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Renewable energies and operational and environmental efficiencies of the US oil and gas companies: A True Fixed Effect model

Sami Jarboui *

Abstract

Energy economics and environment protection are important issues in a modern society that aspires to aim at sustainable development. The evaluation of environmental and operational efficiency would be an important first step towards sustainable development. Renewable energies, especially hydroelectricity, geothermal, solar and wind, are playing an increasingly important role in the energy sector. Therefore, oil & gas companies are progressively transforming into energy companies following an energy transition policy. This raises the question whether the renewable energies promote the environmental and operational efficiency of petroleum companies. First, this paper examines two types of efficiency measures—operational and environmental—for 45 US oil & gas companies during the period 2000–2018 using on the true fixed effect (TFE) model. Second, this research aims to study the effect of renewable energies on both types of efficiency. The results reveal that the overall average operational efficiency (desirable output) of the US oil & gas companies is 76% for a period of 19 years, while the overall average level of CO₂ emissions efficiency (undesirable output) of the oil & gas companies is 79%. The results highlight that US oil & gas companies have begun to transition to low CO₂ emission in recent years. Furthermore, the renewable energies and biomass energies contribute to destroying the operational efficiency and to promote the environmental efficiency of oil & gas companies.

Keywords: Renewable energies, Biomass energy, Operational efficiency, Environmental efficiency, Oil & gas companies, True fixed effect model.

JEL Classification: O12, K32, H21, P28, Q51

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1. Introduction

Global warming and climate change have been critical global issues in recent years. Since the Kyoto Protocol in 1997, public have become more aware of these issues and interested in action, spurring reform policy and technological innovation. More recently, in 2015, the “Paris Agreement” formed a global consensus on global warming and sought to control the increase in average global temperature to less than 2°C during this century (United Nations, 2015). In order to achieve this objective, all countries should cooperate to reduce Carbon Dioxide (CO₂) emissions that result from human activity. However, to fulfill the Paris Agreement, only 13% of the world's crude oil reserves must be exploited. Therefore, all countries should strive to achieve sustainable development and green growth. In addition, despite significant changes in the energy structure and the increase in reliance on renewable energy in the world, oil still retains a large share of the energy market. The United States (US) is among the world's largest oil and gas producing countries and the world's second largest contributor to energy-related CO₂ emissions, with a global share of 14.58%, behind China with a share of 27.21%, in 2017. In 2019, US energy production has exceeded energy consumption, and fossil fuels represent the highest share of U.S. energy production. The share of coal in energy production has decreased in the U.S. by 16% (from 30% in 1957 to 14% in 2019); However, the share of crude oil production has decreased by only 7% (from 38% to 31%) (U.S. Energy Information Administration, 2020).

According to United States Energy Information Administration, energy consumption in the U.S. has been relatively limited for the past two decades. Since 1950, oil has acquired the highest share of US energy consumption, despite being 9% lower than its peak in 2005. The consumption of coal in the U.S. has decreased by almost 50% since 2008 mainly due to its replacement with renewable energies and natural gas, especially in the electricity sector (U.S. Energy Information Administration, 2020). The first step in the energy transition is natural gas consumption, which has increased by approximately 35% in the U.S. since 2000 and reached a record level in 2019. US renewable energy consumption, which includes the production of Electricity from renewable sources, biomass and biofuels, increased 88% over the same period, and its consumption share was almost the same as coal in 2019 (U.S. Energy Information Administration, 2020).

Furthermore, energy-related CO₂ emissions in the U.S. increased by 2.7% in 2018. Since 2009, natural gas-related CO₂ emissions in the U.S. have increased annually, decreased 1.3% in 2017, and then increased 10.2% in 2018. Since 2009, natural gas-related CO₂ emissions have increased by 32%. The natural gas-related CO₂ emissions exceeded total coal emissions in 2015, while coal related-CO₂ emissions decreased by 33% in 2018 compared to 2009 (U.S. Energy Information Administration, 2019). This overview reveals that environmental protection and climate change are not a priority for U.S. energy policies, which is clearly justified by the Trump administration's decision to leave the Paris agreement in 2017.

Following the increase in the new technology exploration for environmental protection and energy efficiency, company managers face great pressure to invest in this technology and take necessary action and decisions to promote the company's sustainability. Furthermore, they are also keen to make a high profit for shareholders and to stay in a competitive global market. Therefore, company managers' need to strike a balance between, on the one hand, operational and financial success and, on the other, environmental protection, as this balance ensures companies remain in a competitive global market and maintain a reputation. Generally,

consumers prefer environmentally conscious services and products and avoid products from companies that are not environmentally friendly. Therefore, companies must comply with the latest environmental regulations. In general, consumers are choosing the products and services of companies interested in environment protection and avoid the products of companies harmful to the environment. Therefore, companies should take the necessary measures to comply with the latest environmental regulations.

The administration's awareness of environmental conservation importance is very important in light of recent developments, especially the energy sector companies, due to their significant contribution to the total CO₂ emissions. Moreover, the petroleum industries not only produce primary energy essential to economic growth and different petroleum products used as intermediate goods for several industries, but they also emit greenhouse gases directly into the air. Hence, policymakers, corporate managers and individuals concerned with environmental protection should strive to reduce CO₂ emissions in the petroleum industry. However, many oil companies were not interested in adopting high standards for pollution reduction or environmental protection, although they may achieve a high level of operational efficiency. Therefore, environmental and operational efficiency evaluation of these companies is an important first step to reduce CO₂ emissions and environmental protection for corporate sustainability and sustainable development.

This paper aims to examine the environmental and operational efficiencies and evaluate the inefficiencies determinants for the desirable (operational revenue) and undesirable (CO₂ emission) outputs of US oil & gas companies during the period 2000–2018. It also discusses policy implications for energies transition, and reveals the effect of different renewable energies on environmental and operational efficiencies. In the framework of Stochastic Frontier Analysis (SFA) approach, this research adopts the True fixed effect model to measure the environmental and operational efficiencies.

In order to achieve the research objectives, this study aims to answer the following:

- What are the operational and environmental efficiency levels of US oil & gas companies?
- To what extent do renewable energies influence the efficiency of oil & gas companies?

The rest of this paper is organized as follows. Section 2 presents a literature review of the environmental and operational efficiency studies applied to energy issues. Section 3 discusses the data set and the true fixed effect model formulations. Section 4 presents the results on environmental and operational efficiency measures and renewable energies effect on efficiency scores. Section 5 concludes and suggests future research.

