9707	3
Mexico	0.3611	12	0.7762	11
Nicaragua	0.3586	13	0.5561	14
Panama	0.9733	**1**	**1**	**1**
Peru	0.4145	10	0.8848	6
Venezuela	0.6766	3	0.9347	5

Notes: The Stata command *xtfrontier* and *dea* were used.

When using the DEA approach to assess economic efficiency, two countries (Chile and Panama) receive an efficiency score of one (see **Table 7**). Nevertheless, using the SFA model, we do not conclude that this shows that the parametric SFA model has a higher differentiation power than the non-parametric DEA model (Zhou et al., 2012). Both approaches (SFA and DEA) appoint that Panama is the most economically efficient country in the LAC region, followed by Chile. In contrast, Brazil (SFA) and Nicaragua (DAE) are the least economically efficient among LAC countries. **Figure 1** reveals the technical efficiency of LAC countries.

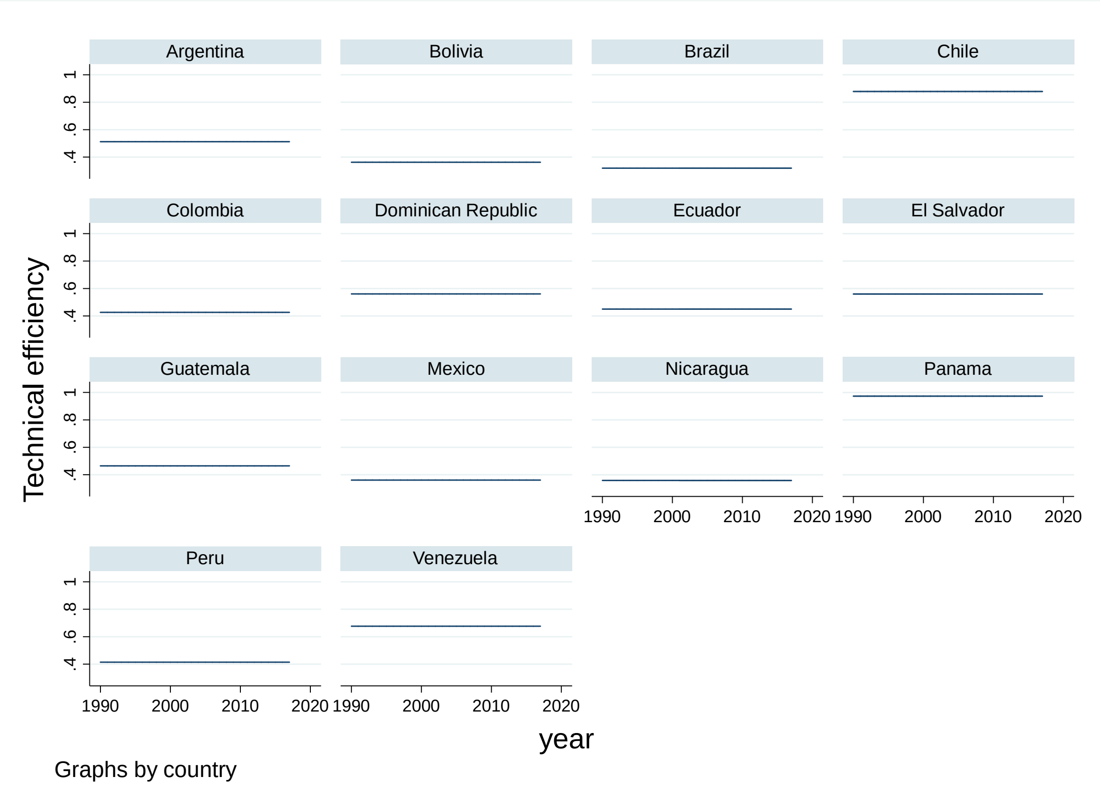

Figure 1. Technical efficiency of LAC countries. The Stata command *xtline* was used.

6. Discussion

The purpose of this study was to measure the economic efficiency performance in LAC countries. As mentioned in **Section 4.2**, two models, stochastic production frontier (SFA) and data envelopment analysis (DEA), have been used to achieve this goal in this study. According to **Table 7** and the SFA model, Panama has the highest economic efficiency performance with a coefficient of 0.9733 compared to other LAC countries. This result means that Panama has been able to maximise its GDP based on a set of inputs. Also, according to the DEA model, Panama still has the highest performance, so it no matter which model is used. For other countries, however, the choice between SFA and DEA affects rankings.

