Energy efficiency and environmental productivity: Analysis of Ecuadorian oil companies

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Abstract

This study delves into the imperative to mitigate greenhouse gas emissions within the oil sector by promoting energy efficiency and environmental productivity. Specifically, it investigates the primary drivers influencing efficiency and productivity in private oil companies operating in Ecuador, a key South American oil producer. The overarching research objective is to discern the factors impacting energy efficiency and productivity while considering both polluting and non-polluting aspects of productivity variation.

Our analysis encompasses a sample of 18 Ecuadorian private oil companies, spanning the years 2012-2020. We employ a non-parametric model and the Malmquist index to comprehensively assess energy efficiency and productivity in two distinct scenarios, accounting for both polluting and non-polluting factors.

The study reveals compelling insights into the factors affecting efficiency and productivity within Ecuador's private oil companies. Notably, we observe a significant influence of company size and technological change, particularly among firms employing more polluting inputs in their production processes. Over the study period, on average, companies display limited positive changes in efficiency and productivity, underscoring the need for targeted public policies aimed at reducing energy consumption in these firms. Furthermore, consideration of electricity subsidies may incentivize more efficient and environmentally conscious consumption practices.

This research highlights the pivotal role of energy efficiency and environmental productivity in the oil sector's sustainability efforts. The findings emphasize the necessity for proactive public policies to curb energy consumption within private oil companies in Ecuador, aligning economic growth with environmental responsibility. These insights are invaluable for policymakers and industry stakeholders striving to strike a balance between profitability and ecological stewardship within the Latin American oil industry, with Ecuador serving as a pertinent case study.

Keywords: energy, efficiency, productivity, environmental productivity, oil, companies.

1 INTRODUCTION

According to the International Energy Agency, the oil industry contributes to approximately a third of the world's total carbon emissions (IEA 2021). Thus, oil companies must become more efficient and balance pollution mitigation and economic performance. Some studies show the importance of energy efficiency in improving the economic performance of oil companies by reducing costs (Midor, et al. 2021, Yáñez, et al. 2018, Longwell 2002). However, when assessing the energy efficiency of oil companies, most studies have frequently ignored environmental aspects (Hou, et al. 2019, Jung, Kim and Rhee 2001). Therefore, fewer studies are focusing on the environmental performance of oil companies. According to the literature in production economics, environmental productivity refers to the efficient utilization of pollution abatement and how this might influence the costs of alternative production and pollution abatement technologies (Kaneko and Managi 2004). Studies in this field are scarce, and most have been developed in developed countries and Asia.; (see, e.g., Tavana et al. (2019), Wegener and Amin (2019), Sueyoshi and Wang (2014, 2018), Da Silveira et al. (2017), Azedeh et al. (2015), Song et al. (2015), Sueyoshi and Goto (2015), among others). To the author's knowledge, no studies have been developed in which energy efficiency and environmental productivity change in the oil sector is evaluated in Latin America, nor has a specific case study been done on the oil sector in one country in the region. Therefore, the research problem focuses on "How is energy efficiency related to environmental productivity in the Latin American oil sector, and how do these variables impact the economic performance of oil companies in a specific country within the region?"

This study aims to address the gap in the academic literature by examining the relationship between energy efficiency and environmental productivity within the Latin American oil industry and assessing their impact on the profitability of oil companies in a specific context. Furthermore, it seeks to contribute to the knowledge base on industrial-level energy efficiency analysis within a developing nation. Specifically, the research objective is to investigate the operational dynamics of drivers and barriers influencing energy efficiency in Ecuador's industrial sector. Through empirical investigation, this study will shed light on the resource utilization practices of private oil companies in this South American country, with a particular focus on energy resources. Ultimately, the primary goal is to provide valuable insights that can help oil companies optimize resource usage, enabling them to maximize profits while reducing their environmental emissions.

For this study, it was considered a sample of 18 Ecuadorian private oil companies associated with crude oil extraction and refining activities in Ecuador was considered. Ecuador is the fifth oil producer in South America. In 2019 oil extraction was 193.8 million barrels, of which 40.96 million barrels (21%) were extracted by private companies. Among all industry sectors, the petroleum industry is of particular interest to Ecuador because of its economic and environmental significance. Public and private companies own the oil industry in Ecuador. The public sector plays a more significant role due to more production and higher investment (World Bank 2018). Although, between 2000 and 2006, the sector was led by private investment. A shift in contract agreements in 2011 resulted in a decrease in the investment made by private operators. Oil is also essential for the Ecuadorian energy sector; in 2018, Oil represented 86.9 percent of the national energy supply. According to the Third National Communication on Climate Change and First Biennial Update Report (UNFCCC 2017), in Ecuador, the energy sector produced 37 594 Gg of carbon dioxide equivalent (CO_2e), representing 47 percent of total GHG emissions in 2012. The energy industry is a significant contributor to GHG emissions in the country, especially for the burning of fossil fuels. In 2012 this activity accounted for 36 822.54 Gg (CO_2e), representing 97.95 percent of energy sector emissions.