2. Literature review

Many previous studies have assessed the environmental and operational efficiency of oil & gas companies. Using the Data Envelopment Analysis (DEA), Thompson et al. (1992) studied the efficiency of 45 independent oil & gas companies during the period 1980-1986, equipped with the principles of assurance region. They show that the efficiency measures had different characteristics during the period 1980–1982 compared to the period 1983–1986. Sueyoshi and Goto (2012b) proposed a non-radial DEA model including unified output for desirable and undesirable production unification. This DEA model is reformulated for the environmental evaluation. They applied the model to a dataset including international oil companies (IOC) and

national oil companies (NOC) and compared the efficiency between the two groups. The results showed that in terms of environmental efficiency, IOCs outperform NOCs, while NOCs outperform IOCs in terms of operational efficiency. Using the dataset including IOC and NOC, Sueyoshi and Goto (2012a) measured the returns to scale of oil companies and damage to scale. The authors proposed two alternative strategies for oil companies to reduce the CO₂ emissions related to their operations.

In order to measure two types efficiency, Sueyoshi and Wang (2014) adopted a DEA models for a sample of integrated and independent oil companies in U.S. The GHG emissions adopted as an undesirable output. Their results affirmed that integrated companies outperformed independent companies following their longer supply chain. Their results revealed that the longer supply chain system enhanced company sustainability. On the one hand, using DEA and SFA methods, Eller et al. (2010) affirm that the international companies are more efficient than national companies. Their findings revealed that the different objectives of IOCs and NOCs influenced the companies' efficiency. Moreover, in order to reach a consensus with regards to the effectiveness of a given ownership model in comparison to the other by estimating the operational and financial efficiency differentials of NOCs and IOCs, Al-Mana et al. (2020) used 10 indicators (3 financial and 7 operational) to perform four analyses (financial analysis; operational analysis; Stochastic Frontier Analysis; and Data Envelopment Analysis) for a sample consists of 50 firms (composed of 16 NOCs and 34 IOCs) during 2002–2016. Their results suggest that, in general, IOCs perform better than NOCs but the role of privatization on the performance and efficiency of NOCs remains contentious since some NOCs perform as well as the best IOCs. Nevertheless, on average, it is safe to imply that privatization may lead to improved performance and efficiency since shareholder-owned firms, generally, perform better than the national players. For that matter, even some partially privatized firms show evidence of better performance in comparison to NOCs (Al-Mana et al., 2020). Due to the specifics of the petroleum sector, the companies tend to be large and have a significant direct and indirect influence on the oil industry as a whole (Filimonova et al., 2020). However, Filimonova et al. (2020) compared Russian and international companies in the oil and gas sector and identified the distinctive features of each group. The results of Filimonova et al., (2020) show that the profit of each major oil and gas company is affected by revenue, production costs, and tax deductions. The key interest rate set by the Central Bank of Russia is also important for the activities of oil and gas companies. A distinctive factor for petroleum corporations is the negative impact of financial leverage on the profits of domestic companies and the negative impact of investment in the environmental area for foreign companies.

In recent years, the SFA method has been extensively used to assess the firm production efficiency (Jarboui et al., 2012 and 2015a, Jarboui, 2016). Sun et al. (2017) adopted the method of SFA examine the oil companies' efficiencies of China. According to the SFA method, Tu and Xiao (2005) have decomposed the productivity of total factor of industrial companies and show that technical efficiency has an important effect on improving productivity. The SFA method measures the deviation of companies from the production frontier and separates the inefficiency from individual heterogeneity (He, 2012). The SFA method detects the deviation of companies from the production frontier and separates individual heterogeneity from inefficiencies (He 2012, Jarboui et al., 2015b). Some problems and limitations may occur when carrying out a study used SFA method. For example, the technical efficiency absolute level is sensitive to distribution assumptions; the SFA method requires the use of a large number of firms; the SFA method suffers from the regressor endogeneity and it violates the monotony conditions (Jarboui et al., 2012, Ben Mohamed and Jarboui, 2017). Therefore, these problems

and limitations should be taken into consideration when choosing to adopt the SFA method. However, the deterministic parametric approach has been proposed by some research as an alternative methodology (Du et al., 2016b; De Clercq et al., 2019) to overcome the above-mentioned limitations.

Among research that adopted the SFA method for the production efficiency evaluation, the current methods developed by Battese and Coelli (1995) make it possible to overestimate the term of inefficiency, which leads to a distortion between the estimated efficiency results and the actual situations. However, Greene (2004; 2005a; 2005b) focused on the heterogeneity impact on the efficiency measurement. Greene (2004) studied the health care service efficiency of 191 countries using the World Health Organization panel dataset, and showed that it is interesting to distinguish between inefficiency and heterogeneity. In addition, Farsi et al. (2005) adopted SFA cost method to panel data and compare their ability to distinguish inefficiency variation from unobserved heterogeneity. More and more research in recent literature has stressed the important effect of heterogeneity in the efficiency estimation. In this context, Wang and Ho (2010) have shown that individual heterogeneity must be adequately controlled, otherwise the heterogeneity effect would be incorporated into the inefficiency term and also in the assessment of efficiency. To have consistent estimates of efficiency, Cechura (2010) showed that the specifications of the model making it possible to grasp the firm's heterogeneity invariable over time. Zhang and Choi (2013) proposed the CO₂ emission performance index using non-radial Malmquist meta-frontier which could allow the incorporation of non-radial play and group heterogeneity in the of CO₂ emission performance evaluation. Wang et al. (2015) found that the production technologies heterogeneities linked to energy economics and reduced emissions in Chinese cities. The energy efficiency estimations will be biased after ignoring technological heterogeneity. Song et al. (2016a) developed a model with fixed effects on the impact of environmental efficiency on railway transport.

Greene (2005a) proposed a True fixed effect model that distinguished the time-variant inefficiency from the time-invariant unobserved heterogeneity. In the true fixed effect model, the heterogeneity is an individual term that is constant with time, while the inefficiency term varies with time; furthermore, the inefficiency term and heterogeneity are independent of each other, eliminating the main limitations of panel data. Liang and Wang (2013) indicate that the heterogeneity observed among the different international petroleum companies comes mainly from the growth and management process of the companies, and the typical heterogeneity exists from the institutional difference. In addition, a large number of unobserved factors such as histories, different social cultures and customs, can also lead to unquantifiable heterogeneity among oil companies. (Yu and Shen, 2010).

