Forecasting the Innovation Efficiency of Oil and Gas Industry: remarks about the future in 2030

Prevendo a Eficiência da Inovação na Indústria de Petróleo e Gás: considerações sobre o futuro em 2030

Previsión de la Eficiencia de la Innovación en la Industria del Petróleo y el Gas: comentarios sobre el futuro en 2030

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Murilo Alvarenga Oliveira
Professor Associado do Departamento de Administração e Administração Pública da Universidade Federal Fluminense
http://orcid.org/0000-0003-2626-551X

Renata Giovinazzo Spers
Professora Associada do Departamento de Administração da Faculdade de Economia, Administração e Contabilidade da Universidade de São Paulo
http://orcid.org/0000-0003-1240-0530

Luccas Assis Atílio
Professor do Departamento de Economia da Universidade Federal de Ouro Preto
http://orcid.org/0000-0002-5497-1043

Alexandre Lopes Gomes
Professor Associado do Departamento de Economia da Universidade Federal de São Carlos
http://orcid.org/0000-0002-7006-5083

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Nanachara Carolina Sperb

Abstract

Purpose: This paper predictively analyzes the efficiency of oil and gas operators in their innovation process for the year 2030.
Design/methodology/approach: The research design combined two steps, data envelopment analysis (DEA) and panel data analysis, to forecast innovation efficiency by the year 2030. The data envelopment analysis (DEA) method was used to measure efficiency and its evolution. The input was the amount of investment in research and development, and the outputs were net sales and the number of patents. Panel data analysis was used to predict efficiency.
Originality/relevance: Some contributions and innovation efficiency for organizations were identified. This study provides theoretical and managerial implications for future oil and gas industry studies.
Findings: Regarding forecasts, net revenues once again stood out as the primary predictor. On average, efficiency in 2030 will rise from 0.66 (average efficiency between 09-20) to 0.85, with wide heterogeneity when observing the individual behavior of firms.
Theoretical/ /methodological contributions: The future of the O&G industry has become the ground for research with various methods to study the finite life of this resource, global climate change, the prospect of low-carbon economies, and the transition of energy to renewable sources.
Social and management implications: These future identifications can be used in organizations' strategic planning to improve their respective performance based on what firms considered the most efficient have accomplished.

Keywords: Forecasting; Data envelopment analysis; Panel data analysis; Oil & gas; Future studies.

Resumo

Objetivo: Este artigo analisa de forma preditiva a eficiência dos operadores de petróleo e gás no seu processo de inovação para o ano de 2030.
Metodologia/abordagem: A pesquisa combinou duas etapas, análise envoltória de dados (DEA) e análise de dados em painel, para prever a eficiência da inovação até o ano 2030. O método de análise envoltória de dados (DEA) foi utilizado para medir a eficiência e sua evolução. O insumo foi o montante do investimento em pesquisa e desenvolvimento, e os resultados foram as vendas líquidas e o número de patentes. A análise de dados em painel foi utilizada para prever a eficiência.
Originalidade/relevância: Foram identificadas algumas contribuições e eficiência da inovação para as organizações. Este estudo fornece implicações teóricas e gerenciais para futuros estudos da indústria de petróleo e gás.
Resultados: Em relação às previsões, a receita líquida mais uma vez se destacou como principal preditor. Em média, a eficiência em 2030 passará de 0,66 (eficiência média entre 09-20) para 0,85, com grande heterogeneidade quando se observa o comportamento individual das empresas.

Contribuições teóricas/metodológicas: O futuro da indústria de petróleo e gás tornou-se o terreno para pesquisas com vários métodos para estudar a vida finita deste recurso, as alterações climáticas globais, a perspectiva de economias de baixo carbono e a transição da energia para fontes renováveis.
Contribuições sociais e para gestão: Essas identificações futuras podem ser utilizadas no planejamento estratégico das organizações para melhorar seu respectivo desempenho com base no que as empresas consideradas mais eficientes realizaram.

Palavras-chave: Previsão; Análise envoltória de dados; Análise de dados em painel; Petróleo e gás; Estudos do futuro.

Resumen

Objetivo: Este artículo analiza de forma predictiva la eficiencia de los operadores de petróleo y gas en su proceso de innovación para el año 2030.
Metodología/enfoque: La investigación combinó dos pasos, análisis envolvente de datos (DEA) y análisis de datos de panel, para predecir la eficiencia de la innovación hasta el año 2030. Se utilizó el método de análisis envolvente de datos (DEA) para medir la eficiencia y su evolución. El insumo fue el monto de inversión en investigación y desarrollo, y los resultados fueron las ventas netas y el número de patentes. Se utilizó análisis de datos de panel para predecir la eficiencia.
Originalidad/relevancia: Se identificaron algunos aportes y eficiencia de la innovación para las organizaciones. Este estudio proporciona implicaciones teóricas y de gestión para futuros estudios de la industria del petróleo y el gas..
Resultados: En cuanto a las previsiones, los ingresos netos volvieron a destacar como principal predictor. En promedio, la eficiencia en 2030 aumentará desde 0,66 (eficiencia promedio entre 09-20) a 0,85, con gran heterogeneidad al observar el comportamiento individual de las empresas.
Contribuiciones teóricas/metodológicas: El futuro de la industria del petróleo y el gas se ha convertido en terreno para la investigación con diversos métodos para estudiar la vida finita de este recurso, el cambio climático global, las perspectivas de economías bajas en carbono y la transición energética hacia fuentes renovables.
Contribuciones sociales y de gestión: Estas identificaciones futuras se pueden utilizar en la planificación estratégica de las organizaciones para mejorar su desempeño respectivo en función de lo que hayan logrado las empresas consideradas más eficientes.