Based on production value added during 2011-2020, the following sectors had the most significant share in GDP: Manufacture (14.10%), National trade (10.50%), Agriculture and fishing (9.18%), and Oil and quarrying (8.53%). Also, in the period analyzed, oil exports accounted for 54.83% of total exports, and oil revenues for 30% of overall fiscal income (Central Bank of Ecuador 2021).

To assess environmental efficiency and environmental productivity in Ecuador's oil companies, a non-parametric production model (Tulkens 1993) is applied as a practical approach to evaluating the pollution-adjusted productivity change of Ecuadorian petroleum companies. This method is widely applied in the literature for production analysis (Sueyoshi, Yuan and Goto 2017, Zhou, Ang and Poh 2008). Unlike parametric models, this type does not require explicitly specifying a mathematical form for the production function. Moreover, it allows for assessing the environmental efficiency of multi-inputs and multi outputs production units by relaxing the convexity property of the pollution-generating technologies. To the best of the author's knowledge, no research has been performed in the oil industry field that analyses environmental productivity change considering a pollution-generating production model. Knowing the prominent drivers of energy efficiency and environmental productivity change is a significant concern in the applied economics literature (Miao, et al. 2019, Shen, Boussemart and Leleu 2017, Valadkhani, Roshdi and Smyth 2016) This chapter displays the main components of the pollution-adjusted productivity variation considering Ecuadorian oil companies. Identifying the primary sources of pollution-adjusted productivity change allows for displaying internal (technological processes, management skills, Etc.) or external (environmental policies, economic context, etc.) constraints that influence productivity variation. The results suggest efficiency and productivity losses relate to energy consumption levels and lack of technical change during the period.

The remainder of this research is structured as follows. Section 2 displays the studies that approach the driver of energy efficiency and the non-parametric models to estimate energy efficiency. The parametric and non-parametric approach is presented in Section 3. The empirical illustration is provided in Section 4. Finally, Section 5 focuses on the discussion and conclusions of this research.

2 LITERATURE REVIEW

2.1.1 Environmental productivity

In a context where natural resources are increasingly constrained, it is important to consider that a company's environmental productivity (EP) is an essential piece of information that companies needs to contemplate when they want to improve their performance. It is helpful to review what is meant by the term "productivity." Productivity expresses a relationship between the quantity of goods and services produced by a business, or an economy and the quantity of labor, capital, energy, and other resources needed to produce those goods and services (Finman & Laitner, 2001). Meanwhile, EP involves the analysis of a company's relative efficiency in its use of and impact on natural resources (Wang & Shen, 2016). According to the literature in production economics, environmental productivity refers to efficient utilization of pollution abatement and how this might influence the costs of alternative production and pollution abatement technologies (Kaneko & Managi, 2004). Studies related to environmental productivity are scarce, and most have focused on developed countries (Beltrán-Esteve, Giménez, & Picazo-Tadeo, 2019) and Asia (Kaneko & Managi, 2004).Most studies reviewed focus on implementing environmental regulation to improve environmental productivity in companies and countries (Wang & Shen, 2016; Dewar, 1984). Also, some of these issues are widely covered over industrial energy efficiency. studies in this field have found that improving energy efficiency and incorporating energy efficiency technologies have significant benefits on environmental productivity and allows to meet sustainable development goals (Cagno, Worrell, Trianni, & Pugliese, 2013).

