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Comparative Analysis of Efficiency in the Economic Sectors of Lima Stock Exchange

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ABSTRACT

Lima Stock Exchange is considered one of the smallest capital markets in Latin America, despite its favorable growth in the last five years. The performance of listed companies in the stock market may be compromised with national macroeconomic gaps and impact on the development of the economic sector, which is why this study aimed to estimate the financial efficiency of companies listed on the Lima Stock Exchange to know their performance by economic sector during the period 2015-2020. The non-parametric technique of Data Envelopment Analysis was used in a set of 76 companies belonging to the Agrarian, Industrial, Public Services, and Mining sectors; finally, the change in performance was estimated through the Malmquist Productivity Index. The results indicated that 2016 was the most efficient year for companies and 2018 the least efficient year. The most efficient sector was Mining with an efficiency of 0.56, Agrarian sector was the least efficient and with the highest volatility. Likewise, productivity results concluded that technological change does not contribute to productivity, while efficiency change contributed positively to all sectors. In addition, a trend of annual growth and stability of the Mining sector was evidenced, which, in the face of the economic crisis, only had a slight drop of -1.7% in its productivity, unlike the other sectors that were notably affected. Results of this study reflected that the macroeconomic indicators of the country often don't affect the performance of the economic sector, to know the performance of the companies it is necessary to analyze the characteristic factors of each sector. It is recommended to use the results of this study as a complementary instrument for making investment decisions in Lima Stock Exchange-listed companies.

CCS CONCEPTS

• **Applied computing**; • **Operations research**; • **Decision analysis**;

KEYWORDS

Efficiency, Data Envelopment Analysis, Lima Stock Exchange, Malmquist Productivity Index

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1 INTRODUCTION

Lima Stock Exchange has shown a favorable development in the last five years, doubling its public debt size from 8.1% in 2015 to 15.7% of GDP in 2019 [1]. However, the Peruvian stock market is considered a small stock market compared to other Latin American countries, due to the reduced level of listed companies, the strong concentration of capital in the few issuers, and mainly due to its low liquidity of 2.3% compared to 6.9% of Colombia and 21% of Chile in 2019 [2]. However, to ensure a safe financial environment and facilitate the financing of economic agents that contribute to the economic development of the country [3], it is necessary to know the efficiency of the Peruvian capital market from the perspective of accessible financial information. As is known, an accurate estimate between the performance of the stock market and the basic macroeconomic elements is essential for investors to be able to predict the movement of the share price and make a better decision about portfolio investment [4]. At this point, knowing the performance of each of the listed companies is essential to examine their response to gaps in the economic development of the country and the incidence of fundamental factors of the economic sector to which they belong.

Several studies have used tools such as Capital Assets Pricing Model [5], Modern Portfolio Theory [6], or Stochastic discount factors [7] to measure the financial performance of companies, however, in this study, the Data Envelopment Analysis (DEA) is proposed since it measures relative efficiency, where the efficiency score is influenced by the general group of companies, that is, these serve as a benchmarking tool.

DEA has previously been applied to measure the financial performance of companies listed on the stock market through the analysis of their financial statements, to highlight those companies that may be the most and least attractive for their investment. Ong et al. [8] used this methodology to measure the efficiency of 20 listed companies in Bursa Malaysia through two different combinations of inputs and outputs that included as inputs: total assets, current assets, current liabilities, total expenses, current ratio, and debt ratio, and as outputs: net income after taxes, revenue, return on investment, ROE and earning per share, concluding that efficiency depends on the selection of variables and the result of the DEA analysis serves as a first step for investors to decide because it discards those firms that have low performance. Hassan et al. [9] demonstrated that financial variable and ratio averages are points

of reference to evaluate and measure firms' future financial performance, for this, they used a classifier whose outcomes will be enhanced by Diverse Ensemble Creation by Oppositional Relabeling of Artificial Training Examples (DECORATE) Ensemble method as a complement to DEA in 53 companies in the industrial sector that are listed on Amman Stock Exchange from 2012 to 2015.

