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Posted Date: 4 November 2024

doi: 10.20944/preprints202411.0205.v1

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Article

Measuring the Impact of Pre-Salt on the Productivity of the Oil and Natural Gas Extraction Sector

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Abstract: Based on productivity and efficiency indicators, we investigated the performance of the Brazilian oil and gas exploration industry, comparing the performance of this sector with other industrial sectors. We associate productivity with the concept of total factor productivity (TFP), while efficiency is measured using the stochastic frontier production model. Our sample was assembled from the Annual Industrial Survey (PIA) for 29 Brazilian industrial sectors from 2007 to 2019. The results derived from both methods allow us to affirm that the policies resulting from the Pre-Salt have significantly boosted the oil and natural gas extraction sector in terms of technological progress and efficiency. Between 2007 and 2009, the sector was among the least efficient, ranking 29th. However, in 2019 it reached first place in terms of efficiency. This structural change, which began in 2010 as a result of the technological innovations resulting from investments in R&D, has undergone a change since 2010, reflected in the upward trend towards pre-salt exploration promoted by Petrobras, as well as the new regulatory framework and government incentives for oil exploration in Brazil. Unfortunately, these productivity gains have not been exported to other branches of industry connected to the oil industry.

Keywords: oil exploration industry; pre-salt; total factor productivity; stochastic production frontier; bayesian inference

1. Introduction

The exploration of new, increasingly deeper and challenging oil fields always presents new hurdles. In Brazil, due to the scale of the endeavors, the discovery of pre-salt production fields imposed even greater challenges. These challenges were not only due to the inherent uncertainties in upstream oil activities but also the barriers that had to be overcome for the project to be viable. Barriers were primarily related to the technological development required for oil exploitation. However, it was also necessary to overcome limitations in economic, institutional, and logistical spheres. In the technological field, the discoveries made by Petrobras in the Tupi field in 2007 opened a new frontier, representing a technological milestone for the Brazilian oil industry. However, the pursuit of pre-salt did not constitute a complete break from the company's previous trajectory, as although the depth of the pre-salt layer is very high, it does not differ significantly from the post-salt layer. The challenges lie in other aspects.

Furtado [1] identifies the following technological obstacles faced by pre-salt exploration to enable commercial oil extraction:

- Limited knowledge about reservoir rocks, posing a challenge to seismic use.
- High drilling costs at great depths under the salt layer, resulting from issues with high pressures, lack of stability, and corrosion. Overcoming these problems requires the

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development of new drilling and well completion techniques to adapt equipment to the challenging conditions of deep wells.

- The need for the development of new materials more resistant to high pressures.
- The high proportion of CO_2 in reservoirs posed significant technological challenges in submarine pumping operations.
- Acute acidity resulting from both hydrocarbons and CO_2.
- The design of platforms and floating production systems that can adapt to increasing depths and the needs of processing plants increasingly distant from the coast.

In conclusion, all these barriers highlight the remarkable technological advancement required to overcome the challenges of pre-salt exploration and ensure the economic viability of oil extraction in this region.

To face these challenges, Petrobras undertook a significant change in investment volume between 2008-2012. This investment was of such magnitude that it represented about five times the investment that began in 2004, jumping from $9 billion to around $45 billion in 2010. This had a productive effect on Petrobras, also significantly impacting the rest of the oil and gas sector. The expansion effort did not only occur in the upstream but extended to refining and investment in natural gas transportation and consumption infrastructure.

Although uncertainties about the technological barriers to be overcome were significant, there was also strong expectation of project success. A significant impact on the economy was anticipated due to the multiplier effect of this industry. Seventeen years after the first pre-salt discoveries in Brazil in 2006 in the Santos Basin, off the coast of the states of São Paulo and Rio de Janeiro, we can say that this discovery marked a milestone in the Brazilian oil industry, placing the country among the players in this industrial segment and significantly changing Brazil's energy and economic landscape. Furthermore, there was a recovery in certain industrial sectors, such as the Brazilian shipbuilding industry, which regained full vigor during the 2000s. The effects of pre-salt exploration were also felt in the volume of jobs generated. APE [2] estimated that the volume of investment in the oil industry between 2007 and 2010 corresponded to 51.6% of the total industry investment. According to the 2010 PIA , the investment in the petroleum sector represented about 32% of the total investment in the manufacturing industry.