2.1.2 Energy Efficiency and environmental productivity

Some studies review the relationship between energy efficiency improvement measures and productivity in the industry. Finman & Laitner (2001) reviewed more than 77 industrial case studies. the authors suggest that energy efficiency investments yield significant non-energy benefits, which are often not calculated. The description of energy-efficient technologies as opportunities for larger productivity improvements has significant implications for re-thinking how we quantify the savings associated with capital investment and the leverage points for promoting energy efficiency but may even challenge methods to use for conventional economic assessments. Blumstein et al. (1980) identifies six kinds of barriers that firms face to achieving industrial energy efficiency: 1) misplaced incentives, meaning the economic gains of obtaining energy efficiency are not always perceived by the decision makers. 2) lack of information. 3) regulation. referring to existing legal framework that conflicts with cost-effective measures. 4) market structure. as for example, the energy efficiency solution is not offered on the market. 5) financing, such as technologies that requires high initial investment. 6) firm's customs, as company practices that generate low energy efficiency performance. However, when assessing energy efficiency and industry productivity, most studies have frequently ignored environmental aspects to improve productivity (Jung, Kim, & Rhee, 2001). In addition, few studies focus on the environmental performance of oil companies (Hou, et al., 2019).

In the case of developing countries, the adoption of energy efficiency technologies and better practices with clear sustainable goals by firms are rarely explored in the literature. One of the reasons may be the lack of management support, prioritizing growth over environmental protection (Grover & Karplus, 2020). The findings of Karplus, Shen, and Zhang (2020) suggest that companies in China do not usually consider energy efficiency interventions with return periods longer than one year. Energy efficiency efforts are essential in improving processes, minimizing the Impacts of oil quality depletion, and achieving sustainable development (Keskin, Dincer, & Dincer, 2020). Affordable clean energy and climate action are among the seventeen sustainable development goals. Energy security and environmental protection have become one of the most important issues on today's international agenda.

2.1.3 Energy efficiency and environmental productivity estimation methods

Knowing the primary sources of efficiency and productivity variation is of particular interest in the economic literature. Non-parametric programming modelings for production analysis are broadly applied to assess these issues. Some studies employed a DEA methodology using linear programming techniques (Boussofiane, Dyson, & Thanassoulis, 1991) to deal with undesirable outputs, such as GHG emissions, which ultimately affect companies' efficiencies. Many approaches have been put forward to account for this issue, such as parametric output and input distance functions (Färe, Grosskopf, Knox, & Yaisawarng, 1993; Coggins & Swinton, 1996; Hailu & Veeman, 2001; Ho, Dey, & Higson, 2006) and DEA methods (Skevas, Lansink, & Stefanou, 2012; 2014; Serra, Chambers, & Lansink, 2014; Kabata, 2011; Yang, Wei, & Chengzhi, 2009; Ramli, Munisamy, & Arabi, 2013).

Song, Zhang, and Wang (2015) applied the

Network DEA model to divide efficiency scores into two subcategories, thus feeding back more accurate results. In China, production and environmental efficiency changes were evaluated in twenty local oil companies. Sueyoshi and Goto (2015) incorporated Malmquist's index in the environmental assessment of oil companies' studies. Azedeh, Mokhtari, Sharabi, and Zarrin (2015) demonstrated the usability of DEA in studies related to health, safety, and the environment in an oil refinery, improving ergonomic features in the business. Tavana et al. (2019) defined a fun multi-objective multi-period network DEA model customized to evaluate the dynamic performance of oil refineries in the presence of undesirable outputs. Considering the above, this empirical study proposed a non-convex DEA modelling and a parametric model to analyze oil industry energy efficiency and productivity with undesirable outputs in private companies in Ecuador.

2.2 Methodological Framework

To analyze the issue of energy efficiency and environmental productivity in private oil companies in Ecuador, this research employs a DEA model. DEA is an efficiency evaluation method based on the concept of relative efficiency. There are different types of DEA model such as SMB—DEA model, that is non-radial and non-input or non-output oriented, directly utilizes inputs and outputs to determine the efficiency measurement of DMUs. In line with this study's purpose, the SMB—DEA model with undesirable output is applied to estimate the energy efficiency and environmental productivity of 18 private oil companies in Ecuador. This study only incorporates variables whose values can be changed in a reasonable period by decision-making units (Çelen, 2013), and that allows for maximizing the benefits of oil extraction and minimizing undesirable outputs. To study and compare the dynamic efficiency of energy productivity among oil companies the Malmquist Productivity Index (MPI) is adopted. The MPI approach assesses the multi-faceted and multi-output environmental impact of time frame changes. This approach is used to account for the change in industry policy efficiency, with the advantage of estimating the functional association betweeninputs and outputs. The Malmquist and DEA approach are among the most used tools to estimate energy efficiency in industry (Zhou, Ang, & Poh, 2008; Zheng, 2021). These methods are presented in more detail in the following sections.