Referring to the above analysis, this research adopted the true fixed effects model to study the environmental and operational efficiencies of US oil & gas companies during the period 2000-2018. The contributions of this research are summarized as follows: first, this paper examines two types of efficiency measures—operational and environmental— using on the true fixed effect model by distinguishing inefficiency from heterogeneity in the study of environmental and operational efficiency. Second, this research aims to test the effect of renewable energies and biomass energies on environmental and operational efficiencies.

3. Methodology

3.1. True fixed effect model and Unobservable heterogeneity

The SFA method form is presented as follows (Pitt and Lee, 1981):

$$y_{it} = \alpha + \beta x'_{it} + \varepsilon_{it}, \quad i = 1, 2, \dots, N, \quad t = 1, 2, \dots, T \quad (1)$$

$$\varepsilon_{it} = v_{it} - u_i$$

$$v_{it} \sim N(0, \sigma_v^2)$$

$$u_i \sim N^+(0, \sigma_u^2)$$

where, y_{it} represents the output produced by the i -th company in the t -th period; x'_{it} represents the input of the i -th company in the t -th period; β is the estimated parameter; ε_{it} is the error term, which is decomposed in v_{it} and u_i ; v_{it} represents the random error, and u_i represents the error related to the technical inefficiency. After the study of Pitt and Lee (1981), many researchers conducted a series of research on distribution and time-varying conditions of u_i ; the most commonly used models are those developed by Battese and Coelli, 1995. However, the term α is fixed in both models, which implies that the inefficiency term is time invariant. Therefore, deviations caused by heterogeneity are often viewed as inefficient values, resulting in confusion of inefficient values and heterogeneity, and estimated results deviations (Belotti et al., 2013).

Greene (2005a) proposed a complete understanding overview of the heterogeneity impacts. Greene (2008) affirmed that the firm would be homogeneous if each firm had the same parameters except for the terms of random disturbance; otherwise, there would be individual heterogeneity. Inefficiency and heterogeneity are completely different concepts. Therefore, the reason of heterogeneity existence lies in the ignorance of the explanatory variables, which are difficult to quantify, such as the omission of the time invariant input variables.

Following a very diverse production environment, different companies have their own characteristics and are influenced by a variety of factors. Moreover, economic development levels, companies reform processes, social cultures, and government policies vary from one country to another. These institutional factors or these unobservable heterogeneities may affect the company efficiency. Oil & gas companies have important differences in aspects such as management policies, companies' characteristics, investment directions, modes of operation. These factors do not change in the short term, they would affect the outputs of companies and not the production process. Moreover, the effects of these factors on the oil & gas companies' production may not be directly observed (Sun et al., 2017).

In order to study whether time-invariant heterogeneity would have an impact on the inefficiency, this article uses the true fixed effect model developed by Greene (2005a):

$$y_{it} = \alpha_i + \beta x'_{it} + \varepsilon_{it}, \quad i = 1, 2, \dots, N, \quad t = 1, 2, \dots, T \quad (2)$$

$$\varepsilon_{it} = v_{it} - u_{it}$$

$$v_{it} \sim N(0, \sigma_v^2)$$

$$u_{it} \sim N^+(0, \sigma_u^2)$$

In this model, x'_{it} , v_{it} and u_{it} are independent. u_{it} represents the technical inefficiency score of oil & gas company, which can change over time and between companies in the model. α_i represents the simulation of Heterogeneity among different companies. α_i controls the individual effects and represents the individual response of i -th company, is the time-invariant factor. Therefore, α_i indicates the unobservable heterogeneity. α_i , which affects the output, is beyond the company's regulation scope. Therefore, heterogeneity can be separated from null values by defining the random parameters in the unobserved heterogeneity measurement (Sun et al., 2017).

The current true fixed effect model has different characteristics compared to the models of Battese and Coelli (1995). First, heterogeneity is invariant over time. Otherwise, heterogeneity indicates the company individual effect, which can reflect the operational mode, the relevant policies, and differences of corporate property among company. Second, it can ignore the heterogeneity problem interference on the efficiency score. In addition, the efficiency score varies over time. Therefore, it can reflect the technological progress companies, and it is suitable for panel data (Belotti et al., 2013).

The purpose of this article is not only to measure the environmental and operational efficiency of oil & gas companies, but also to identify the possible sources of inefficiency assigned to each company in our sample. Indeed, we adopt the recommended model of Wang and Ho (2010). Their model is presented as follows:

$$y_{it} = \alpha_i + \beta x'_{it} + \varepsilon_{it}, \quad i = 1, 2, \dots, N, \quad t = 1, 2, \dots, T \quad (3)$$

$$\varepsilon_{it} = v_{it} - u_{it}$$

$$v_{it} \sim N(0, \sigma_v^2)$$

$$u_{it} = h_{it} \times u^*_i$$

$$h_{it} = f(\delta z_{it})$$

$$u^*_i \sim N^+(\mu, \sigma_u^2)$$

u_{it} represents the technical inefficiency and z_{it} represents the vector of variables explaining the inefficiency. The model exhibits the "scaling property" in the sense that, conditional on z_{it} , the one-sided error term equals a scaling function h_{it} multiplied by a one-sided error distributed independently of z_{it} . With this property, the underlying form of distribution of inefficiency is the same for all individuals, but the distribution scale is reduced by observation-specific factors z_{it} . The time-invariant specification of u^*_i makes it possible to correlate the inefficiency u_{it} over time for a given individual.

3.2. Empirical model

In this research, we adopt the translog functional form of production function to propose the empirical SFA model based to the true fixed effects model. Therefore, the form of the used model is expressed as:

$$\ln Y_{it} = \alpha_i + \beta_t t + \beta_k \ln k_{it} + \beta_l \ln l_{it} + \beta_{kl} \ln k_{it} \times \ln l_{it} + \beta_{k2} \ln k_{it} \times \ln k_{it} + \beta_{l2} \ln l_{it} \times \ln l_{it} + v_{it} - f(\delta z_{it}) u_{it}^* \quad (4)$$

$$i = 1, 2, \dots, N, \quad t = 1, 2, \dots, T$$

$$h_{it} = \delta_1(\text{Wood})_{it} + \delta_2(\text{Biofuels})_{it} + \delta_3(\text{Total Biomass})_{it} + \delta_4(\text{Hydroelectric})_{it} + \delta_5(\text{Geothermal})_{it} + \delta_5(\text{Solar})_{it} + \delta_5(\text{Wind})_{it} + \delta_5(\text{Total renewable Energy})_{it} \quad (5)$$

where Y_{it} represents the output of the i -th oil and gas company at the period t ; l_{it} represents the labor input; k_{it} represents the capital input; z_{it} is the vector of variables explaining the inefficiency; α_i , β and δ are the estimated parameters; v_{it} is the random error.