While the benefits of pre-salt for the oil extraction sector are undeniable, it is also essential to examine the effects of this change in at least three directions. First, despite strong indications that technological progress has been significant, this does not negate the need for a formal evaluation of this measure. Second, what about efficiency, that is, the optimal use of production factors? Finally, another point that deserves attention is the expectation regarding the spillover effect that pre-salt could have on other industrial sectors, such as the shipbuilding industry. Here, it is not about measuring the derived demand that occurred on industrial sectors interacting with the oil industry but checking whether such an effect reflected on the productivity and efficiency indicators of these industries. The spillover effect will not guarantee economic sustainability if there are no gains in terms of productivity and efficiency in such sectors. This issue will be examined by comparing the performance of industrial sectors with the oil extraction industry.

Thus, the objective of this study is to investigate the performance indicators of productivity and efficiency as follows. Productivity is associated with a measure of technological progress known as Total Factor Productivity (TFP), while efficiency is measured by the distance of production observed in relation to its optimal production level. This measure can be estimated through stochastic production frontier analysis.

Regarding efficiency, it is proposed to measure it based on the stochastic production frontier model. One of the advantages of the stochastic production frontier model is that this methodology allows purging the effect of unmanageable factors since production can be affected by factors that are beyond the control of firms, such as exchange rate variation, supply shocks, crises, etc. The choice of estimation through the Bayesian approach also aims to provide greater flexibility in specifying the stochastic production frontier model [3]. The econometric approach employed is also capable of addressing the temporal dynamics of efficiency, showing how sectors are using production factors over time.

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The database was assembled from the Annual Industrial Survey (PIA) of the Brazilian Institute of Geography and Statistics (IBGE) at the level of National Classification of Economic Activities (CNAE) 2.0 divisions for the period from 2007 to 2019, covering a subdivision with 29 industrial sectors. In addition to this introduction, this study is organized as follows. In section 2, we seek to identify the factors responsible for the increase in productivity and efficiency during the pre-salt era. The description of the methodologies for measuring Total Factor Productivity and using the stochastic production frontier model to assess efficiency appears, respectively, in sections 3 and 4. The database, including the method for developing the capital stock series, is described in section 5. Results are presented and analyzed in section 6. Finally, final comments are provided in section 7.

2. Factors Responsible for the Increase in Productivity and Efficiency in the Pre-Salt Era

The vastness of estimated pre-salt reserves prompted significant investments in the development of technologies and infrastructure to exploit them. As we will demonstrate later, there has been a tremendous increase in productivity and efficiency in the oil extraction sector, attributed to various factors. While technological development resulting from research and development (R&D) investments during the pre-salt era is possibly the most important factor in enabling commercial oil extraction from the pre-salt, other factors have also played a crucial role. Among them are the formation of strategic partnerships, improvement of logistical infrastructure, and possibly the new regulatory framework and government incentives.

Investments in research and development (R&D) played a crucial role in the success of pre-salt exploration and production. Without these investments, the possibility of economically viable oil extraction from the pre-salt would not have been feasible. Some of the key technological developments associated with the pre-salt are listed below. These developments occurred in various fields such as deepwater drilling technology, subsea production systems, reservoir technologies, high-resolution seismic, well control technology, well recovery technologies, and environmental technologies.

In addition to R&D investments, strategic partnerships between Petrobras and international companies specialized in offshore exploration technologies played a significant role. These partnerships facilitated the transfer of knowledge and expertise, accelerating the development of local capabilities. Alliances were formed with various companies, including BG Group (now part of Shell), Total (France), Petrogal (Galp Energia), and Statoil (now Equinor). According to Furtado [1], Cenpes (Petrobras Research Center) hosts research facilities for various supplier companies in its R&D laboratories, such as Schlumberger, Baker Hughes, Halliburton, etc.