2.2.1. Non-parametric model: DEA model and environmental productivity adjusted Malmquist Index.

This section displays the efficiency evaluation and productivity indices. The DEA method takes an economic system or a production process as an activity, where an entity (a unit) produces a certain number of "productions" by investing a certain number of elements within a limited range (Li, Li, & Wu, 2013). These entities (units) are called decision-making units (DMUs). Many DMUs constitute to be respective evaluation groups. The efficient production frontier is built on evaluating, with each input or output indicator's weight as the variable under the analysis of input and output ratios. In the end, an efficient DMU or an inefficient DMU can be determined according to the distance between this DMU and the efficient production frontier (Debreu, 1951; Farrell, 1957; Shephard, 1953). These distance functions fully multiple inputs-outputs production processes. The following definition presents the multiplicative distance function (Abad, 2018).

Definition 1.

$$For\ any\ (x_t,\ y_t) \in\ R_+^{n+m}, where\ y_t = (y_t^d, y_t^u)\ \in\ R_+^m\ , the\ multplication\ adjusted\ distance\ function, D^{\emptyset}:\ R_+^m \to R\ \cup \infty\ is\ defined\ below:$$

$$D^{\emptyset}(x, y) = \begin{cases} inf_{\beta}\{\beta \in [0,1]: (\beta^{\alpha} x_t, \beta^{\gamma^d} y_t{}^d, \beta^{\gamma^u} y_t{}^u) \epsilon T\} \\ if\ (\beta^{\alpha} x_t, \beta^{\gamma^d} y_t{}^d, \beta^{\gamma^u} y_t{}^u) \epsilon T, \beta > 0 \\ else \\ \infty \end{cases}$$

$$where\ \emptyset = (\alpha, \gamma^d, \gamma^u) \epsilon \{0,1\}^{m^d} x \{0,1\}^{m^u}$$

The multiplicative pollution adjusted function is employed to compute the Malmquist index. According to Nishimizu and Page (1982), this index can be discomposed into technical change (TEC) and technical efficiency change (EC) when examining productivity change. TC was defined as change in the best practice production frontier, while EC was defined to include all other productivity change, including 'learning by doing, diffusion of new technological knowledge, improved managerial practice, scale efficiency and so on'.

The next equations display the productivity index for the model:

$$MPI = TEC * EC = M(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \times \left[\frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^t(x^{t+1}, y^{t+1})} * \frac{D^t(x^t, y^t)}{D^t(x^t, y^t)}\right] \quad (3)$$

If the efficiency changes in $EC^{\emptyset}{}_{t,t+1}$ is greater than 1 then, efficiency progress arises over the periods (t) and (t + 1). Moreover, technological improvement occurs between the periods (t) and (t + 1) when $TC^{\emptyset}{}_{t,t+1}$

Where:

$(x^t, y^t), (x^{t+1}, y^{t+1})$ are outputs and inputs vectors in t and $t + 1$

D^t, D^{t+1} are the distance functions between t and $t + 1$

2.2.2. Parametric model: Panel regression

We investigated the relationship between productivity index and economic variables using a Tobit panel regression model to specify individual DMU effects and cross-section data commonalities (Liu & Liu, 2016). The standard linear model is not appropriate for such analysis, because the predicted values of efficiency scores may lie outside the unit interval. As the accumulation of scores at unity is a natural consequence of the DEA approach, the Tobit model was employed (Riaño & Larres, 2021).

The relationship between energy practices and oil companies and the efficiency score is described using the model below:

$$MI_{it} = \beta_0 + \beta_1 Energy_{it} + \beta_2\ Capital_{it} + \beta_3 Employment_{it} + \beta_4 Emmisions_{it} + \beta_5 Oilproduction_{it} + \varepsilon_{it} \quad (6)$$

Where MI is the dependent variable, representing the scores obtained from the efficiency evaluation. Emissions represents CO2 emissions per capita, introduced in logarithms and Capital in level, measured by the capital to labor ratio. Employment and is the labor, measured in person, and Energy is energy consumption measure in kwts/hour.

2.3 Data in brief

A sample of 18 private oil companies in Ecuador is considered over the period 2011–2020. The data set used in this research is built with the population of registered oil Ecuadorian formal firms, constructed from the balance sheets and financial statements registered on the official website of the Superintendencia de Compañias, Valores y Seguros (SCVS). This information is reported annually directly by firms to the SCVS.