Palabras clave: Previsión; Análisis Envolvente de Datos; Análisis de datos de paneles; Petroleo y Gas; Estudios futuros.

1. INTRODUCTION

The petroleum is one of the most important commodities in the world. It is vital to the current energy supply, making up thirty-three percent of the global energy matrix in 2022 (Ahmad & Zhang, 2020; BP, 2022). Thus, oil is considered a strategic natural resource. The sector is composed of firms that explore, develop, and operate oil and gas fields. Is referred to as the oil and gas exploration and production industry, or O&G. The oil and gas industry's profits in 2022 were four trillion dollars from an average of one and a half billion dollars in recent years, which currently accounts for about four percent of the global economy (IEA, 2023).

Some concerns about the future of the O&G industry include the finite life of this resource, global climate change, and the energy transition to renewable sources. Estimates place the peak of oil production at the end of the 2030s (BP, 2022). Thus, this scenario is approaching as the oil demand slows and the demand for renewable sources grows, increasing fivefold by 2040 and providing about fourteen percent of global primary energy (Ahmad & Zhang, 2020; Pickl, 2019). Climate change is also decisive to the future of the sector. Carbon dioxide emissions continue to rise (IPCC, 2021). Oil accounts for one-third of these emissions (Friedlingstein et al., 2019) Thus, efforts towards establishing low-carbon economies and the energy transition are estimated to reduce fossil energy per capita by 2050 (King & van den Bergh, 2018).

The complex and uncertain context of the O&G industry outlines a problem that generates scientific concern to investigate the future of firms, so the guiding question of this study is: What is the innovation efficiency perspective for 2030 for O&G firms?

To this end, the purpose established in the study focuses on prospecting a future configuration of firms in the O&G industry based on the efficiency of investments in R&D. To achieve this purpose, it was necessary to identify the efficiency trajectory of firms in the industry over the last decade and, based on information from the sampling units over time, the projected efficiency over the next ten years was estimated.

The research is relevant given the trends and characteristics of the O&G industry, such as excess oil supply and drop in the price of a barrel, search for lower costs, reduction in CO2 emissions, and search for renewable energy sources through the development of new technologies (Ahmad & Zhang, 2020; Hunt et al., 2022; IEA, 2023; Pickl, 2019). Therefore, in this scenario, being efficient is synonymous with a company that produces more at a lower cost, and this is only possible through the innovation process. Therefore, understanding the innovation capabilities of the most efficient operators becomes a critical factor in global competition.

2. INNOVATION AND EFFICIENCY

We bring together two perspectives to analyze the innovation process of firms in the oil and gas (O&G) industry: the perspective of innovation capabilities, and the perspective of efficiency. The efficiency perspective is related to productivity and is characterized by the ratio between output and input (Emrouznejad & Yang, 2018). Some studies evaluate the efficiency of the innovation process of countries or organizations (Aytekin et al., 2022; Chiu et al., 2012; Chun et al., 2015; Hashimoto & Haneda, 2008).

Considering that the O&G sector is one of those that invests the most in research and development (Ribeiro et al., 2019; Shuen et al., 2014), it is responsible for dominating the economic activities of several countries, and use the amounts invested to discover and explore oil reserves, so that they are economically viable (Hunt et al., 2022) considering the risks associated with this exploration(Adams et al., 2019), this work directs studies towards O&G operators.

In the study about of the efficiency of high-technology companies was investigated by applying data envelopment analysis (DEA). They indicated that organizations that execute the R&D process will tend to generate more patents and sales (Chiu et al., 2012). Similarly, other study evaluated the innovation efficiency of manufacturing firms by applying DEA. According to them, to evaluate the innovation process as a whole, it is also necessary to consider the commercial process, as in addition to technological results, such as patents, there is also the generation of sales and profits (Chun et al., 2015). A highlight studied activities related to innovation during two stages of growth experienced by new energy firms: the research and development (R&D) process and the marketing process. A non-radial data envelope analysis method was used to construct indices to measure R&D, market, and integrated innovation efficiency(Wang et al., 2016).

The number of employees engaged in R&D (Chiu et al., 2012) and sales(Chiu et al., 2012; Chun et al., 2015) are indicators of the operational process and the commercial process, in contrast, who do not separate these two processes to evaluate the efficiency of the innovation process (Hashimoto & Haneda, 2008; Wang et al., 2016). Even if considered separately, the two processes are interdependent. In addition to studies investigating efficiency, others relate investments to growth or performance of organizations(Ma et al., 2020).

The variables used in this study aim to enable the analysis of the efficiency of O&G firms' innovation processes. Investment in R&D is part of the innovation process, therefore it is an input (Arranz et al., 2019; Oliveira et al., 2023). It is easier to use investment in R&D as one of the indicators of the innovation process in large firms, as they usually publish data on investments. This may not be the case for small companies, as they often do not have a formal area dedicated to research (Dziallas & Blind, 2019).

According to both Hashimoto & Haneda (2008) and Wang et al. (2016), investing in R&D tends to promote innovation in products and increase sales. Therefore, they considered total sales revenue as an output variable in their study of Japanese pharmaceutical companies. Other reference also used sales as an output variable to investigate the relationship between innovation intensity and sales growth of firms identifying a positive relationship (Arranz et al., 2019).