The exploitation of the pre-salt in Brazil required significant changes in logistical infrastructure to meet the specific demands of this activity. Changes in logistical infrastructure resulting from the pre-salt include the development of specialized ports to support exploration platform operations, support vessels, and the movement of equipment and supplies needed for offshore operations. Other initiatives were also essential for improving the logistics of the pre-salt, such as the expansion of shipyards to enable the construction and repair of subsea equipment, support vessels, and other offshore structures.

A set of measures with economic, institutional, and geopolitical reach are embedded in the new regulatory framework and incentives instituted by the government. The regulatory framework for the pre-salt in Brazil refers to a set of measures that established rules and conditions for the exploration and production of oil and natural gas in pre-salt areas.

One of the main regulatory milestones related to the pre-salt is Law No. 12,351, dated December 22, 2010, known as the "Pre-Salt Law." Among its key points is the exploration of the pre-salt, in which the Union becomes a partner in exploration contracts with the right to a share of the oil produced in addition to royalties and taxes inherent to the activity. The result was that the regulatory framework for the pre-salt created favorable conditions to attract investments and ensure a stable business environment with oil. Since then, numerous companies participated in bidding rounds and auctions for the concession of exploration areas. Operationally, the new framework also established the

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creation of the state-owned company Pre-Sal Petróleo S.A (Petro-Sal), specifically to act as the Union's representative as a manager of profit-sharing contracts and in exploration and production consortia.

Finally, it is worth mentioning the local content policy (LCP) in the oil extraction sector in Brazil, which establishes minimum percentages of national goods and services to be used in oil activities. The effects of this policy are not unanimous, although it potentially has positive impacts on increasing productivity in the pre-salt era, such as technology generation, technology transfer, and local human capital development; this policy is not without criticism. Among them are the increased costs due to rigid targets, negative effects on productivity and competitiveness resulting from increased costs and operational delays. Therefore, the effectiveness of the LCP requires balancing the economic benefits and costs arising from operational efficiency, technological advancement, and international competitiveness.

Brazil has a long tradition of implementing LCP since the creation of Petrobras in 1953 to develop technologies and establish companies to address technological challenges in the oil industry. However, it was from 1997, with the Oil Law and the first bidding round (1999), that a new phase of LCP was introduced, where measures to promote local content became part of the oil industry regulation [4]. Such measures had as their main instrument the commitments made by participating companies in the bidding rounds for exploratory blocks. These commitments were extended to the three stages of oil activities: exploration, development, and exploitation. In 2001, the criteria for fines in case of non-compliance with contractual commitments were introduced. Since then, LCP has been intensified with the introduction of new instruments such as the adoption of minimum LC percentages in 2003, a more rigorous process of LC certification in 2005, and the increased application of fines in 2011.

Given the technological challenges of the pre-salt, new incentive mechanisms were sought, culminating in the creation of PEDEFOR in 2016. At this point, when the policy of inspection and application of fines was already being questioned, the government sought to introduce mechanisms that allow for the fulfillment of LCP commitments through new incentive instruments.

3. Total Factor Productivity

There is a consensus that productivity is a key element in explaining the level of economic development in a country. Developed countries, as a rule, are prosperous because they produce high value-added per worker. In a market economy, factor incomes are proportional to their (marginal) productivities. Specifically, if labor productivity is low, wages will also be low. We are particularly interested in understanding "Total Factor Productivity (TFP)," which is the portion of the total output variation not explained by variations in factors of production, for each industry.

Since the pioneering work of Solow [5], Kendrick [6], and Denilson [7], numerous studies have aimed to measure TFP, its determinants, and its contribution to economic growth. In Brazil, the issue of productivity measured by TFP has been addressed in several studies, such as Ellery [8], Jacinto and Ribeiro [9], Messa [10], Barbosa Filho et al. [11], Ferreira et al. [12], Rocha [13], and Gomes et al. [14]. Ferreira et al. [12] assert that the decline in total factor productivity in the Brazilian economy between the 1970s and 2000 is robust, given that it persists for different productivity measurement forms. Barbosa Filho et al. [11] assess the evolution of TFP in the Brazilian economy and show that TFP grew by 11.3% between 1992-2007. Messa [10] also notes that different ways of measuring the total factor productivity of the Brazilian economy do not substantially modify the result of a decline in this variable from the 1970s.