The inputs and outputs selected are used in other DEA studies before for efficiency analysis of energy related industries to assess and monitor technical efficiency performance across a sample of companies, these inputs and outputs are directed related to the production process and have a greater relevance on the enterprises management level (Perreto et al. (2022).. Three inputs are selected: (i) number of formal employees of each company and (ii) net tangible assets (capital stock). Information about the number of legally registered employees (i) is declared by each company. The capital stock (ii) is set as the sum of the real dollar value of buildings, machinery and vehicles by assuming a depreciation of 5, 10, and 20 percent. Precisely, the methodology of Camino-Mogro and Bermudez-Barrezueta (2021) is employed. Hence, the capital stock is valued considering the gross investment in equipment in year (t), net fixed assets in real value (physical capital in year (t – 1)), a depreciation rate and the price index for equipment at the industry level obtained from the Ecuadorian National Institute of Statistics. And, the energy consumption of firms, measure in kilowatts/hour, that considers the energy consumption of fossil fuels registered by firms in the official statements provided by SCVS. These in-puts permit to produce different outputs. Thus, we consider one desirable output, (iii) number of oil barrels and one undesirable output represented by (iv) CO2 emissions.

The number of extracted barrels of oil (iii) is defined based on the variable "sales" (American dollars) reported in the balance sheets and financial statements registered on the official website of the SCVS. Obviously, we divide it by the price (American dollars/barrel) to obtain the variable "number of extracted barrels of oil". The reference price (WTI) is considered allowing comparisons with another international research in the same field. The CO2 emissions (tons of CO2 equivalents) (iv) is measured by using the methodology of the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Table 1. Characteristics of inputs and outputs

Table 1. Characteristics of inputs and outputs

Variables	Min	Max	Median	S.D.	Mean
Labor	0	6.55	2.30	2.06	2.73
Capital stock (constant)	7.47	18.97	13.26	2.12	13.48
Energy Consumption	8.14	19.85	15.64	2.89	14.89
Oil production	5.95	16.44	12.89	2.30	12.27
CO_2 emissions	1.31	22.41	8.79	4.93	9.75

Source: Author, Notes: All variables in logarithms

Table 1 presents the descriptive statistics of the variables used in this study. The statistical description of the data set displays variation in the database. The standard deviation (S.D.) values indicate unbalanced growth of private oil companies in Ecuador over the period 2012-2020.

2.3 Correlation matrix

This table represents the correlation matrix for the input and output variables in the sample. The variables selected as inputs are highly correlated with the outputs conferring validity to our empirical strategy. The high correlation found also confirms the association between the selected inputs and outputs as statistically significant at 90%.

Table 2. Correlation Matrix

Variables	Energy consumption	Employment	CapitalO	il production	CO_2
Energy Consumption1					
Employment	0.0285	1			
Capital	0.4267***	0.4442***			
Oil production	0.7483***	0.7483***	0.5080***	1	
CO_2 emissions	0.2839***	0.1361*	0.2045***	0.5132***	1

Source: Author , Notes: *p<.1, **p<.05, ***p<.01

3 RESULTS

To study energy efficiency for oil companies in Ecuador, this research used the SMB-DEA model to consider for undesirable output. This analysis presents two scenarios. In scenario 1, energy inputs and outputs are involved in the production of good and bad outputs. In contrast, scenario 2 only considers energy input to produce the desirable output. The results of these two scenarios—Technical-factor energy efficiency (TFEE) and Particular-factor energy efficiency (PFEE) allows a deeper exploration of energy efficiency in extraction incentive industries. Then the Malmquist index productivity is calculated to understand the change in energy productivity across the time period. Additionally, a Tobit panel regression is conducted to analyze the potential drivers of energy efficiency for these Ecuadorian oil firms.

3.1. Analysis of technical-factor energy efficiency (TFEE) and Particular-factor energy efficiency (PFEE)

In a DEA model the companies whose efficiency is 1 or greater than 1 make up the production frontier compared to those whose efficiency is less than 1, which are DEA inefficient. Table 3 reveals that in Scenario 1 (the production function with undesirable and o desirable outputs), only 4 companies showed inefficiency scores. On the other hand, in Scenario 2, 6 firms registered an energy productivity scores less than one. Thus, these results are consistent with the findings of Wang et al.(2019) and Tachega et al.(2020), who suggest that a production function that integrates energy and traditional economic inputs can increase oil production and reduce CO2 emissions with overall good efficiency score levels.