The parameters of β , σ_v and σ_u can be estimated using the proposed method in this research. To measure the efficiency score, we calculate the value of u_{it} . Jondrow et al. (1982) proposed the method of JLMS to measure the contribution of u_{it} to $\varepsilon_{it} = v_{it} - u_{it}$. For the case that u_{it} follows the semi normal distribution:

$$E[u_{it} | \varepsilon_{it}] = \frac{\sigma \lambda}{1 + \lambda^2} \left[\frac{\phi(\gamma_{it})}{1 - \Phi(\gamma_{it})} - \gamma_{it} \right] \quad (6)$$

where $\sigma = \sqrt{\sigma_v^2 + \sigma_u^2}$, $\lambda = \frac{\sigma_u}{\sigma_v}$, $\gamma_{it} = \pm \frac{\varepsilon_{it} \lambda}{\sigma}$; $\Phi(\gamma_{it})$ indicates the function of cumulative distribution of γ_{it} . $\phi(\gamma_{it})$ represents the function of probability density of γ_{it} , (Greene, 2005a). λ , indicates the ratio of the inefficiency standard deviation to the error term standard deviation. Therefore, it measures the model estimation validity. In addition, the value of λ reflects the robustness of the estimated results.

Referring to the method developed by Battese and Coelli (1988), technical efficiency can be presented as

$$TE = \exp(-\hat{u}) \quad (7)$$

where, $\hat{u} = \hat{E}[u_{it} | \varepsilon_{it}]$.

Technical efficiency in production measures the ratio of the observed output over the optimal output, and $0 \leq TE \leq 1$. If $TE=1$, it indicates that the company output lies in its production frontier, which achieves the technical efficiency. If $TE < 1$, this indicates that the company's output is below the production frontier and that it is in inefficiency state.

According to Greene (2005a), the true fixed effect model estimation adopts the maximum likelihood method of dummy variable. The log likelihood function for the fixed effects model of SFA is expressed as:

$$\ln L = \sum_{i=1}^N \sum_{t=1}^T \ln \left[\frac{1}{\phi(0)} \Phi \left(-\lambda \left(\frac{y_{it} - \alpha_i - \beta x_{it}}{\sigma} \right) \right) \Phi \left(\frac{y_{it} - \alpha_i - \beta x_{it}}{\sigma} \right) \right] \quad (8)$$

4. Data and statistical description

The data used in this research comprises 45 oil & gas companies in the US energy sector. All of them were included in the Thomson Financial Database for the time period 2000–2018. This research adopts one desirable output, two inputs, and one undesirable output for the true fixed effect model application (see Table 1). The undesirable output is the amount of CO2 emissions

from the production and exploration sectors. This study evaluates the environmental efficiency using CO₂ emissions as an undesirable output, and the operational efficiency using the operational revenue as a desirable output.

This paper adopts the number of employees and the operating expenses as the indicators of labor and capital inputs, respectively (see Table 1). The operational revenue is used as the desirable output index, the undesirable output is the amount of CO₂ emissions (Mrabet and Jarboui, 2017). In order to evaluate the effects of US energy policies, especially the effect of renewable energy on the environmental and operational efficiency of oil & gas companies, Wood, Biofuels, Total Biomass, Hydroelectric Power, Solar energy, Wind energy, and Total Renewable Energy are used as the determinants variables of the inefficiency components. There are the major renewable energy sources. We apply the logarithm to all variables except time. The description of the selected variables and data are as follows:

Desirable output

Operational revenue: Although oil & gas companies have several outputs, all sales and production would be converted to operational revenue, and therefore, the operational revenue is the appropriate index that reflects the output of a company. Higher revenue generally implies business success and higher profits for the companies. This variable also indicates the operational size of the companies. Furthermore, if a company incurs substantial costs, it may be inefficient even if it has a large revenue stream.

Undesirable output

CO₂ emissions: This variable reflects the amount of CO₂ emissions from the company's production and exploration sectors. Following the magnitude of current emissions, investment in prevention policies may be evolved.

Inputs

The number of employees: This variable reflects the company's investment in human capital. As an industry dependent on labor intensity, investing in human capital is critical to measuring the technical efficiency of oil & gas companies.

Total assets: this variable includes the total of all current and non-current assets including all components as they are presented in the balance sheet. This variable reflects a company's investment in capital, such as production plants investments and production facilities investments. Therefore, in this research, we adopt total assets as an indicator of capital input.

Inefficiency determinants

The production of *renewable energy* types is used in this study as factors affecting the environmental and operational efficiency of petroleum companies. The major types of renewable energy sources are Biomass (Wood and Biofuel), Hydropower, Wind and Solar. Renewable energy is a key factor in reducing CO₂ emissions. Thus, the use of renewable energy reduces the use of fossil fuels, which have the largest share of CO₂ emissions in the U.S.

(Insert Table 1 here)

5. Empirical results

5.1. Results of the True fixed effects Stochastic Frontier model

Using the data of US oil & gas companies, this study constructs the true fixed effect model to estimate the environmental (Model 1 and 2) and operational efficiencies (Model 3 and 4) of oil & gas companies based to Equation (3) (see Table 3). The results of estimation are presented in Table 2. The results of estimation presented in Table 2 indicate that the coefficients of time factor “ t ” are not significant for the desirable and undesirable output; the estimated coefficients of total assets “ $\ln k_{it}$ ” and total assets multiplied by number of employees “ $\ln k_{it} \times \ln l_{it}$ ” are positive and statistically significant at the 1% level for all estimated Models presented in Table 2 and 3; the estimated coefficients of squared total assets “ $\ln k_{it} \times \ln k_{it}$ ” are negative and significant at 1% level for the desirable output (operational revenue), but they are positive and significant at 1% level for the undesirable output (CO2 emission); the estimated coefficients of number of employees “ $\ln l_{it}$ ” are negative and statistically significant at the 5% level for all estimated Models presented in Table 2 and 3; and the coefficients of squared number of employees “ $\ln l_{it} \times \ln l_{it}$ ” are negative and statistically significant at 5% level only for the estimation of the CO2 emissions model. The above results are still insufficient to determine the effect of time on the estimated efficiency results. Referring to the estimated results, σ_u is the standard deviation of the inefficient term “ u_{it} ”; $\lambda = \frac{\sigma_u}{\sigma_v}$ is the ratio of σ_u over σ_v , it measures the validity of the SFA estimation. Specifically, the level of effectiveness of the model estimation results depends on the value of λ and its level of significance. Referring to the regression results, σ_u and σ_v are significant at the 1% level; the value of λ is 1.067 at the 1% level of significance (see Table 2), showing that it is suitable to use the TFE model combined with the SFA model to evaluate the efficiencies of the US oil & gas companies.