For the calculation of TFP, we follow the methodology initially proposed by Solow [5], interpreted as a measure of technological progress. It represents the portion of the increase in production not explained by an increase in input use. It is, therefore, a kind of residue (Solow's residual) representing technological change. Thinking about an aggregate Cobb-Douglas production function with constant returns to scale, TFP is defined as:

$$PTF = \frac{VA}{K^{\alpha}L^{1-\alpha}} \qquad (1)$$

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where VA corresponds to the value added of production, K is the capital stock, and L is the labor factor. The parameter α represents the share of capital income in total income. So, if the value added by production increases more than the existing technology can explain with increases in capital and labor, it implies that capital and labor are becoming more productive, equivalent to technological advancement.

3.1. Stochastic Production Frontier

Once we evaluate the industry's performance through total factor productivity (TFP), in this section, we propose another mode of assessment through stochastic frontier analysis. The stochastic frontier model was simultaneously proposed by three groups of researchers: Aigner et al. [15], Meeusen and Van den Broeck [16], and Battese and Corra [17]. This approach was an attempt to overcome the limitations of deterministic frontiers that did not allow for the presence of a random error (beyond the control of firms), considering all residuals as technical inefficiency. In the stochastic frontier model, the random component consists of two parts: one that measures technical efficiency, controllable by firms, and another that captures random errors, beyond the control of firms. Thus, the stochastic frontier analysis can overcome the limitation of TFP, where Solow's residual incorporates both manageable and unmanageable factors, thus polluting the measure of technological progress.

In formal terms, the stochastic production frontier is an econometric model aimed at estimating a production function, $f \in R_+$, which, in turn, is the maximum quantity produced for a certain set of inputs. If a firm i is inefficient at time t, then its production. y_{it} must be below the efficient or optimal level $f(k_{it}, n_{it}, \beta)e^{v_{it}}$, that is, $y_{it} < f(k_{it}, n_{it}, \beta)e^{v_{it}}$ where β is the parameter vector of the production function, and v_{it} is a random term, such that $v_{it} \sim N(0, \tau^2)$. It is assumed that v_{it} is independent and identically distributed, indicating the firm's uncontrollable factors. The equality between actual production and efficient production can be established as:

$$y_{it} = f(k_{it}, n_{it}, \beta)e^{v_{it} - u_{it}} \tag{2}$$

where u_{it} is a non-negative random term representing the inefficiency of firm i at time t. Therefore, efficiency η_{it} can be defined as:

$$\eta_{it} = \frac{f(k_{it}, n_{it}, \beta)e^{v_{it} - u_{it}}}{f(k_{it}, n_{it}, \beta)e^{v_{it}}} = exp\,(-u_{it}) \tag{3}$$

For industrial development, monitoring efficiency over time is an important point. Part of the efficiency improvement comes from scale gains provided by market expansion, and as it is a process that occurs over time, ignoring the temporal evolution of efficiency inevitably leads to unreliable results for this measure, making them vulnerable to criticism. Measuring efficiency over time allows ranking industrial sectors. This information can be used to develop specific policies to encourage specific sectors. To identify efficiency, the concept of misallocation appears in the literature, understood as how much an economy deviates from what would be the optimal allocation of factors, but where the use of factors is related to their opportunity cost, i.e., a situation free from distortions compared to free competition. Therefore, although there are specific methodologies for this type of analysis [18], the stochastic production frontier model helps identify sectors where there is misallocation.