Patents were also considered in the study, as despite not being robust measures of innovation (Han & Sohn, 2017; Roper & Hewitt-Dundas, 2015; Wu et al., 2021) and mitigating to a certain extent the negative effect of information ambiguity (Hussinger & Pacher, 2019), they can be used as mechanisms for technological monitoring, legal protection and barriers to new entrants (Arora et al., 2018; Han & Sohn, 2017). In this sense, patents are indicators of innovation that cannot be ignored, whether in studies that found a strong correlation with investment in R&D, for example, in high technology companies (Kostopoulos et al., 2011; Ponta et al., 2021).

3. FUTURE STUDIES IN O&G

When it comes to studies of the future of the O&G sector, there is a more significant occurrence of issues associated with management and innovation in the sector, with emphasis on the theme of investment and production (Correia et al., 2020; Faraji, 2021; Oliveira et al., 2023) and approach to Forecasting is the most used, reinforcing the notion of seeking efficiency in the sector (Correia et al., 2020; Fergnani, 2022; IEA, 2023). Forecasting techniques are also preferred in topics involving sustainability in the industry; studies predicting energy consumption demand predominate (Faraji, 2021; King & van den Bergh, 2018; Maaouane et al., 2021).

More strategic approaches, such as foresight, involve planning and evaluation studies of energy policies (Gokhberg et al., 2020; Hunt et al., 2022) that require future-oriented techniques in strategic decision-making (Fergnani, 2022; Iden et al., 2017). This type of technique is also prevalent in topics such as: "technology and innovation in O&G" (AlNuaimi et al., 2020; Pickl, 2019) indicating the trend in the development of new technologies (IEA, 2023) and which reinforces, to a certain extent, the sector's constant association with climate change (Ahmad & Zhang, 2020).

4. RESEARCH METHOD

We divided the research into two steps. First, we used Data Envelopment Analysis, an acronym in English DEA (Data Envelopment Analysis). We identified the firms that showed the most significant progress in efficiency regarding innovation investment. In the second phase of the research, we used panel analysis to predict the innovation trajectory of O&G firms that showed more significant progress in efficiency due to investment in R&D. Table 1 presents the components of the research design.

Table 1
Summary of the research design

	Data base	Variables	Analysis method	Goal
Step 1	European Commission Industrial R&D	Input: Investment in R&D. Output:	DEA BCC model with output orientation.	Identify the efficiency trajectory of firms in the O&G industry

	Investment Scoreboard reports. Derwent Innovations Index (DII).	Net revenue and patents.	Logic: increase the level of outputs (net revenue and patents) while maintaining the level of input (investment in R&D).	
Step 2		Independent variables: Net revenues (rec_{it}), number of patents (pat_{it}), investment in R&D (pd_{it}) Proxy to control firm's size: Number of employees (emp_{it}). Endogenous variable: Efficiency index in DEA BCC output (eff_{it}).	Panel data model It allows obtaining econometric relationships between company variables over time: it is possible to analyze which variables have statistical significance in explaining the efficiency index.	Estimate the projected efficiency of O&G firms over the next ten years.

Source. Authors' own elaboration

Due to the number of firms, called decision-making units (DMUs), that met the requirements for the DEA, in the first step, it was decided not to use the number of employees involved in R&D, as the DEA model requires that the number of DMUs is greater than the number of variables. The literature indicates that the number of employees engaged in R&D (Chiu et al., 2012) and sales (Chiu et al., 2012; Chun et al., 2015) are indicators of the operational process and the commercial process, but also, like Hashimoto & Haneda (2008) and Wang et al. (2016), who do not separate these two processes to evaluate the efficiency of the innovation process.

In this sense, the use of employees involved in R&D processes in phase two of this research is justified, based on (Quintana-García & Benavides-Velasco, 2004) thus incorporating the number of employees into the model (emp_{it}) as a proxy to control the size of the firm.

We used secondary data in this research. In the first stage of the research, we extracted data from the EU Industrial R&D Investment Scoreboard reports published by the European

Commission (Nindl et al., 2023), which contains the firms that invest the most in Research and Development in the world, and we also extracted data from the Derwent Innovations Index (DII) extraction base. In the second stage, we extracted data regarding the innovation process from the most efficient firms' annual reports. Therefore, the analysis encompasses 12 firms that appeared in the reports between 2009 and 2020, as indicated in Table 2.

Table 2
Sample of firms

Firm	Country	Firm	Country
Chevron	United States	Gazprom	Russia
China Petroleum & Chemicals	China	Idemitsu Kosan	Japan
CNOOC	Hong Kong	PetroChina	China
ConocoPhillips	United States	Petrobras	Brazil
Cosmo Oil / Energy	Japan	Sasol	South Africa
Exxon Mobil	United States	Statoil / Equinor	Norway

Source. Industrial R&D Investment Scoreboard of the European Commission (2008 to 2021)

A restriction in the sample was the absence of five significant producers in the sector, as they were not present in all editions of the survey, the British BP and the French Total did not participate between 2009 and 2011, Royal Dutch Shell was absent from 2009 to 2012, the Chinese Sinopec began its participation in 2017 and the Saudi Arabian Oil only began participating in 2019.

The European Commission reports contain firms' economic and financial information, such as their investment in R&D and net revenue, two indicators used in this research. Another research indicator is the number of patents; the Derwent Innovations Index (DII) extraction base was used. Table 3 indicates the variables used in the steps of the research.