(Insert Table 2 here)

The true fixed effect model proposed by Greene (2005a) guarantees the robustness of production efficiency estimation. It is capable to account separately for the country-specific effect in time-invariant and the inefficiency effect (Sun et al., 2017). For a fixed effect model, Wang and Ho (2010) also indicated that the number of fixed effect parameters increases with the number of companies (N). Therefore, the true fixed effect model estimation would be biased because since it includes both the fixed individual effects and inefficiency effect. Wang and Ho (2010) proposed a different model of SFA that has the specification of the true fixed-effect model and nevertheless allows model transformations to be carried out while maintaining the processable likelihood function.

In order to test the results stability and analyze the time variable effect on the results of estimation, we introduce the time square and the cross terms with time in Model 1. Results reveal that the time variable has little effect on Model 1, indicating the robustness of the estimated efficiency scores.

5.2. Results of the inefficiencies modeling

In order to study the effects of environmental policy on the environmental and operational efficiency of oil & gas companies, we include the different types of renewable energy as variables explaining the inefficiency based on the developed model of Wang and Ho (2010)

presented in the equation. The results of Wang and Ho (2010) model estimation are presented in Table 3.

Firstly, we tested the effect of total renewable energy production and total biomass energy production on the environmental and operational efficiency of oil & gas companies, which are presented in model 1 and 3 in Table 3. However, the estimated coefficients of total biomass energy production (z_{3it}) and total renewable energy production (z_{8it}) are positive and significant at the 1% level, which shows the positive relationship between the operational inefficiency of oil & gas companies and these two variables (model 1). This indicates that the total production of renewable energy and the total production of biomass energy contribute to reduce the operational efficiency of oil & gas companies. While the estimated coefficients of total biomass energy production (z_{3it}) and total renewable energy production (z_{8it}) are negative and significant at the 1% level, which shows the negative relationship between environmental inefficiency and these two variables (model 3). This indicates that the total production of renewable energy and the total production of biomass energy contribute to improve the environmental efficiency of oil & gas companies.

Secondly, we tested the effect of different types of renewable and biomass energies on the environmental and operational efficiencies of oil & gas companies, which are presented in model 2 (desirable output) and 4 (undesirable output) in Table 3. Our Results reveal that the estimated coefficients of wood energy production (z_{1it}) are positive and significant at the 10% level and the estimated coefficient of geothermal energy production (z_{5it}) is not significant (Model 2). While the results show that the estimated coefficients of biofuel production (z_{2it}), hydroelectric power production (z_{4it}), and wind power production (z_{7it}) are positive and significant at the 1% level, and the coefficient estimated solar energy production (z_{6it}) is positive and significant at the 5% level (Model 2). This result shows the positive relationship between the operational inefficiency of oil & gas companies and these different variables. This indicates that the production of renewable energy and the production of biomass energy contribute to destroying the operational efficiency of companies, which confirms the result of Model 1. Referring to the results of model 4 estimation, which tests the effect of different types of renewable energy and biomass energy on the environmental efficiency, the estimated coefficients of biofuel production (z_{2it}), hydroelectric power production (z_{4it}) and wind power production (z_{7it}) are negative and significant at the 1% level and the estimated coefficient of solar energy production (z_{6it}) is negative and significant at the level of 5%. This result shows the negative relationship between the environmental inefficiency of oil & gas companies and these different variables (model 4), which indicates that the different types of renewable and biomass energies contribute to improving environmental efficiency, which confirms the result of Model 3. This result confirms the conclusions of Gray and Shadbegian (2003), Wagner (2005) and Lanoie et al. (2008). The above studies indicate that environmental regulations reduce the efficiencies of companies in the high-carbon industry.

(Insert Table 3 here)

5.3. Operational an environment efficiency scores

The average environmental and operational efficiencies of US oil & gas companies measured from the true fixed effect model are summarized in Tables 4 and 5.

For a given level of inputs, a company lost revenue due to its operational inefficiencies which are a minus the efficiency score for the 19-year period. The overall average efficiency of the oil & gas companies is 76% for a period of 19 years (2000-2018), which means that without changing the level of inputs, the oil & gas companies had a margin to increase their efficiency by 24%. Furthermore, the overall average level of CO₂ emissions efficiency (undesirable output) of the oil & gas companies is 79% for a period of 19 years, which means that with this level of inputs, the oil & gas companies have controlled their CO₂ emissions by 21%. Otherwise, the overall average environmental efficiency level of oil & gas companies is 21% for a period of 19 years.

Table 4 presents the average of environmental and operational efficiency for each oil and gas company for the period 2000-2018. None of the companies is able to achieve full efficiency equal to one. Daleco Resources Corporation and Glen Rose Petroleum Corporation had the worst level of operational efficiency which is equal 0.38. Furthermore, four companies have the highest operational efficiency scores for all nineteen years, namely Anadarko Petroleum Corporation, Chevron Corporation, PDC Energy, and the Reserve Petroleum Company, with average operational efficiency scores of 0,9166, 0,9313, 0,9628 and 0,985, respectively. These results are partially confirmed by Atris and Goto (2019) and Sueyoshi and Wang (2018). However, generally, companies of the worst operational efficiency scores, recorded the lowest level of CO₂ emissions, similar to Daleco Resources Corporation and Glen Rose Petroleum Corporation, with average CO₂ emission efficiency scores of 0,3621 and 0,3631, respectively. Moreover, companies of the highest operational efficiency scores recorded the highest CO₂ emissions scores, Chevron Corporation and PDC Energy, Inc., with average CO₂ emission efficiency scores of 0,9313 and 0,9628, respectively. This implies that the company makes efforts to advance in environment protection; however, its environment policy may not be well-balanced with its operational efficiency, which confirms our results presented in section 5.2 on the negative correlation between renewable energies and companies' operational efficiency.