A study with Chinese stock market companies [10], grouped the financial variables for the DEA into three comprehensive indicators that measured the capital allocation, investment level and operation, then it focuses on the different weights of each one, its results showed a favorable development of the market, with problems such as inefficient operation, the prevailing wind of speculation, the irrational investment behavior and the half-baked investment and financing function impeded its continued growth. Similarly, Balseiro et al. [11], evaluated the financial efficiency of 69 companies listed in the Colombian stock market from 2012 to 2017, for which it applied the Data Enveloping Analysis using the variables of operating income, property, plant and equipment, and inventories, concluding that only 26.82% of the companies achieved efficiency in addition to the fact the type of scale used in the model is not decisive for results obtained.

Likewise, other studies used the DEA together with the Malmquist Productivity Index (MPI), to assess the change in performance in more than two consecutive periods, such as Mashhadi et al. [12], which used as inputs from the DEA the variables of the final product cost, fixed asset, current assets, net sale, total liabilities, total assets and financial ratios of liquidity, activity, investment, benefits such as outputs to measure the performance of petrochemical companies listed on the Stock Exchange Organization between 2006-2011, and found changes in productivity through the MPI. Also, Sharif et al. [13] detected an increase in productivity in Bursa Malaysia during the period 2007-2016 mainly due to a positive change in technology and technical efficiency, for which, they applied the DEA-MPI approach to 26 companies in the financial sector using as inputs the variables of market capital, total volume, dividend per share, financial leverage, price to book ratio and as outputs: return on equity, return on assets and price-earnings ratio. Finally, Pumisancho et al. [14] evaluated the efficiency with DEA and the evolution of productivity through the MPI of 164 SMEs in the Metropolitan District of Quito grouped into seven productive sectors, using financial variables to compare their performance, concluding that the Construction sector was the one with the lowest efficiency and all sectors presented a positive productivity change during the period 2010-2015.

As shown, multiple studies showed the validity of this methodology to compare the performance of companies, therefore, this study focuses on estimating the financial efficiency of companies listed in Lima Stock Exchange to know their performance by economic sector during the period 2015-2020 through the Data Envelopment Analysis.

2 LITERATURE REVIEW

2.1 Data Envelopment Analysis (DEA)

It is a non-parametric technique that is based on Farrell's production function concepts [15]. It is defined as the measure of relative efficiency that compares a DMU (Decision-Making Unit) with another, to obtain a weight defined by the quotient of the weighted sum of the outputs between the weighted sum of the inputs [16], where the efficiency greater than or equal to 1 is considered efficient, and that inefficient unit depends on a set of DMU of which it takes a reference, these units are known as peers. This methodology solves a linear programming problem whose objective function depends on the orientation of the model; thus, an input-oriented model suggests a maximum reduction of inputs without altering the production frontier; on the other hand, an output-oriented model seeks the maximization of the results given the permanence in the proportion of inputs [17].

$$\begin{aligned} Max_{\mu,y} \quad & W_0 = \left(\sum_{r=1}^{s} u_{i0} y_{i0}\right) \\ s.t. \quad & \left(\sum_{i=1}^{m} v_i x_{i0}\right) = 1 \\ & \left(\sum_{r=1}^{s} u_{r0} y_{rj}\right) - \left(\sum_{r=1}^{m} v_{i0} x_{ij}\right) \leq 0 \\ & \mu_r, v_i \geq \varepsilon \end{aligned} \tag{1}$$

The mathematical model in oriented input model is shown in (1), which looks for the weights of outputs u_i and inputs v_i that maximize the efficiency score of a unit, where x_{i0} and y_{i0} represent the inputs and outputs respectively, s_r and m_i are the input and output slack variables, while ε is a positive real number that allows the variables not to take negative or zero values.