Table 3
Search step variables

Steps	Variables	Drives	Reference

	Investment in R&D.	Input	Chiu et al. (2012); Chun et al. (2015); Hashimoto & Haneda (2008); Kostopoulos et al. (2011); Arranz et al. (2019); Dong et al. (2020); Stornelli et al. (2021).
Step 1 and 2	Net revenue	Output	Chiu et al. (2012); Chun et al. (2015); Hashimoto & Haneda (2008); Kostopoulos et al. (2011); Arranz et al. (2019); Dong et al. (2020); Stornelli et al. (2021); Dziallas & Blind (2019)
	Patents.	Output	Chiu et al. (2012); Chun et al. (2015); Hashimoto & Haneda (2008); Kostopoulos et al. (2011); Dong et al. (2020); Srivastava et al. (2015); Ponta et al. (2021)
Step 2	Number of employees	Control	Quintana-García & Benavides-Velasco (2004); Chiu et al. (2012); Chun et al. (2015); Hashimoto & Haneda (2008);Wu et al. (2021); Wang et al. (2016)

Source. Authors' own elaboration, based on Chiu et al. (2012); Chun et al. (2015); Hashimoto & Haneda (2008); Kostopoulos et al. (2011); Arranz et al. (2019); Dong et al. (2020); Stornelli et al. (2021); Dziallas & Blind (2019); Wu et al. (2021); Wang et al. (2016).

4.1.Data Envelopment Analysis (Dea)

The DEA method is used to analyze the efficiency of decision-making units, DMU (Decision Making Units), which have input and output variables in common, varying only in their levels. DEA is one of the most used methods to calculate R&D efficiency(Chiu et al., 2012; Chun et al., 2015; Guan et al., 2016).

There are two basic models in the literature: the CCR and BCC. The first was proposed by Charnes, Cooper, and Rhodes (CCR) in 1978; it is a model where inputs and outputs are proportionally and directly related; that is, the production function has a constant return to scale (Charnes et al., 1978). The second was proposed by Banker, Charnes, and Cooper (BCC) in 1984. The production function has a variable return to scale in a model where inputs and outputs are not proportionally and directly related (Banker et al., 1984).

Innovation is not a linear process, where inputs are automatically transferred into outputs; however, to identify differences in the efficiency of R&D investments, it is necessary to obtain the relationship between outputs and inputs (Arora et al., 2018; Roper & Hewitt-Dundas, 2015). As it is not a proportional and direct relationship, the model considered in this research was the BCC, which also favors relative analysis involving organizations of different sizes.

In this research, the output perspective aims to increase the level of products (net revenue and patents) while maintaining the level of input (investment in R&D). In formulation (1), we have the DEA BCC model with output orientation:

Max h_0 (1)

s.a.

$x_{i0} - \sum_{k=1}^{n} x_{ik}\,\lambda_k \geq 0$

$- h_0 y_{j0} + \sum_{k=1}^{n} y_{jk}\,\lambda_k \geq 0$

$\sum_{k=1}^{n} \lambda_k = 1$

$\lambda_k \geq 0$

Where x_i refers to the DMUi input vector, y_j to the DMUi output vector, λ are the model variables. The first restriction means that each input of the DMU under analysis must be, at least, equal to the linear combination of the same inputs from all DMUs. The second restriction means that each output of the DMU under analysis must be, at most, equal to the linear combination of the same outputs of all DMUs considered. The third restriction refers to convexity, which considers scale variation (Banker et al., 1984).

4.2. Panel Data Analysis

Since the sample consists of 12 firms, with data between 2009 and 2020, the panel data method fits this type of database. More than the database configuration, panel data provides information that fits the objectives of this article. The first is to show, through statistical significance, the relevance of specific variables to explain the domestic variable. In the present case, the incorporated variables can be evaluated based on their importance in explaining the efficiency index. The second characteristic of the method is that it allows the construction of future scenarios based on the estimates obtained.

Equation (2) below illustrates the basic structure of panel data with fixed effects. The term y_{it} is the endogenous variable, explained by the model, where the subscripts *i* and *t* denote the firms and time, respectively. On the right side of equation (2), x_{it} represents the independent variables, which help to understand the variations in x_{it}. The β coefficients are the values the model will provide after the estimations. The unobserved effect, a_i, aggregates unobserved information, which does not vary over time but affects y_{it}. The last term is the idiosyncratic error, u_{it}.

$$y_{it} = \beta x_{it} + a_i + u_{it}. \quad (2)$$

To eliminate the unobserved effect, equation (3) is averaged over time:

$$\bar{y}_i = \beta \bar{x}_i + a_i + \bar{u}_{it}, \quad (3)$$

onde: $\bar{y}_i = T^{-1} \sum_{t=1}^{T} y_{it}$, $\bar{x}_i = T^{-1} \sum_{t=1}^{T} x_{it}$, $\bar{u}_i = T^{-1} \sum_{t=1}^{T} u_{it}$.