(Insert Table 4 here)

Table 5 and Fig. 1 describes the annual average environmental and operational efficiencies scores of oil & gas companies during the period 2000-2018. The results reveal that the annual average scores of environmental and operational efficiencies have the same tendency during the study period. Moreover, CO₂ emissions level increases following the operational efficiency increase, and decreases following their decrease. However, the gap between the operational efficiency level and the CO₂ emissions level are greater when the annual average scores of operational efficiencies exceed 75% or when its curve is ascending. Furthermore, this gap decreases or disappears following the drop in operational efficiency or when its curve is falling.

(Insert Table 5 here)

Referring to Figure 1, the results highlight that US oil & gas companies have begun a transition to low CO₂ emission in recent years. Since 2015, date of the Paris agreement, the gap between operational efficiency trend and CO₂ emission efficiency trend begins to decrease or disappear, this is reflected in the decline of operational efficiency which leads to a decrease in CO₂ emissions and improvement of environmental efficiency following an energy transition policy adopted by US oil & gas companies towards renewable energies. In low-CO₂ emission actions, some oil & gas companies choose to adopt renewable energy routes, while some companies choose to follow energy efficiency routes, the renewable energy development is currently

focused on solar energy, geothermal energy and wind energy, and oil & gas companies should have good experience in applying these energies (Lu et al., 2019).

The U.S. has undergone rapid changes in its stated emission commitments from the Obama administration to the Trump administration. The Trump administration's decision to quit the Paris agreement in 2017 has been widely viewed by the international community as an abdication of U.S. leadership in climate policy. Climate change and emissions have not been a priority for the Trump administration, especially, since 2014, oil & gas companies have recorded a decrease in operational efficiency as shown in Figure 1.

Figure 1 depicts the deterioration of operational efficiencies of companies which is very likely to be caused by the crash of oil price in the periods (e.g. 2007-2009). In addition, since mid-2014, when oil price is above 100 dollars, the oil price has fallen roughly 50%. The falling oil price creates a difficult situation for the companies even to operate and survive. Therefore, the operational efficiencies are influenced by the change of energy prices. Equally, the environment efficiencies variations are very likely to be caused by the variations of oil price. Inexpensive oil can be detrimental to the energy transition. Indeed, expensive oil encourages consumers to turn to alternative energy sources, first among which are renewable energies. Conversely, if oil becomes cheaper, these energies are less competitive and therefore less attractive. In addition, companies specializing in these renewable energies, and the oil companies themselves, risk curbing their investments intended for the development of alternative energy technologies.

Furthermore, the environmental and operational efficiencies are influenced by governmental regulations and environmental protection policy and energy security. The Environmental Protection Agency (EPA) has been pushing for increasingly stringent regulations on carbon emissions from oil and oil operations in recent years. In the US, EPA is charged with the responsibility of monitoring and controlling the air pollution from the petroleum industry. The US EPA has proposed numerous regulations directly related to the activities of the oil industry to reduce and control CO₂ emissions (Atris and Goto, 2019). The low efficiency of oil & gas companies may be related to the US Environmental Protection Agency's fine that was imposed on the company for a violation of environmental regulations that could have adversely affected the company's revenue.

(Insert Fig. 1 here)

6. Conclusion

Saving energy and protecting the environment are essential issues in a modern society that aspires to sustainable development. In order to achieve sustainable development, nations have sought to cooperate to reduce CO₂ emissions by adopting protocols and agreements, namely the Kyoto Protocol in 1997 and the Paris Agreement in 2015. Thus, an energy transition is necessary for environmental protection and climate change. However, oil production must be reduced in accordance with the current development model. In order to fulfill the Paris Agreement, only 13% of the world's proven reserves of crude oil must be exploited (Atris and Goto, 2019). Besides, although the energy structure in the world is undergoing important changes and the renewable energy status is increasing, oil and gas still represent half of the energy market. The United States is among the world's largest producers of oil & gas and the second largest contributor to energy-related CO₂ emissions.

This paper examines the environmental and operational efficiencies and evaluated the inefficiencies determinants for the desirable (operational revenue) and undesirable (CO₂ emission) outputs of 45 US oil & gas companies during the period 2000–2018 and discusses policy implications for energies transition, and reveals the effect of different renewables energies. This research applies the true fixed effect model under the framework of SFA approach to measure the environmental and operational efficiencies.

The empirical results of this study reveal that US oil and gas companies had a margin to increase their operational efficiency by 24% since the overall average operational efficiency for desirable output is 76% for a period of 19 years (2000 -2018). However, the environmental efficiency of US oil and gas companies is 21%, this deduced by the overall average level of CO₂ emissions efficiency (undesirable output) which is equal to 79% during the study period. Moreover, the results affirm that the annual average scores of environmental and operational efficiencies have the same tendency during the study period. However, the gap between the operational efficiency level and the CO₂ emissions level are greater when the annual average scores of operational efficiencies exceed 75% or when its curve is ascending.

The empirical findings reveal that the total production of renewable energy and the total production of biomass energy contribute to reduce the operational efficiency of oil & gas companies and contribute to improve the environmental efficiency of oil & gas companies. However, biofuel production, hydroelectric power production, wind power and solar energy production contribute to destroying the operational efficiency of oil & gas companies and contribute to promote the environmental efficiency. The above studies indicate that environmental regulations or the energy transition affect the efficiencies of companies in the high-carbon industry.

Our empirical results highlight that US oil & gas companies have begun a transition to low CO₂ emission in recent years. Since 2015, date of the Paris agreement, the gap between operational efficiency trend and CO₂ emission efficiency trend has begun to decrease or disappear, this is reflected in the decline of operational efficiency which leads to a decrease in CO₂ emissions and improvement of environmental efficiency following an energy transition policy adopted by US oil & gas companies towards renewable energies. Climate change and emissions have not been a priority for the Trump administration, especially, since 2014, where oil & gas companies have recorded a decrease in operational efficiency. This made Trump administrations quit the Paris Agreement in 2017. Furthermore, the environmental and operational efficiencies are influenced by environmental policy and governmental regulations.