Table 3. Energy efficiency scores for TFEE and PFEE

	SCENARIO 1	SCENARIO2
AMODAIMI-OIL COMPANY. S.L.	1.091	1.163
ANDES PETROLEUM ECUADOR LTD.	0.383	1.122
CARLOS PUIG & ASOCIADOS S.A. CIA. DE EXPLORACION DE MINERALES Y SERVICIOS MINEROS	1.813	0.648
COMPAÑIA SUDAMERICANA DE FOSFOROS DEL ECUADOR FOSFOROCOMP S.A.	1.017	1.426
ENAP SIPETROL S.A.	0.53	1.099
EQUIPENINSULA S.A	2.515	1.087
EQUIPO PETROLERO S.A. EQUIPETROL	0.611	0.84
ERINCORP S.A.	1.22	1.096
HILONG OIL SERVICE & ENGINEERING ECUADOR CIA. LTDA.	0.584	0.919
LOGISPETROL SERVICIOS PETROLEROS CIA. LTDA.	1.832	0.825
OVERSEAS PETROLEUM AND INVESTMENT CORPORATION	1.21	1.34
PDVSA ECUADOR S.A.	0.612	0.72
PETROLEOS SUD AMERICANOS DEL ECUADOR PETROLAMEREC S.A.	1.471	1.0
PETROORIENTAL S.A.	0.965	0.97
PETRORIVA S.A.	1.045	1.129
REPSOL ECUADOR S.A.	0.469	1.49
SAXON ENERGY SERVICES DEL ECUADOR S.A.	1.331	0.72
TECPECUADOR S.A.	1.16	1.034
AVERAGE	**1.103**	**1.037**

Source: Author

3.2. Malmquist Index pollution-adjusted productivity

The results outlined in the table 4 reveal the PM productivity indices scores and their decompositions over the period 2011-2020. The first column displays the Malmquist index scores (MC), and the other two columns show the main drivers of the environmental productivity change, namely the technological change (TC) and the efficiency variation components (EC), respectively.