The unobserved effect appears in equations (2) and (3) because it does not vary over time. Therefore, to eliminate it, just subtract (2) from (3):

$$y_{it} - \bar{y}_i = \beta(x_{it} - \bar{x}_i) + u_{it} - \bar{u}_{it} \leftrightarrow \ddot{y}_{it} = \beta \ddot{x}_{it} + \ddot{u}_{it}. \quad (4)$$

It is worth remembering that the transformation carried out previously resulted from the suspicion that the unobserved effect correlates with some of the explanatory variables, $Cov(x_{it}, a_i) \neq 0$. In this case, the use of fixed effects can address this issue. However, it may be that a_i is not correlated with any explanatory variable. If the transformation in (4) were applied, there would be inefficient estimators. This situation portrays random effects. Formally:

$$Cov(x_{it}, a_i) = 0, t = 1,2,3, \dots, T. \quad (5)$$

Another concern is verifying that the explanatory variables are not correlated with the error term; that is, we want $Cov(x_{it}, u_{it}) = 0$. The model will produce biased and consistent estimates if this condition is unmet. The strategy for dealing with this type of endogeneity is to use instrumental variables (z_{it}), as long as they present the following conditions: $Cov(z_{it}, u_{it}) = 0$ and $Cov(z_{it}, x_{it}) \neq 0$. Equation (6) presents the addition that is added to the model to mitigate the endogeneity problem:

$$x_{it} = \gamma z_{it} + \varepsilon_{it}. \tag{6}$$

In this equation, γ is the coefficient of the instrumental variable, and ε_{it} is the error term. It is expected, as previously stated, that γ is non-zero.

Regarding the database, the endogenous variable is the efficiency index obtained previously (eff_{it}). Following the DEA method, net revenues (rec_{it}), the number of patents (pat_{it}), and investment in research and development (pd_{it}). Were included as independent variables. Based on Quintana-García & Benavides-Velasco (2004), the number of employees (emp_{it}) was incorporated into the model as a proxy to control the firm's size. The data source was the European Commission's Industrial R&D Investment Scoreboard report for investment in R&D, net revenue, and employees involved in R&D activity. At the same time, the number of patents was extracted from the Derwent Innovations Index (DII) database. All variables are treated in log form. Equation (7) presents the econometric model:

$$eff_{it} = \beta_1 rec_{i,t-1} + \beta_2 pat_{i,t-1} + \beta_3 emp_{i,t-1} + \epsilon_{it}. \tag{7}$$

The independent variables are lagged by one period to reduce possible occurrences of endogeneity and understand that there is an inevitable lag between their variations and their respective effects on the dependent variable. Regarding patents, care was taken to implement it, according to equation (8):

$$pat_{i,t-1} = \pi_1 pat_{i,t-2} + \pi_2 pd_{i,t-1} + \delta_{it}. \tag{8}$$

This equation denotes that patents are explained by the patents themselves lagging in two periods and by spending on research and development. The term δ_{it} represents the model errors. The following section presents the results of the econometric exercises.

5. ANALYSIS OF RESULTS

The average investment in R&D, net revenue, and number of patents between 2009 and 2020 are presented based on reports from the Industrial R&D Investment Scoreboard of the European Commission and the Derwent Innovations Index (DII), as shown in Table 4.

Table 4

Average of research variables from 2009 to 2020 (step 1)

			Average 2009 to 2020		
Firm	**Country**	**Cod.**	**R&D (€ millon)**	**Net revenue (€ million)**	**Patents**
Chevron	USA	CHE	465	141.125	261
China Petroleum	CHN	CPC	763	289.748	5.526
CNOOC	CHN	CNO	179	26.058	555
ConocoPhillips	USA	COP	147	63.427	70
Cosmo Oil / Energy	JPN	COO	31	22.904	34
Exxon Mobil	USA	EXX	865	267.790	641
Gazprom	RUS	GAZ	357	96.366	143
Idemitsu Kosan	JPN	IDE	121	33.579	250
Petrobras	BRA	PTB	617	85.232	55
PetroChina	CHN	PTC	1.612	245.438	1.999
Sasol	ZAF	SAS	89	12.743	16
Statoil / Equinor	NOR	STL	296	65.237	50

Source. Industrial R&D Investment Scoreboard of the European Commission (2008 to 2021) and Derwent Innovations Index (DII) (2022).

In the simple description of the average data, it is clear that there is a group with three firms having the highest averages in the variables of the analysis model: PTC (PetroChina) with the highest average investment in R&D, CPC (China Petroleum) with the highest average in net revenue and generation of patents and EXX (Exxon Mobil) which, despite not having the highest average in any of the three variables, presents higher averages than the other groups of firms.

In a second group with average R&D investments, between six hundred and three hundred million euros and net revenue, between one hundred and forty and eighty million are PTB (Petrobras), CHE (Chevron), and GAZ (Gazprom). In this group, the generation of patents has a different effect.

In the third group, formed by STL (Statoil / Equinor), CNO (CNOOC), COP (ConocoPhillips), and IDE (Idemitsu Kosan), the oscillation between the variables increases, even though firms in the third range of average investment in R&D, only STL and COP follow a net revenue trend, but fall in terms of patent generation. However, CNO and IDE have a much higher generation of patents than their group, even with relative average revenues below the others.

There is still a fourth group of firms that presented an average investment in R&D below one hundred million euros: SAS (Sasol) and COO (Cosmo Oil / Energy); these firms also present relatively modest average values in terms of net revenue and patent development.

When applying DEA BCC with output orientation, the evolution of efficiency revealed variable trajectories between firms; this indicates that despite the magnitude of resources, firms can present successful performances about others, and the opposite can also be indicated. Table 5 shows the efficiencies of the firms studied between 2009 and 2020.