3.2 Bayesian Approach to Econometric Estimation

We will assume, as was done to calculate TFP, that the functional form f is Cobb-Douglas. Then, the stochastic cost frontier model can be specified as follows:

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$$log(y_{it}) = \beta_1 \log(k_{it}^{'}) + \beta_2 \log(n_{it}^{'}) + v_{it} + u_{it}^{'}$$

$$v_{it} \sim N(0, \tau^2) \ (4)$$

To simplify notation, let's define $x = (log(k_{it}^{'}), log\ (n_{it}^{'}))$ and $\beta = (\beta_1, \beta_2)$. Thus, the model can be rewritten as:

$$log(y_{it}) = x_{it}^{'}\beta + v_{it} + u_{it}^{'}$$

$$v_{it} \sim N(0, \tau^2) \quad (5)$$

To capture efficiency variation over time, we will employ an econometric approach proposed by Tsionas [19] using Bayesian methods to estimate stochastic frontier models. Within Bayesian practice, there are various models that can be employed to estimate the stochastic frontier model. They can be framed within a historical perspective. Initially, Koop et al. [20] assume that parameters related to the stochastic frontier are the same for all units over time. Tsionas [21] extends this approach by assuming that parameters are time-invariant but allowing for cross-sectional heterogeneity using random coefficients. Other extensions assume that parameters are constant at the firm level but may vary over time [20]. Migon and Médici [22] present a more general model where parameters related to the frontier vary over time and at the firm level, and they also define some structures for technical inefficiency. Another contribution using panel data appears in Fernandez et al. [23], where it shows a formal discussion of the existence of the posterior distribution in stochastic frontier models with improper priors.

The model proposed in this study for estimating the stochastic production frontier closely follows that which appears in Tsionas [19], which incorporates into the model a generating process for the term $log(u_{it}^{'})$, allowing inefficiency to vary over time. Here inefficiency is represented by a first-order autoregressive process (AR(1)), so that the equation for the logarithm of technical inefficiency is such that

$$log\, u_{it} = \varphi\, log\, u_{it-1} + \varepsilon_{it}$$

$$log\, u_{it} \sim N(\eta_t, \sigma_u^2)$$

$$\varepsilon_{it} \sim N(0, \sigma^2) \quad (6)$$

$$\varphi \in (-1,1)$$

' Defining $u = (u_1, \dots, u_N)$ with $u_i = (u_{i1}, \dots, u_{iT})$ e $y = (y_1, \dots, y_N)$ with $y_i = (y_{i1}, \dots, y_{iT})$, where the vector x is defined in the same way. Thus, the joint density function for u and y is given by the following equation:

$$\begin{aligned} p(y,u \mid x,\beta,\tau^2,\sigma^2,\phi) &= p(y \mid u,x,\beta,\tau^2)\, p(u \mid \sigma^2) = \\ &= (2\pi\tau^2)^{-\frac{NT}{2}} \left(\exp\left[-\frac{1}{2\tau^2} \sum_{t=1}^{T} \sum_{i=1}^{N} \left(y_{it} - x_{it}\beta + u_{it} \right)^2 \right] \right) \times \\ &\times (2\pi\sigma^2)^{-\frac{NT}{2}} \left(\exp\left[-\frac{1}{2\tau^2} \sum_{t=1}^{T} \sum_{i=1}^{N} \left(\log u_{it} - \phi \log u_{it-1} \right)^2 \right] \right) \end{aligned} \quad (7)$$

The model proposed in this study for estimating the stochastic production frontier closely follows that in Tsionas [19], incorporating a generative process for the term $log(u_{it}^{'})$, allowing

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inefficiency to vary over time. Here, inefficiency is represented by a first-order autoregressive (AR(1)) process, so that the equation for the logarithm of technical inefficiency is such that:

$$
\begin{aligned}
&log\, u_{it} = \varphi\, log\, u_{it-1} + \varepsilon_{it} \\
&log\, u_{it} \sim N(\eta_t, \sigma_u^2) \\
&\varepsilon_{it} \sim N(0, \sigma^2) \\
&\varphi \in (-1,1)
\end{aligned}
\quad (6)
$$