There are two types of returns to scale in DEA, (1) shows CRS (constant returns to scale) or CCR approach, a model proposed by [18], which supports the axiom of proportionality between inputs and outputs, that is, an increase in inputs generates a proportional increase in outputs. On the contrary, the VRS (variable returns to scale) or BCC model considers the influence that economies of scale can have by dividing efficiency into global technical efficiency (GTE) and pure technical efficiency (PTE) obtained from the quotient between the CCR and BCC models respectively [19].

2.2 Malmquist Productivity Index (MPI)

The Malmquist Productivity Index (MPI) was first introduced by [20], from the study on the quantity index in Malmquist input analysis [21]. It is defined as the distance function of the radial input and output distance measured through the total factor productivity change (TFPCH), which calculates the increase in productivity from one period to another [15]. Unlike other productivity indices, this one does not require considering input or output prices in its structure, nor does it require assuming an orientation towards maximizing results or minimizing costs [22], which makes it attractive for studies in the approach of production.

The TFPCH can be measured in two components [23]: efficiency change (EFFCH) which indicates whether companies tend to approach the production frontier and technical change (TECHCH) which measures changes in technology, i.e., that the production frontier is moving outwards over time, which is defined as innovation [24]. The mathematical expression of MPI is shown in (2), where an increase in productivity is considered when the value of M (or TFPCH), reaches a value greater than or equal to 1, it is also verified that the EFFCH and the TECHCH improved if they reach

an individual score greater than the unit [25].

$$M_{(t,t+1)} = \left[\frac{D_{t+1}(X_{t+1},\ Y_{t+1})}{D_t(X_t,\ Y_t)}\right]\left[\frac{D_t(X_{t+1},\ Y_{t+1})}{D_{t+1}(X_{t+1},\ Y_{t+1})} \times \frac{D_t(X_t,\ Y_t)}{D_{t+1}(X_t,\ Y_t)}\right]^{0.5} \quad (2)$$

Where $D_{t+1}(X_{t+1},\ Y_{t+1})$ is the distance function between two consecutive periods $(t, t+1)$, the change in technical efficiency (EFFCH) is represented by $[\frac{D_{t+1}(X_{t+1},\ Y_{t+1})}{D_t(X_t,\ Y_t)}]$ and the technology change (TECHCH) is expressed as $[\frac{D_t(X_{t+1},\ Y_{t+1})}{D_{t+1}(X_{t+1},\ Y_{t+1})} \times \frac{D_t(X_t,\ Y_t)}{D_{t+1}(X_t,\ Y_t)}]$.

3 METHODOLOGY

3.1 Companies Selection

Seventy-six companies listed on the Lima Stock Exchange were selected during the 2015-2020 period that had financial information available, belonging to the sectors: Agrarian (12 firms), Industrial (30 firms), Public Services (19 firms) and Mining sector (15 firms). It should be mentioned that the financial structure of the companies is homogeneous, so a comparison can be made by sectors, likewise, those that presented lost values in one of these periods were previously excluded from the study.

3.2 Variables Selection

The variables used by [8, 12, 13] were taken as a reference, which analyzed the efficiency of companies listed on the stock exchange of other countries through the DEA. Therefore, the preliminary variables were as inputs: current assets, total assets, total liability, non-current assets, and as outputs asset circulation, debt ratio, current ratio, and quick ratio.

To comply with Banker's rule [19] that indicates that the product of inputs and outputs must be less than or equal to one-third of the amount of DMU, the multicriteria analysis proposed by [26] was performed, to limit the number of variables to those that best satisfy the criteria of level of discrimination measured by the number of efficient units and those with the best fit to the frontier found through the average efficiency. The product of both is reflected through the S value, where through iterations where 1 variable is introduced each time, the variable that yields the highest S value must be chosen since it is the most preferred for the DEA model.

To do this, it was taken as the initial pair input-output to current assets-current ratio; the first iteration added total assets variable, while the second iteration added non-current assets variable. Thus, they were finally left as inputs: current assets, total assets, non-current assets, and as output: current ratio.