As shown in **Table 7** and **Figure 1**, according to the SFA model, Brazil has the lowest economic efficiency performance with a coefficient of 0.32, while based on the DEA model, Nicaragua has the lowest economic performance with a coefficient of 0.5561 among LAC countries. In addition, in **Table 7**, the two countries have a rank of unity in the DEA model and are not comparable when using the DEA model, even though this does not happen when using the SFA model. This result means that the SFA model often has higher discriminating power than the DEA model, which may be considered an advantage of SFA over DEA in economic efficiency performance (Zhou et al., 2012). As mentioned before, this section showed the results and their possible explanations for the results that were found in our empirical investigation. Finally, in the next section, conclusions will be discussed.

7. Conclusions

From the stochastic production frontier model applied to a group of 14 countries from the LAC region, in the period between 1990 and 2017, it was possible to study the impacts of the factors of production, that is, K, L and E, in the GDP of each LAC country, as well as the measurement of their macroeconomic efficiency from the production point of view. Two approaches were used to identify countries' economic efficiency, SFA and DEA.

The results indicate that the countries of the LAC region are not efficient in the use of their resources during the analysed period. This result can be seen from the average efficiency scores of the SFA and DEA models, which are 0.5228 and 0.8332, respectively. These scores are given relatively. When efficiency is analysed individually, i.e., for each country concerning the studied region, the results are different. The results of the SFA model show that none of the countries studied had a total score equal to 1. Thus, none of these countries is fully efficient in the use of their resources. However, compared to other countries, Panama has the highest efficiency performance, which is 0.9733. Next comes Chile, with a performance of efficiency of 0.8788. It is important to highlight that the results of the DEA model are different and show that Panama and Chile have been efficient in the use of their resources concerning the countries of the studied region, as they received a total efficiency score equal to 1. The worst performances regarding the efficiency of the LAC region are with Brazil (0.3200 through the SFA model) and Nicaragua (0.5561 through the DEA model).

Given the above, the empirical results of this study have important implications for LAC policy, as it contributes to the development of policies that lead to the efficient use of resources, social well-being and sustainable economic growth.

Countries that do not use their resources efficiently have the political implication of limited potential growth because of low investment, slow productivity growth, a fragile business environment, and poor infrastructure and education. In addition, political uncertainty, associated with an unstable environment, can reduce investment. Policymakers can increase the country's economic efficiency by adopting reforms that foster growth and drive their economies towards sustainable development and macroeconomic and political stability. Furthermore, they can stimulate competitiveness and increase the participation of the national economy in international markets. Greater efficiency in the use of resources promotes increased economic growth and the level of social well-being.

Countries need to develop public policies to achieve higher productivity levels in economies through diversification, technological modernisation and innovation, including through labour-intensive sectors to improve resource efficiency.

In addition, to achieve greater efficiency in the use of resources, countries can implement policies to encourage innovation through public investment in science and technology in universities, patent protection, encouragement of foreign direct investment, development of technological valleys and nationalisation policies of technologies. Some countries in the LAC region have adopted these policies, such as Brazil, Chile, Colombia, Mexico and Panama.

The inefficiency in the use of resources is related to the lack of investments in education and technological innovation, low capacity to attract investments, economic and political instability, more fragile financial systems, lack of commercial and economic opening, excessive bureaucracy, high cost of labour (related to heavy labour legislation) and low educational level. These structural problems are present in several LAC countries, except for Chile, Colombia and Panama, which are investing in these aspects to become more competitive concerning the rest of the world.

A limitation found for carrying out this study was the extension of the time series due to data availability for all variables. Therefore, it was decided to use the period from 1990 to 2017.

As a suggestion for future research, a possibility of development is pointed out: it would be interesting to try to replace input E (energy) with renewable energy to identify whether the economies of the LAC region are in the process of transition to a green economy. It is understood that the suggested research is essential for the development of the line developed in this study and relevant to specialised literature.

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