Table 5

Firm efficiency path from 2009 to 2020 (step 1)

Firm	Country	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
CHE	USA	0,76	0,77	0,7	0,78	0,69	0,61	0,61	0,62	0,67	0,73	0,7	0,82
CPC	CHN	1	1	1	1	1	1	1	1	1	1	1	1
CNO	CHN	0,36	0,45	0,61	0,35	0,92	0,41	0,52	0,65	0,43	0,35	0,7	0,46
COP	USA	1	1	1	0,52	0,45	0,4	0,35	0,26	0,39	0,55	0,64	0,51
COO	JPN	1	1	1	1	1	1	1	1	1	1	1	1
EXX	USA	1	1	1	1	0,97	0,93	0,85	0,81	0,65	0,68	0,66	0,8
GAZ	RUS	0,35	0,37	0,35	0,53	0,72	0,58	0,55	1	1	1	1	1

IDE	JPN	1	1	0,73	0,56	0,83	0,71	0,66	0,61	0,48	0,44	0,55	0,66
PTB	BRA	0,39	0,33	0,28	0,29	0,3	0,3	0,4	0,4	0,53	0,57	0,7	1
PTC	CHN	0,5	0,6	0,68	0,75	0,85	0,88	0,87	0,86	0,85	0,81	0,85	0,92
SAS	ZAF	0,22	0,18	0,15	0,24	0,23	0,22	0,29	0,17	0,23	0,21	0,31	0,4
STL	NOR	0,45	0,42	0,39	0,54	0,46	0,42	0,48	0,34	0,37	0,45	0,43	0,57

Note: CHE (Chevron), CNO (CNOOC), COO (Cosmo Oil / Energy), COP (ConocoPhillips), CPC (China Petroleum & Chemicals), EXX (Exxon Mobil), GAZ (Gazprom), IDE (Idemitsu Kosan), PTB (Petrobras), PTC (PetroChina), SAS (Sasol) e STL (Statoil / Equinor).

In general terms, CPC confirmed the efficiency of investment in R&D to generate net revenue and develop patents; EXX started the series as efficient but lost performance from 2012 onwards. PTC, one of the most significant R&D investments, had an opposite trajectory, gradually increasing its performance and approaching the reference efficiency level in 2020 (0.92).

Among intermediary firms, we have COP on a decreasing trajectory from 2011; GAZ, on the contrary, began an increasing trajectory in 2016. It is observed that CHE presented a stable performance, but FDI fluctuated throughout the decade. STL had a modest performance in the years analyzed, but from 2017 onwards, PTB began to improve its performance, reaching the efficiency standard in 2020. SAS confirmed its position in firms with more modest R&D investment in the sample. However, the COO proved to be a relevant case for analysis, as it efficiently used its resources (investment in R&D) to generate results and had the standard of relative efficiency in all years analyzed.

The CPC and COO firms that are standards of efficiency, in a relative comparison with others, can project the evolution of their growth. EXX can improve its performance with adjustments based on references from efficient firms. CHE and IDE would need to increase their results to reach new efficiency standards.

Regarding improving performance, COP has shown more significant stagnation in recent years. In contrast, CNO and STL, even with regular performance, have relative growth potential, which can also be indicated for PTB and SAS, which have shown significant growth in recent years. However, growth potential based on the history of the relative efficiency of the firms studied indicates GAZ and PTC as players capable of becoming new references in the sector.

Before starting to present the results using panel data, Table 6 displays the linear correlations between the efficiency variable and some independent variables. It is observed that net revenues, employees, and patents are positively related to efficiency. The same is true for the last variable, resulting from the division of patents by employees, pat/emp. The highest correlation arises from net revenues, with a value of 0.56. Table 6 highlights a characteristic of the regressions carried out in Table 7: the employees variable will no longer be positively related to efficiency to present a negative relationship. This is because Table 6 only presents simple correlations, not controlling for other factors that may affect efficiency. On the other hand, the regressions in Table 7 control "cleaning" the effect that the employee variable has on efficiency.

Table 6
Correlations of the efficiency variable

Variable	Efficiency
rec	0.56
emp	0.28
pat	0.42
pat/emp	0.15

Regarding estimations using panel data, there are some recommendations before producing estimates substantiated by carrying out tests. The first step was the Wald test to check for signs of heteroscedasticity, the second the Wooldridge test to identify autocorrelation, and the third the cross-section dependence test. Heteroscedasticity is characterized by violating the constancy of the variance of the model's errors. In its presence, properties such as asymptotic efficiency are lost, and hypothesis tests are no longer valid (Wooldridge, 2013). Autocorrelation denotes that model errors are correlated over time, generating potential problems for estimates, such as loss of efficiency of estimated parameters (Wooldridge, 2013). Cross-section dependence in panel data can arise due to several factors, such as standard shocks, unobserved factors, and spatial dependence. Its occurrence can produce inefficient estimates and biased standard errors (De Hoyos & Sarafidis, 2006). After implementing these tests, it was observed that there is evidence of heteroscedasticity and cross-section dependence. In this case, cluster standard errors were used to minimize these two issues.

Given the time from 2009 to 2020, the stationarity of the variables may need to be revised. The Im-Pesaran-Shin unit root test was used. Under the null hypothesis, this test evaluates the existence of a unit root in the panels. Rejecting this hypothesis may mean the model fit is inappropriate (Im et al., 2003). As the test indicated that some variables are non-stationary, it was checked whether there are long-term relationships between them, that is, cointegrations. The Kao, Pedroni, and Westerlund tests indicated favorably the existence of cointegrations. If there are series with a unit root, it is recommended to check whether these series have long-term relationships (cointegrations) in the long term, indicating a balance between them. Although a unit root raises doubts about the relationships between the series, cointegration shows that, in the long term, there is a balance between these series (Kao, 1999).