Table 4. Malmquist Index scores for 2012-2020

2012			2013			2014			2015			2016			2017			2018			2019			2020		
MI	EC	TC	MI	EC	TC	MI	EC	TC	MI	EC	TC	MI	EC	TC	MI	EC	TC	MI	EC	TC	MI	EC	TC	MI	EC	TC
0.99	1.03	0.96	0.90	0.94	0.96	0.98	1.00	0.98	1.04	1.00	1.04	0.94	1.00	0.94	1.16	1.00	1.16	1.10	1.00	1.10	1.45	1.04	1.40	1.34	0.98	1.37
0.47	1.00	0.47	0.47	1.08	0.44	0.37	1.01	0.37	0.42	1.00	0.42	0.41	1.00	0.41	0.33	1.00	0.33	0.30	1.00	0.30	0.35	0.99	0.36	0.36	1.02	0.36
2.51	1.00	2.51	2.05	1.00	2.05	2.04	1.00	2.03	1.85	1.00	1.85	1.78	1.00	1.78	1.69	1.00	1.69	1.91	1.00	1.91	1.18	0.89	1.32	1.21	0.93	1.30
1.19	1.00	1.19	1.06	0.98	1.08	0.85	0.97	0.87	1.07	1.00	1.07	0.90	0.99	0.91	0.88	1.00	0.88	0.93	1.00	0.93	1.21	1.11	1.09	1.16	1.08	1.08
0.36	1.00	0.36	0.45	1.02	0.44	0.52	1.01	0.51	0.49	1.00	0.49	0.58	1.01	0.58	0.61	0.98	0.62	0.55	1.00	0.55	0.60	0.96	0.63	0.64	1.00	0.64
2.81	1.00	2.81	2.67	1.00	2.67	2.31	1.01	2.28	2.30	1.00	2.30	2.75	1.00	2.75	2.81	1.02	2.77	2.60	1.00	2.60	1.94	0.95	2.05	2.05	1.00	2.05
0.63	0.89	0.71	0.56	0.87	0.64	0.64	0.88	0.73	0.75	1.00	0.75	0.54	0.95	0.57	0.55	0.94	0.59	0.56	0.93	0.60	0.57	1.06	0.54	0.50	0.93	0.54
1.01	1.02	0.99	1.16	1.09	1.06	1.27	1.13	1.13	1.28	1.00	1.28	1.35	1.06	1.28	1.32	1.07	1.23	1.30	1.07	1.21	1.22	0.92	1.32	1.43	1.08	1.32
0.55	1.04	0.53	0.54	1.00	0.54	0.51	1.00	0.50	0.49	1.00	0.49	0.52	1.00	0.52	0.52	1.00	0.52	0.60	1.00	0.60	0.86	1.15	0.74	0.73	1.00	0.73
2.40	1.06	2.27	2.33	1.05	2.23	2.04	1.00	2.04	1.87	1.00	1.87	1.87	1.00	1.87	1.77	0.98	1.81	1.86	0.91	2.05	0.96	0.77	1.25	1.10	0.91	1.21
1.10	1.00	1.10	0.99	0.91	1.09	1.00	1.00	1.00	1.07	1.00	1.07	1.06	1.00	1.06	1.07	1.02	1.05	1.15	1.10	1.04	1.92	1.30	1.48	1.65	1.09	1.51
0.55	0.99	0.56	0.59	1.10	0.54	0.57	1.00	0.57	0.56	1.00	0.56	0.70	1.00	0.70	0.73	1.00	0.73	0.74	1.00	0.74	0.59	0.99	0.60	0.53	0.88	0.60
1.70	1.01	1.69	1.72	0.98	1.76	2.06	1.00	2.06	2.04	1.00	2.04	1.32	1.00	1.32	1.00	1.00	1.00	1.05	1.00	1.05	1.09	0.95	1.15	1.31	1.15	1.15
0.93	1.00	0.94	0.94	1.01	0.93	0.92	0.98	0.93	0.95	0.99	0.96	0.99	1.00	0.99	0.95	1.00	0.95	0.96	1.00	0.96	1.04	0.98	1.06	1.07	1.00	1.07
1.10	1.01	1.09	1.07	0.98	1.09	1.11	1.02	1.09	1.06	1.01	1.04	1.01	1.00	1.01	1.05	1.00	1.05	1.03	0.99	1.04	0.98	1.08	0.91	0.91	1.00	0.91
0.41	1.00	0.41	0.44	1.03	0.42	0.34	0.99	0.35	0.45	1.00	0.45	0.35	1.00	0.35	0.56	0.98	0.57	0.54	1.01	0.54	0.60	1.01	0.59	0.55	0.94	0.58
1.07	1.00	1.07	1.11	0.99	1.12	1.34	1.01	1.33	1.02	0.99	1.03	0.94	1.00	0.94	1.95	1.02	1.92	1.96	1.00	1.96	1.11	0.67	1.65	1.72	1.06	1.62
0.82	0.94	0.87	0.94	0.96	0.97	0.83	0.99	0.84	1.07	1.00	1.07	1.18	1.00	1.18	0.67	1.00	0.67	0.66	1.00	0.66	1.02	1.41	0.72	0.71	1.00	0.71

Source: Author

3.2.1. Analysis of overall efficiency (MI)

Table 4 reports the average annual PM productivity indices for the 18 oil companies in Ecuador over the analyzed period. In the DEA model, the companies whose efficiency is 1 or greater than 1 make up the production frontier, compared to those whose efficiency is less than 1 which are DEA inefficient. Therefore, the results in Tables 4 for the overall energy efficiency (MI) score showed that more than half of the companies are inefficient during the time frame. The group of companies have an average of energy efficiency score of 1.80. From this group, only 3 companies have a higherMalmquist Index Score than the average. In order words, only three firms perform better than the average. The slowdown in productivity scores could be linked to firms with higher levels oil and gas production and CO2 emissions during the analyzed period, as most firms with low consumption of fossil fuels have a better ratio between output and pollution, and consequently, are more sustainable. On the other hand, the energy efficiency scores for most companies exhibit an important decrease between 2012-2019 as seen in figure 2.1., this period coincides with important reforms in Ecuador referring to private contribution in the oil sector, resulting in lower investment in capital projects and less resources designated for innovation in these companies (World Bank, 2018).

3.2.2. Analysis of technical and efficiency variation changes

The mean technical efficiency change (TC) for the 18 companies selected in the period analyzed was - 0,091%, meanwhile there was not a significant scale change (EC) over time. Globally, the results suggest that the energy efficiency performance of the Ecuadorian oil industry is dependent on the technical change in production, but it is important to note:

1. In relation to the overall energy efficiency scores for 2011-2012, 2012-2013 and 2014-2015, most companies presented a drop in the technical and efficiency component scores during the period analyzed. This means that the energy inefficiency of these firms was driven by less technological advances without any commensurate efficiency improvements in the internal management of the firms.