The DEA output-oriented model was chosen, since it is easier for inefficient units to seek to maximize the result to achieve efficiencies [8], likewise, several authors affirm that this model is convenient when evaluating the possibility of expansion of results over time without the need to modify inputs [13, 27]. Regarding returns to scale, numerous studies applied to equity markets use both BCC and CCR. [11] shows in his study that the type of scale used is not a determining factor in the efficiency result obtained for a particular period, that is, if the effect of economies of scale is eliminated under the BCC model, the results do not differ significantly.

4 RESULTS

4.1 Data Envelopment Analysis Results

The average efficiency score by sector from 2015 to 2020 was calculated WITH the BCC model, these are shown in Table 1. The joint average efficiency from 2015 to 2020 is 0.406, the year 2016 showed outstanding performance with an efficiency score of 0.417, where approximately 21.9% of the companies are efficient, which is consistent with the 4% growth in GDP for that year [28].

By contrast, 2018 presented the lowest average efficiency with a score of 0.383 and only 13.5% of efficient companies, even though the inflation rate in 2018 was 1.32%, the lowest value of the decade [29].

In the analysis by sectors, the Mining sector obtained the highest average efficiency of 0.563 with 40% of companies that achieved the efficiency of this sector in 2015 and 2016, this can be justified with the Mining GDP peak of 15.7 and 21.2% respectively in these two years [30]. Conversely, the Agrarian sector obtained the lowest average efficiency with 0.323 percentage points, in addition to being the most unstable sector since it presents the highest standard deviation ($\sigma = 0.058$) of the sample. The Industrial sector stands out for being the most stable ($\sigma = 0.021$), however, it had the lowest proportion of efficient companies compared to other companies, since only 6.7% of companies were efficient from 2015 to 2019. Finally, Public Services shows a slight increase in its average efficiency during the 2016 and 2017 periods, but this falls again for 2018, making it the second most volatile sector below the Agrarian sector.

4.2 Peer Analysis

The know the company by sector that was taken as a peer (reference for other companies) more frequently, the times that they were references of other companies were counted, and this proportion was divided according to the number of participating companies in their respective sector.

The results in Table 2 show that the leading company in the Agrarian sector is "Empresa Agricola Sintuco", which served as an efficiency benchmark for 75% of the companies in the sector throughout the period under study except in 2017-2018 where it had an even greater influence. Likewise, the Industrial sector had as an outstanding peer to "Consorcio Industrial de Arequipa" and the practices were references up to 93.3% of the sector, and it was the most influential company for the entire sample. Also, "Peruana de Energía" was the most influential in the Public Services sector, with a high percentage of influence during the entire period except in 2017, where it referred to only 10.5% of the companies. Finally, in the Mining sector, the outstanding one was "Minera Andina de Exploraciones", which shows a constant fluctuation in its participation throughout the period under study.

4.3 Malmquist Productivity Index Results

In Fig. 1, the change in performance by sector was calculated with the Malmquist Index, where an average TFPCH value greater than or equal to 1 means an increase in productivity [25], and the progress rate of its components of EFFCH and TECHCH to find out why they impact the TFPCH. The value of the annual progress rate

Table 1: Efficiency scores by sector

	Period	Sector				Average
		Agrarian	Industrial	Public Services	Mining	
Average efficiency	2015	0.373	0.386	0.292	0.595	0.412
	2016	0.369	0.372	0.324	0.601	0.417
	2017	0.243	0.361	0.439	0.603	0.412
	2018	0.260	0.373	0.382	0.516	0.383
	2019	0.323	0.419	0.343	0.548	0.408
	2020	0.367	0.369	0.376	0.513	0.406
% Efficient units	2015	8.3	6.7	10.5	40.0	16.4
	2016	25.0	6.7	15.8	40.0	21.9
	2017	16.7	6.7	21.1	20.0	16.1
	2018	16.7	6.7	10.5	20.0	13.5
	2019	25.0	6.7	10.5	13.3	13.9
	2020	25.0	10.0	10.5	13.3	14.7
Average efficiency by sector		0.323	0.380	0.359	0.563	0.406
Efficiency standard deviation (σ)		0.058	0.021	0.051	0.042	-
Max.		0.373	0.419	0.439	0.603	-
Min.		0.243	0.361	0.292	0.513	-