The Chow test, which indicates whether the model should be estimated using fixed or pooled effects, and the Hausman test, between fixed and random effects, decided the method for estimating the model. The Hausman test analyzes whether there are significant differences between the estimators of these two forms of estimation based on efficiency and consistency (Hausman, 2015). The Chow test checks whether the estimated coefficients for one of the data are the same as those estimated for the other groups (Gould, 2022). The Chow test indicated that the fixed effects model was more appropriate than the pooled model. In contrast, the Hausman test did not reject the null hypothesis that random effects were recommended over fixed effects. Therefore, panel data with random effects was used, although fixed effects were also used, with estimates in the annexes. After these observations and tests, the model was estimated.

Table 7 presents the results of the regressions. As all variables are in a log, their coefficients can be analyzed as elasticities. For example, in regression (1), the net revenue variable was significant at 1%. Therefore, its 1% increase is related to the 0.31% increase in efficiency. In regression (2), the model's functional form is repeated, only changing the form of its estimation. The robust estimator was used to consider outliers in the data. The estimates suggest that these outliers may interfere with the results, as employment and patents have become statistically significant, contrary to regression (1). The increase in employment is related to a decrease in efficiency, while patents contribute to an increase in efficiency by 0.06%. Net revenues showed a slight increase in their coefficient, rising to 0.47%.

Regressions (3) and (4) follow the same pattern, with the first using the standard form of the model and the second treating outliers. In these two regressions, all explanatory variables are lagged by one period. Despite this configuration, the signals remained the same as seen previously. Again, net revenues were significant in both regressions, with employment and patents improving their statistical significance in the regression treating outliers.

The last regressions deal with endogeneity. In regression (5), only the lagged patents variable (*pat1*) was instrumented, using patents lagged in two periods and spending on research and development lagged in one period. Despite the new arrangement, the results followed the pattern presented. The Sargan test, which checks whether the model is overidentified under the null hypothesis and, therefore, whether endogeneity treatment is necessary (Wooldridge, 2013), casts doubt on the reliability of the estimates, while the Cragg weak instruments test -Donald, focused on indicating whether the instruments used have a relevant correlation with the endogenous variable (Wooldridge, 2013), rejected the null hypothesis that the instruments are unreliable. Regression (6) instruments all variables in the model. The gain of regression (5) is that the Sargan test did not reject the null hypothesis of endogeneity.

Table 7

Regressions with random effects (step 2)

	(1)	(2)	(3)	(4)	(5)	(6)
emp	-0.101	-0.203^{***}				-0.220^{***}
	(0.074)	(0.035)				(0.073)
rec	0.316^{***}	0.472^{***}				0.454^{***}
	(0.113)	(0.048)				(0.067)
pat	0.024	0.060^{***}				0.026
	(0.030)	(0.016)				(0.022)

emp1			-0.117*	-0.164***	-0.356***	
			(0.062)	(0.037)	(0.136)	
rec1			0.305***	0.410***	0.341***	
			(0.068)	(0.052)	(0.071)	
pat1			0.001	0.049***	0.004	
			(0.020)	(0.018)	(0.023)	
R2	0.45	0.51	0.37	0.42	0.57	0.45
N	130	130	122	122	106	101
F		43.23		28.07		
p-value		0.00		0.00		
Wald	15.39		43.50		150.97	56.85
chi2	0.00		0.00		0.00	0.00
Sargan					0.08	0.15
CD					229.71	18.73

On all occasions, net revenues were significant, with coefficients ranging between 0.3 and 0.47%. Then, according to regressions (2) and (4), the role of patents in contributing to efficiency can be reinforced. The employment variable, except regression (1), was significant in every opportunity, always with a negative sign; its increase was related to the drop in efficiency.

The next part of the analysis makes efficiency forecasts for the year 2030. The first step consisted of extrapolating the value of the net revenue series to 2030 values. The average growth rate of this variable between the years 2009 and 2020 was adopted to carry out this task. After this procedure, the estimates of the equation below, very similar to the functional form of regression (5) in Table 7, served as the basis for obtaining future values:

$$eff_{it} = 0.50 + 1.21e^{-6} rec_{i,t-1}. \tag{10}$$

Compared to regression (5), equation (10) does not use the variables in the log, as the objective is not to verify the elasticity between the variables. The remaining coefficients were not reported because they were not statistically significant. However, all adjustment tests, like those in Table 7, were carried out, with estimates suggesting that the model is suitable for estimation.

The results presented and discussed in Table 7 indicated that net revenues are fundamental to understanding fluctuations in the efficiency index. Thus, equation (10) reinforces the role played by this variable. Therefore, the estimates show that net revenues are one of the main ways of predicting the future efficiency of the firms in the sample.

In Table 8, the initial part presents the observed values, with the average efficiency between 2009 and 2020 and the efficiency in 2020. In the last line, the average of the entire sample was calculated. This line aims to compare the average estimates produced by the model with the average observed values.