3.3. Bayesian Inference

From a Bayesian perspective, the model specification is complete only after assigning a distribution to all model parameters. Therefore, a prior distribution must be assigned for each parameter. In this article, it is assumed that the prior distribution for $(\beta, \tau^2, \sigma^2, \phi)$ has the following joint density function:

$$p(\beta, \tau^2, \sigma^2, \phi) = p(\beta)p(\tau^2)p(\sigma^2)p(\phi) \quad (8)$$

where $\beta \sim N_k(\mu_0, \Sigma_0)$, $\tau^2 \sim IG(\alpha_0, \gamma_0)$, $\sigma^2 \sim IG(\alpha_1, \gamma_1)$ and $\phi \sim Beta(v_1, v_2)$. N_k and IG, respectively, denote the multivariate normal density function and the inverse gamma density function. Here, denote the multivariate normal and inverse gamma density functions, respectively, and $(\mu_0, \Sigma_0, \alpha_0, \gamma_0, \alpha_1, \gamma_1, v_1, v_2)$ represents the hyperparameters. Thus, the posterior density function of the parameters is given by the product of the likelihood function and the prior distribution function of the parameters, as defined in equation (7):

$$
\begin{aligned}
&p(\beta, \tau^2, \sigma^2, \phi, u \mid y, x) = p(y \mid u, x, \beta, \tau^2, \phi) p(u \mid \sigma^2, \phi) \times \\
&\times p(\beta) p(\tau^2) p(\sigma^2) p(\phi)
\end{aligned}
\quad (9)
$$

The distribution in (9) is analytically intractable, and therefore, the Gibbs sampler or MCMC algorithm will be used to sample the parameters of interest. In this case, the complete conditional distributions for the parameters $(\beta, \tau^2, \sigma^2)$ are known and available for sampling. Only the conditional distribution of ϕ is not known. Therefore, the Metropolis algorithm [23] will be used for sampling this conditional distribution. The MCMC algorithm will be developed based on the complete conditional distributions appearing in Appendix A.

4. Database

We utilized the Annual Industrial Survey (PIA) from the Brazilian Institute of Geography and Statistics (IBGE). The PIA is divided into two distinct surveys: PIA-Company and PIA-Product. These surveys aim to describe the basic structural characteristics of the industrial business segment in the country and its changes over time. PIA-Company gathers economic and financial information from companies in Extractive Industries and Manufacturing Industries in Brazil, while PIA-Product surveys the products manufactured and services provided by these companies. In this study, we used data from PIA-Company.

Information from the PIA per company is confidential, but the IBGE provides aggregated data on the CNAE classification up to 4 digits on its website. For this study, we considered the classification of activities at the division level of CNAE 2.0 (two digits) from 2007 to 2019, the most

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recent year available in the survey. This subdivision includes 29 industrial sectors. PIA-Company data is obtained through annual surveys, based on a sample of industrial companies from the Central Companies Register - CEMPRE of IBGE, which uses administrative records from the Ministry of Labor, particularly RAIS (Annual Social Information Report) and CAGED (General Registry of Employed and Unemployed).

To represent the value added by production, we used the Gross Value of Industrial Production (VBPI). Several important studies estimating TFP for industrial sectors use value added to represent output [18, 25, 26]. Value added is the gross value of production minus indirect costs[1]. The measurement of labor (L) is usually done through the payroll. In the case of PIA data, we summed salaries and benefits (variables Personnel expenses - benefits granted to employees, and Personnel expenses - salaries, withdrawals, and other remuneration).

The major challenge in building the database is constructing the capital series, considering that this variable is not available in PIA as well as in similar surveys in other countries, which requires the construction of the capital variable for each sector. The methodology used for constructing the capital series per sector is described in the next section. Finally, it is worth noting that monetary values were adjusted for inflation using the GDP deflator for the total industry and the producer price index for industrial sectors. Values were updated to Brazilian currency (R$) 2019.

Each industrial sector in our database is composed of other sub-sectors. Here, we provide the definition of the oil and natural gas extraction sector, which is of particular interest. According to PIA, in addition to oil and natural gas extraction and bituminous shale, this industrial sector encompasses activities related to the preparation and operation of oil and gas fields, such as: directional drilling and redrilling, initial drilling, repair and dismantling of drilling towers, cementing of well pipes, and all oil and gas preparation activities performed on-site by well operators until shipment off the oil field, carried out on-site by well operators[2].