Despite what this study has confirmed and what is mentioned in some studies about the impact of energy and environmental policies on the efficiency of oil & gas companies and the market competition that intensifies with time between renewable energies and these companies, it is possible to search for energy and environmental policies that ensure the oil companies efficiency and at the same time achieve the desired environmental goals without quitting or leaving international environmental agreements, what the Trump administration did in 2017. Among these policies, some oil companies around the world are directed towards the use of renewable energies in their activities in order to reduce production costs and adopt the production of some of them, especially with the fluctuation of oil prices in recent years. European oil companies have taken first steps to shift their oil production and refining operations to electricity, replacing them with natural gas and renewables. The oil companies

have undertaken to buy out electricity production and distribution companies to integrate them into their activities in the fields of natural gas and renewable energies.

Like any other study, this research also has some opportunities for improvement. Firstly, this study has investigated only the US oil & gas companies. The efficiency of the oil & gas companies has not been studied in the countries that have recently expanded their influence in the petroleum industry. Saudi Arabia, China, and Russia, which are excluded from this study, are very important in the global petroleum industry as producing countries. Furthermore, this study needs to reorganize the proposed true fixed effect model by a comparative study based on parametric (stochastic) and non-parametric (DEA) approach. This issue will be discussed in future research as an extension of this study.

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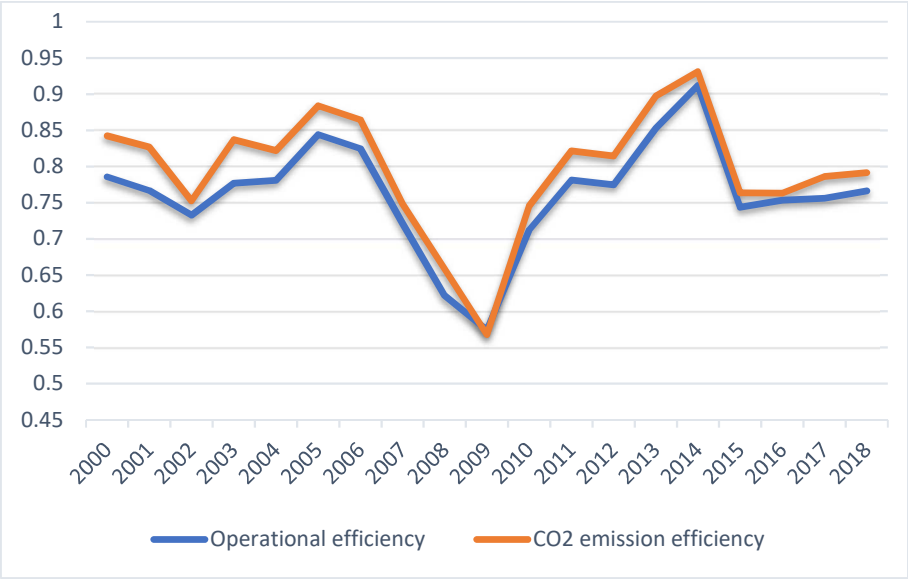


Fig. 1. Average annual operational and environmental efficiency of oil and gas companies

List of Table

Table 1. The statistical description of the sample data.

Variables	Mean	Standard deviation	Minimum	Maximum
Operational revenue (million USDs)	5420,78	26888,79	255112,00	25,35
CO2 emissions (Metric tons)	769,57	232,35	12764,35	457,65
Total assets (million USDs)	4670,16	23354,65	220102,00	20,25
Number of employees (persons)	2460,14	9903,36	67000,00	20,00
Wood Energy Production (Trillion Btu)	2182,42	143,49	2401,08	1935,01
Biofuels Production (Trillion Btu)	1414,43	823,92	2396,57	233,15
Total Biomass Energy Production (Trillion Btu)	4047,50	965,49	5238,48	2624,16
Hydroelectric Power Production (Trillion Btu)	2621,80	198,63	3102,85	2241,86
Geothermal Energy Production (Trillion Btu)	195,10	18,22	214,49	164,36
Solar Energy Production (Trillion Btu)	264,80	315,10	1042,86	57,89
Wind Energy Production (Trillion Btu)	1036,30	912,89	2731,85	57,06
Total Renewable Energy Production (Trillion Btu)	8165,50	2111,83	11636,98	5161,77

Table 2. Results of the true fixed effect (TFE) model.

Variable	Parameters	Desirable output <i>Operational revenue</i>	Undesirable output <i>CO2 emissions</i>
t	β_t	0.007 (0.931)	0.009 (0.597)
$\ln k_{it}$	β_k	1.190 (5.659)***	1.207 (4.079)***
$\ln l_{it}$	β_l	-0.033 (2.165)**	-0.471 (2.122)**
$\ln k_{it} \times \ln l_{it}$	β_{kl}	0.913 (4.033)***	1.301 (2.222)**
$\ln k_{it} \times \ln k_{it}$	β_{k2}	-0.078 (3.655)***	0.185 (2.655)***
$\ln l_{it} \times \ln l_{it}$	β_{l2}	-0.016 (0.738)	-0.028 (2.060)**
	σ_u	0.878 (5.071)***	0.678 (4.765)***
	σ_v	0.122 (4.214)***	0.232 (3.412)***
	λ	1.067 (4.285)***	1.038 (5.285)***
Log likelihood		46.5111	54.271

*, **, and *** significant at the 10%, 5% and 1% levels respectively

Table 3. Results of the TFE model introducing the inefficiency effect.