Table 2: Percentage of peered companies by sector

Sector	Sector featured peer	Period					
		2015	2016	2017	2018	2019	2020
Agrarian	Empresa Agricola Sintuco	75.0	75.0	83.3	83.3	75.0	75.0
Industrial	Consorcio Industrial de Arequipa	76.7	83.3	93.3	93.3	93.3	36.7
Public Services	Peruana de Energía	89.5	84.2	10.5	89.5	89.5	89.5
Mining	Minera Andina de Exploraciones	33.3	13.3	40.0	33.3	66.7	33.3

is obtained by subtracting 1 from the geometric mean of the annual efficiency changes.

Fig. 1 (a) shows that only the Agrarian sector presents positive progress in productivity in all sectors (TFPCH 2018-2019 average = 1,035) because 30% of companies reached total productivity during that period. In addition, continuous growth was manifested from the period 2015 to 2019, because of the increase in the EFFCH with a progress rate of 0.4% and the fact that 50% of the companies had favorable progress in their technical efficiency during the entire study period. These facts are confirmed with the continuous rise in the value of agricultural production from 12,486 (million S/.) in 2015 to 29,553 (million S/.) in 2019 [31]. However, this sector showed a decline in productivity of -43.6% in 2020, the most drastic at the sector level.

The Industrial sector achieved the highest EFFCH scores with an annual progress rate of 0.8% since only the companies "Empresa Siderúrgica del Perú" and "Quimpac" suffered a deterioration in their technical efficiency with an annual decrease of -2.1 and -2.3% respectively. However, it is also the sector that presents the greatest technological disability with a TECHCH annual progress rate of -28.9%, which is evidenced in the large drop that it causes in the TFPCH during the period 2016-2017 as shown in Fig. 1 (b).

On the other hand, Fig. 1 (c) shows high volatility in all the productivity components of the Public Services sector, as corroborated by the results of the DEA analysis in section 4.2. The EFFCH annual progress rate is 0.6%, while its technological growth was the least affected compared to the other sectors, with a TECHCH annual progress rate of -19.9% in the 2017-2018 period. In addition, an increase in productivity stands out in the 2018-2019 period, with a value very close to one (TFPCH = 0.999).

Finally, favorable growth trend of the Mining sector wasn't seriously affected by the COVID-19 recession as in the other sectors during 2020, since it only reduced its productivity by -1.7; This is consistent with its liquidity ratio of 2.2%, which was the highest at the sectoral level during 2020 [32], as shown in Fig. 1 (d).

Also, there is an increase in productivity from 2018 to 2019, which is unusual, since there was a reduction of -0.84% in the Mining GDP from 2018 to 2019 due to the reduction in mining exports, which may indicate that private mining investment sustained this expansion in the sector [30].

5 CONCLUSIONS

The purpose of this study was to estimate the financial efficiency of listed companies in the Lima Stock Exchange to know their performance by economic sector during the period 2015-2020 through the