4.1. Calculation of Capital Stock

For the measurement of the capital stock, we will use the perpetual inventory method according to the methodology presented in Berlemann and Wesselhöft [27]. This methodology allows us to calculate the capital stock of each sector i at time t, once we have information on investments in machinery and equipment, vehicles, real estate, buildings, and other types of investments. The investments are calculated using PIA values for acquisitions and improvements, subtracting disposals, for the mentioned investment categories.

Starting from an initial capital stock K0, we can generate a trajectory for capital based on the depreciation rate δ, which we assume to be 10%, and the investments made. These investments are the difference between the acquisitions of machinery and equipment, means of transportation, and land and buildings, and their respective disposals.

$$K_{it} = (1-\delta)K_{it-1} + I_{it} \tag{10}$$

In equation (10), the initial value K_{i0} is obtained using the Harberger [28] approach, assuming that the economy is in a steady state. In this case, the product and the capital stock grow at the same rate, implying that the capital stock in the initial period equals the observed investment in that period divided by the sum of the growth rate of the product and the depreciation rate, so that[3]

$$\frac{K_{t+1}-K_t}{K_t} = \frac{Y_{t+1}-Y_t}{Y_t} = g = \frac{I_t}{K_t} - \delta \tag{11}$$

---

[1] Corresponds to the sum of the following cost and expense items: consumption of raw materials, auxiliary materials and components; purchase of electricity; fuel consumption; consumption of parts, accessories, etc.

[2] This division does not include support services required for drilling and field operations carried out under contract and mine excavation activity when not carried out by the mineral exploration company.

[3] We delete the index i to avoid overloading the notation.

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Solving for the capital stock, we have

$$K_t = \frac{I_t}{g + \delta} \tag{12}$$

To avoid a possible situation where the initial year of the series is an atypical year with very high or very low growth, we consider the arithmetic average between the GDP growth rates for the initial period (2007), the previous period (2006), and the subsequent period (2008). We assume a depreciation rate of 10% per year, uniform for all sectors and types of investments.

5. Results

4.1. Total Factor Productivity (TFP)

In this section, we discuss the results obtained for the TFP calculated for the 29 Brazilian industrial sectors. For TFP, we used a value of 0.4 for the parameter α [8], which roughly means assuming that the income of capital is equivalent to 40%, and the income of labor is 60% concerning the national income4. The results of TFP are shown in Table 1, and the ranking of the table was done for the year 2019.

Our main goal is to examine the effect of the pre-salt on the sector of oil and natural gas extraction, analyzing its behavior over the period. Unlike other sectors that maintain some regularity in TFP values throughout the series, the oil and gas extraction industry shows an extremely significant structural change. For the first three years of the series, the TFP values for this sector were very low, indicating poor performance. From then on, there is a radical change in its performance, consistently ranking among the top sectors and reaching the first place in 2019. The explanation for the increase in productivity (TFP) in the "Oil and Natural Gas Extraction" sector between 2010 and 2011 resulted from technological innovation stemming from increased investment and changes in Petrobras management regarding pre-salt fields awarded before 2010. The effect of the new regulatory framework for the pre-salt could only be identified by comparing concession fields with profit-sharing fields. However, our dataset is too aggregated to detect such an effect. More details about these changes will be discussed in the next section.

Regarding the impact felt by other sectors due to the discovery of the pre-salt, Petrobras played a crucial role in the policy of promoting "strategic" sectors. The goal was to use oil to stimulate the construction of a national petroleum machinery and equipment industry. However, this strategy seems not to have achieved the expected results. For example, the sector of petroleum derivatives manufacturing (sector 15 in Table 1) shows stagnation in TFP throughout the period.