Variable	Parameters	Desirable output <i>Operational revenue</i>		Undesirable output <i>CO2 emissions</i>	
		Model 1	Model 2	Model 3	Model 4
t	β_t	0.005 (1.027)	0.003 (1.294)	0.007 (0.891)	0.006 (0.891)
$\ln k_{it}$	β_k	2.190 (5.237)***	2.207 (4.079)***	2.165 (5.221)***	2.255 (4.114)***
$\ln l_{it}$	β_l	-1.345 (2.935)***	-1.025 (2.872)***	-0.072 (2.084)**	-0.068 (2.012)**
$\ln k_{it} \times \ln l_{it}$	β_{kl}	0.311 (2.931)***	0.330 (2.945)***	0.012 (2.728)***	0.0098 (2.428)***
$\ln k_{it} \times \ln k_{it}$	β_{k2}	-0.016 (2.738)***	-0.028 (2.461)***	0.323 (3.112)***	0.451 (3.385)***
$\ln l_{it} \times \ln l_{it}$	β_{l2}	-0.003 (1.824)*	-0.0085 (2.097)**	-0.0069 (0.430)	-0.0069 (0.430)
Z_{1it}	δ_1	-	0.032 (1.771)*	-	0.048 (1.071)
Z_{2it}	δ_2	-	0.922 (2.914)***	-	0.977 (3.211)***
Z_{3it}	δ_3	1.765 (3.285)***	-	-1.217 (-3.655)***	-
Z_{4it}	δ_4	-	0.032 (3.332)***	-	-0.068 (-3.611)***
Z_{5it}	δ_5	-	-0.028 (-1.055)	-	-0.032 (-1.755)*
Z_{6it}	δ_6	-	0.198 (2.023)**	-	-0.324 (-2.075)**
Z_{7it}	δ_7	-	1.242 (3.257)***	-	-3.683 (-3.544)***
Z_{8it}	δ_8	2.926 (3.171)***	-	-2.831 (-2.874)***	-
	σ_u	0.121 (4.616)***	0.118 (3.432)***	0.133 (4.087)***	0.128 (3.211)***
	σ_v	0.132 (4.516)***	0.133 (3.622)***	0.146 (4.277)***	0.126 (3.455)***
	λ	1.080 (3.586)***	1.054 (3.092)***	1.070 (3.088)***	1.013 (3.322)***
log likelihood		54.944	58.967	68.307	65.611

*, **, and *** significant at the 10%, 5% and 1% levels respectively

Table 4. Average operational and environmental efficiencies level of oil and gas companies

Company	Operational efficiency	CO2 emission efficiency
1 ABRAXAS PETROLEUM CORPORATION (AXAS)	0,7995	0,8486
2 ADAMS RESOURCES & ENERGY, INC. (AE)	0,7643	0,8134
3 ANADARKO PETROLEUM CORPORATION (APC)	0,9166	0,9257
4 BLUE DOLPHIN ENERGY COMPANY (BDCO)	0,6074	0,6315
5 CHESAPEAKE ENERGY CORPORATION (CHK)	0,7193	0,8284
6 CHEVRON CORPORATION (CVX)	0,9313	0,9424
7 CLAYTON WILLIAMS ENERGY, INC. (CWEI)	0,8102	0,8493

8	CRIMSON EXPLORATION INC. (CXPO)	0,7432	0,7823
9	DALECO RESOURCES CORPORATION (DLOV)	0,3841	0,3621
10	DOUBLE EAGLE PETROLEUM CO. (DBLE)	0,7462	0,7853
11	EARTHSTONE ENERGY, INC. (ESTE)	0,8365	0,8856
12	ENERGEN CORPORATION (EGN)	0,8983	0,9074
13	EPL OIL & GAS, INC. (EPL)	0,7946	0,8437
14	FOREST OIL CORPORATION (FST)	0,8285	0,8776
15	FX ENERGY, INC. (FXEN)	0,4437	0,3428
16	GASCO ENERGY, INC. (GSXN)	0,4921	0,4912
17	GATEWAY ENERGY CORPORATION (GNRG)	0,7207	0,7618
18	GLEN ROSE PETROLEUM CORPORATION (GLRP)	0,3839	0,3631
19	GOODRICH PETROLEUM CORPORATION (GDP)	0,7177	0,7668
20	GULFPORT ENERGY CORPORATION (GPOR)	0,8116	0,8607
21	MARATHON OIL CORPORATION (MRO)	0,7669	0,8269
22	PANHANDLE OIL AND GAS INC. (PHX)	0,8445	0,8936
23	PDC ENERGY, INC. (PDCE)	0,9628	0,9519
24	PETROQUEST ENERGY, INC. (PQ)	0,7487	0,7978
25	PYRAMID OIL COMPANY (PDO)	0,7761	0,8252
26	ROYALE ENERGY, INC. (ROYL)	0,7403	0,7894
27	SM ENERGY COMPANY (SM)	0,7141	0,7932
28	SOUTHWESTERN ENERGY COMPANY (SWN)	0,8096	0,8587
29	SPINDLETOP OIL & GAS CO. (SPND)	0,7956	0,8447
30	STONE ENERGY CORPORATION (SGY)	0,8465	0,8956
31	SWIFT ENERGY COMPANY (SFY)	0,8635	0,9026
32	TEXAS VANGUARD OIL COMPANY (TVOC)	0,8255	0,8546
33	THE RESERVE PETROLEUM COMPANY (RSRV)	0,985	0,9841
34	VAALCO ENERGY, INC. (EGY)	0,7565	0,8056
35	ALTEX INDUSTRIES, INC. (ALTX)	0,4835	0,4661
36	APACHE CORPORATION (APA)	0,8662	0,8853
37	CONOCOPHILLIPS (COP)	0,7864	0,8355
38	DEVON ENERGY CORPORATION (DVN)	0,8488	0,8879
39	EOG RESOURCES, INC. (EOG)	0,8466	0,8957
40	EXXON MOBIL CORPORATION (XOM)	0,6675	0,7466
41	MURPHY OIL CORPORATION (MUR)	0,7649	0,8011
42	NEWFIELD EXPLORATION COMPANY (NFX)	0,8456	0,8847
43	NOBLE ENERGY, INC. (NBL)	0,8326	0,8717
44	OCCIDENTAL PETROLEUM CORPORATION (OXY)	0,8453	0,8824
45	ZAZA ENERGY CORPORATION (ZAZA)	0,7253	0,7614
Average efficiency level		0,7622	0,7958

Table 5. Average annual operational and environmental efficiencies of oil and gas companies

Year	Operational level	CO2 emission level
2000	0,7859	0,8423
2001	0,7667	0,8268
2002	0,7326	0,7527
2003	0,7771	0,8372
2004	0,781	0,8221
2005	0,844	0,8841
2006	0,8246	0,8647
2007	0,7217	0,7488
2008	0,6216	0,6587
2009	0,5742	0,5679
2010	0,7124	0,7455
2011	0,7816	0,8217
2012	0,7746	0,8147
2013	0,8531	0,8972
2014	0,912	0,9311
2015	0,7437	0,7638
2016	0,7536	0,7635
2017	0,7563	0,7864
2018	0,7664	0,7914
Mean	0,7622	0,7958
Standard deviation	0,0758	0,0832
Min	0,5742	0,5679
Max	0,9120	0,9211