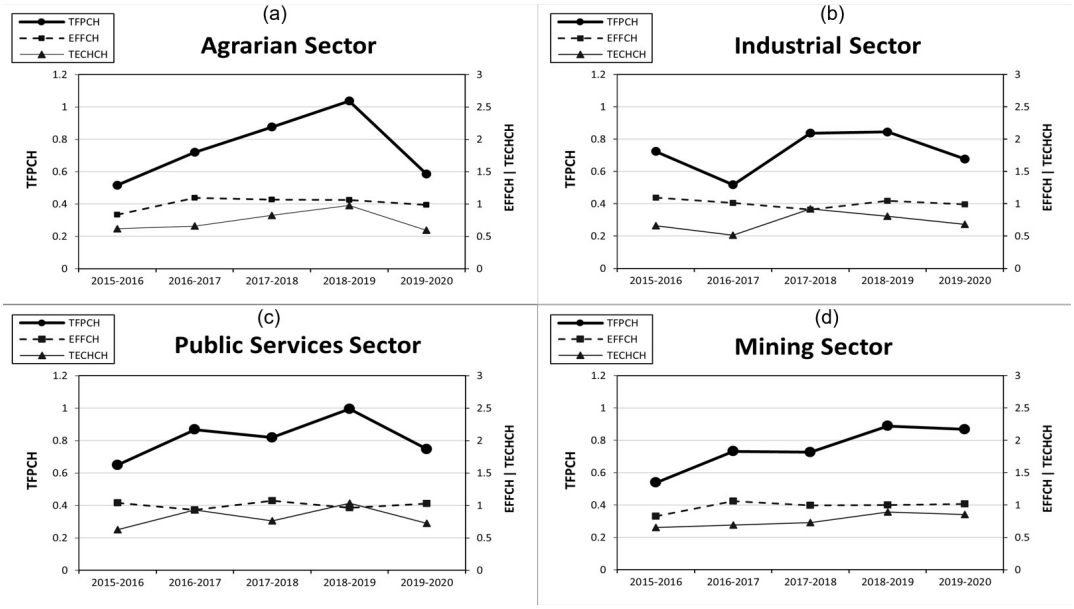

Figure 1: Variation of the total factor productivity change (primary axis) as a product of efficiency change and technical change (secondary axis) during the period 2015-2020.

Data Envelopment Analysis. This methodology made it possible to measure the relative financial efficiency of 76 companies in the sectors: Agrarian (12 firms), Industrial (30 firms), Public Services (19 firms), and Mining, for which variable inputs were used: current assets, total assets, non-current assets, and as output: current ratio.

The results of the Data Envelopment Analysis indicated efficiency of 0.406 during the 2015-2020 period, the year 2016 stood out for having the highest efficiency of 0.417, and 2018 had the lowest efficiency score. The scores by sectors indicated that the Mining sector is the most efficient (average efficiency = 0.563), mainly during 2015 and 2016 where 40% of the companies were efficient, possibly due to the Mining GDP peak during those years. On the contrary, the Agrarian sector turned out to be the least efficient (average efficiency = 0.323), in addition to being the most unstable sector. Likewise, the Peer Analysis was carried out to find out those companies that were references for inefficient units in their sector, the company "Empresa Agricola Sintuco" stands out in the Agrarian sector, for remaining as an important reference for its sector throughout the study period.

Likewise, Malmquist Productivity Index was applied to determine productivity, it was concluded that technological change (TECHCH) doesn't contribute to productivity progress in any sector, since all present negative rates, while the efficiency change (EFFCH) had a positive progress rate in all sectors. Regarding the total factor productivity change, Agrarian sector was the only one that presented a significant increase in productivity (average TFPCH = 1.035) in the period 2018-2019, in addition, a trend of improvement in the productivity of this sector was noted from 2015 to 2019. The impact of the 2020 economic crisis on the productivity of all sectors was evidenced, Mining sector was highlighted as the one that was not affected in a large proportion (-1.7%) and the Agrarian sector, which was the most affected by falling his score at -43.6%.

This study detected a possible relationship between the variation of the sector's own indicators such as production capacity, annual income, exports, and private investment, such as those that can influence the efficiency of listed companies. Likewise, it was evidenced that the alteration of some macroeconomic indicators such as GDP and the inflation rate often doesn't affect the performance of the sector, since companies that have better practices to deal with the environment can contribute a greater proportion to the growth of this. For this reason, it is recommended to use the results of this study as a complementary instrument for making investment decisions in the future.

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