Table 8
Efficiency forecasting (step 2)

Firm	Observed values		Model 1 predictions		
	eff average (09-20)	*eff* (2020)	*eff* average (09-20)	*eff* (2020)	*eff* (2030)
CHE	0.70	0.82	0.68	0.66	0.69
CNO	0.51	0.46	0.54	0.54	0.65
COO	1	1	0.53	0.53	0.53
COP	0.58	0.51	0.58	0.54	0.53
CPC	1	1	0.86	0.96	1
EXX	0.86	0.80	0.83	0.78	0.86
GAZ	0.70	1	0.62	0.63	0.73
IDE	0.68	0.66	0.54	0.56	0.63
PTB	0.45	1	0.61	0.59	0.62
PTC	0.78	0.92	0.80	0.89	1
SAS	0.23	0.4	0.52	0.52	0.51
STL	0.44	0.57	0.58	0.57	0.59
Average	**0.66**	**0.76**	**0.64**	**0.64**	**0.85**

Note 1: CHE (Chevron), CNO (CNOOC), COO (Cosmo Oil / Energy), COP (ConocoPhillips), CPC (China Petroleum & Chemicals), EXX (Exxon Mobil), GAZ (Gazprom), IDE (Idemitsu Kosan), PTB (Petrobras), PTC (PetroChina), SAS (Sasol) e STL (Statoil / Equinor).

The average efficiency indicated by the econometric model (0.64) is very close to the efficiency index calculated for the sample (0.66), suggesting a good fit for the model. In the case of 2020 efficiency, the fit was not as close, showing a difference of 0.12 between the observed and predicted values.

The main interest in Table 8 lies in the last column, with efficiency forecasts for 2030. Before analyzing each company individually, it is worth noting that the average efficiency value in 2030 (0.85) is higher than the efficiency average between 2009 and 2020 (0.66) for efficiency in 2020 (0.76). This result indicates that firms will experience efficiency gains over time, with net revenues leading this process. Appendices A (Table A.1) and B (Table B.1) show the regressions with fixed effects and the respective predictions. Compared to random effects, estimates with fixed effects indicated that the average efficiency in 2030 would be 0.86, very close to that found with random effects (0.85).

6. FINAL CONSIDERATIONS

In the panel data analysis, initially, the estimates indicated that net revenues are the primary variable to understand variations in the efficiency index. Elasticities showed that increases of 1% in net revenue were related to increases of 0.3-0.47% in efficiency. Although patents also showed statistical significance, their values were limited to a maximum of 0.06%. According to Ponta et al. (2021), the low importance of patents can be attributed to the way they are used, that is, as a means of exploring and understanding the technological and technical levels of competing companies, or even to hinder the entry of new firms into the sector in which they operate(Arora et al., 2018), and not strictly to advance the technological frontier of the field as well as patents are also imperfect representatives of innovation, for example, because the quality of patents varies and patents do not reflect the commercial value of innovations (Han & Sohn, 2017; Wu et al., 2021). In this sense, the number of patents would be an imperfect predictor of firm efficiency. The model estimates suggest this may have been the case for the firms in the sample.

Following the elasticity analysis, future scenarios were constructed. The estimates again pointed to net revenues as a potential predictor of firm efficiency. The model that presented the best adjustment was the one that instrumented patents, given the potential for endogeneity that this variable carries (Diaz-Fernandez et al., 2017). Regardless of the functional form chosen, as seen in Tables 8 and 9 (including the tables in appendices A and B), net revenue stood out among the explanatory terms of efficiency.

Regarding the efficiency predicted by the model, firms will generally become more efficient in 2030. Using the values in Table 8, it can be seen that between 2009 and 2020, the average efficiency observed was 0.66. However, the model predicted that by 2030, this average efficiency would rise to 0.85. Despite the heterogeneity that average values hide, the increase in predicted efficiency is still significant. Most of this efficiency gain would be channeled through net revenues.

Shifting the analysis from average values to individual shows the average efficiency from 2009 to 2020 and the expected efficiency in 2030. Based on the variation in efficiency, the investigation can be divided into three groups of firms: those that had gains in efficiency (CNO, GAZ, PTB, PTC, SAS, and STL), those that saw declines in efficiency (COO, COP, and IDE), and those that presented stable values, that is, the average efficiency observed and the efficiency predicted presented (CHE, CPC and EXX). About the group that gained efficiency, of the six firms, SAS (Sasol) more than doubled its efficiency level, from 0.23 to 0.51. In addition, PTC (PetroChina), which reached the maximum efficiency value, can be highlighted. As net revenue is the main factor explaining efficiency, these entities can improve their efficiencies based on deepening revenues.

The remaining groups have three firms each. Of the group that lost efficiency, COO (Cosmo Oil) showed the most significant drop, from efficiency 1 to 0.53. One way to understand this abrupt drop is to check the company's operationalization. As its net revenues have tended to fall in recent years (the peak of its revenues occurred in 2011), this movement has harmed its efficiency. If efficiency is defined primarily by net revenue, this forecast could be a warning for the company's future.

Finally, the last group illustrates firms that maintained their efficiency level practically unchanged. This lack of variation is not inevitably damaging since these firms had a high previous efficiency level, as are the cases of CPC (China Petroleum & Chemicals) and EXX (Exxon Mobil), with respective values of 1 and 0, 86.

A summary of the panel data analysis is the importance indicated for net revenues as a predictor of efficiency, with elasticities between 0.3-0.47% and recurring statistical significance, unlike the other variables, which fluctuated in relevance according to the functional form adopted (Table 7). The relevance of net revenues was reinforced when constructing the scenario analysis. In this way, the econometric model suggests net revenues to understand variations in company efficiency.

In the study, we answered the research question indicating the possible positions of O&G firms in 2030 considering innovation efficiency. We achieved the objective of identifying efficiency in the last decade. This was estimated until the end of this decade when experts and researchers pointed out that this would be the moment of inflection in the growth curve of fossil fuels.

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