2. For 2018-2019 the PMI index show marginally reduce and a then a positive boost in 2019-2020, these results suggest that although in 2020 the industry suffered an important reduction in oil production due to the Covid-19 outbreak, the overall energy efficiency and productivity levels were positive affected, and that could be related to the decrease in CO2 emissions during the period even if there weren't significant technical and energy efficiency change.

3.3. Tobit Panel Regression results

Having obtained the PMI analysis, we want to find the primary economic indicators that affect efficiency scores. The Hausman test[3] is employed to choose between the fixed-effect and random-effect model—suitable for the panel regression analysis. The results indicate the random effect model is more suitable for the panel regression evaluation.

3.- The test proposed by Hausman Invalid source specified. is a chi-square test that determines whether differences are systematic and significant between two estimates. It is mainly used to determine whether an estimator is consistent or whether a variable is relevant or not.

Table 5. Panel regression results

Variables	
Energy consumption	-0.0193*
	(0.0103)
Employment	-0.138***
	(0.0210)
Capital	-0.0139
	(0.0175)
Oil production	0.0508**
	(0.0229)
CO2 emissions	-0.00334
	(0.00307)
Observations	180
Number of n	18

Source: Author

Thus, in the next step, we employ the random effect model to measure the impact of the indicators on PMI (Table 5.). Per the analysis, MI has a weak negative correlation with energy consumption at a 10% significance level. And a negative relationship with employment at a 1% significance level. These results suggest that for Ecuador, the energy and industrial efficiency of oil companies depends on their labor strategy and the consumption of fossil fuels in their extractive activities.

4 CONCLUSIONS

The objective of this study was to analyze the main drivers of efficiency and productivity in private oil companies in Ecuador, with a particular focus on energy efficiency and its relationship with environmental factors.

We conducted this analysis using a dataset comprising 18 Ecuadorian oil companies over the period 2011-2020. To evaluate energy efficiency and productivity, we employed a non-parametric model and the Malmquist index, allowing us to assess both pollution-adjusted productivity and the factors contributing to efficiency.

Our analysis revealed that more than half of the companies in our study were characterized as inefficient based on the DEA model. The average energy efficiency score of 1.80 underlines the industry-wide challenges in achieving optimal energy efficiency. This trend was particularly notable among companies with higher levels of oil and gas production and associated CO_2 emissions during the analyzed period. In contrast, companies with lower fossil fuel consumption demonstrated a more favorable output-to-pollution ratio, highlighting their greater sustainability in terms of energy efficiency.

The declining energy efficiency scores observed for most companies from 2012 to 2019 coincide with significant reforms in Ecuador's oil sector. These reforms led to reduced investments in capital projects and innovation within these firms, as reported by the World Bank (2018). This suggests that policy shifts can have a substantial impact on energy efficiency levels within the industry.

The Malmquist index scores (MC), when decomposed into technological change (TC) and efficiency variation components (EC), provide valuable insights into the industry's performance. The analysis indicates minimal overall changes in scale over time, emphasizing the industry's dependence on technical advancements in production to drive energy efficiency improvements. Two critical observations emerge from our findings. During the periods 2011-2012, 2012-2013, and 2014-2015, both technical and efficiency component scores declined. This indicates that energy inefficiency during these periods was primarily driven by a lack of technological progress without corresponding efficiency improvements in internal management.

In 2018-2019, there was a marginal reduction in the PMI index, followed by a positive boost in 2019-2020. This suggests that, despite a significant reduction in oil production due to the Covid-19 outbreak in 2020, energy efficiency and productivity levels improved. This improvement may be attributed to decreased CO_2 emissions, even in the absence of significant technical and energy efficiency changes.

Correlation Analysis: To further understand the factors influencing efficiency scores, we conducted a panel regression analysis using the random effect model. The results indicated a weak negative correlation between energy consumption and MI at a 10% significance level. Additionally, employment displayed a negative relationship with MI at a 1% significance level. This implies that energy and industrial efficiency in Ecuador's oil companies are closely linked to their labor strategies and fossil fuel consumption in extractive activities.

In conclusion, our study has highlighted the formidable energy efficiency challenges faced by Ecuador's oil industry, with significant implications for environmental sustainability and profitability. Policy reforms, technological progress, and internal management practices all play pivotal roles in shaping energy efficiency outcomes. The findings underscore the industry's need for comprehensive management strategies that address both human resources and resource utilization. As the sector navigates evolving challenges, the imperative to prioritize sustainability and efficiency remains paramount for achieving a harmonious balance between economic growth and environmental responsibility.

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