Table 1. Evolution of TFP in 29 sectors of the Brazilian industry

Sectors	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Extraction of oil and natural gas	0.39	0.63	0.68	2.57	4.95	1.56	1.42	2.28	1.28	1.24	2.03	2.28	1.98
Maintenance, repair and installation of machinery and equipment	2.29	2.51	2.13	2.12	2.03	1.96	2.02	2.06	2.02	1.96	1.96	1.96	1.98
Manufacture of clothing items and accessories	2.11	1.86	1.81	1.88	2.12	2.08	1.96	1.74	1.59	1.69	1.78	1.81	1.84
Manufacture of computer equipment, electronic and optical products	2.27	1.98	1.12	1.43	1.58	1.55	1.73	1.56	1.61	1.61	1.79	1.72	1.72
Manufacture of tobacco products	2.22	2.50	3.02	2.45	2.49	2.78	2.66	2.43	2.35	1.62	1.46	1.59	1.70

4 It is interesting to note that the choice value of the parameter α is close to the estimated value of this parameter in the stochastic production frontier model.

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Manufacture of pharmaceutical products	1.70	1.61	1.34	1.49	1.39	1.38	1.45	1.44	1.40	1.45	1.55	1.62	1.63
Other manufacture products	1.63	1.73	1.64	1.69	1.70	1.79	1.84	1.70	1.56	1.52	1.53	1.50	1.60
Preparation of leather and manufacture of leather goods, travel articles and footwear	1.53	1.62	1.44	1.60	1.49	1.62	1.62	1.59	1.47	1.53	1.61	1.60	1.54
Manufacture of coke, oil products and biofuels	1.50	1.49	1.27	1.20	1.08	0.83	0.85	0.95	0.58	0.91	0.83	1.11	1.39
Manufacture of metal products, except machinery and equipment	1.76	1.80	1.54	1.49	1.52	1.43	1.42	1.32	1.22	1.23	1.20	1.32	1.36
Manufacture of electrical machines, apparatus and materials	1.45	1.56	1.31	1.43	1.36	1.37	1.46	1.28	1.21	1.21	1.17	1.27	1.36
Manufacture of machinery and equipment	1.63	1.67	1.24	1.48	1.50	1.40	1.45	1.40	1.24	1.22	1.18	1.34	1.34
Chemical manufacturing	1.55	1.46	1.09	1.24	1.31	1.27	1.32	1.25	1.39	1.38	1.34	1.37	1.34
Manufacture of wooden products	1.51	1.56	1.25	1.36	1.23	1.32	1.35	1.24	1.17	1.14	1.25	1.36	1.34
Beverage manufacturing	1.58	1.70	1.74	1.73	1.67	1.71	1.41	1.39	1.44	1.31	1.25	1.28	1.33
Printing and playing back recordings	1.49	1.46	1.18	1.31	1.42	1.28	1.38	1.47	1.25	1.26	1.18	1.25	1.25
Furniture manufacturing	1.34	1.37	1.26	1.51	1.47	1.50	1.43	1.42	1.17	1.23	1.22	1.19	1.23
Metallurgy	1.59	1.78	0.97	1.13	0.99	0.99	1.07	1.07	1.04	0.96	1.04	1.41	1.21
Manufacture of textile products	1.33	1.38	1.25	1.29	1.27	1.29	1.26	1.22	1.13	1.11	1.27	1.20	1.18
Manufacture of pulp, paper and paper products	1.22	1.15	1.02	1.05	1.13	1.06	1.10	1.05	1.19	1.15	1.16	1.28	1.15
Extraction of non-metallic minerals	1.41	1.61	1.64	1.73	1.68	1.59	1.45	1.59	1.48	1.19	1.16	1.16	1.13
Manufacturing of food products	0.96	1.09	1.03	1.17	1.18	1.20	1.15	1.14	1.19	1.17	1.21	1.17	1.12
Manufacture of rubber and plastic products	1.21	1.15	1.11	1.17	1.11	1.07	1.10	1.11	1.03	1.04	1.04	0.99	1.06
Extraction of metallic minerals	2.75	3.10	1.85	3.05	3.84	3.20	2.76	2.05	1.90	1.54	2.01	2.04	1.05
Manufacture of non-metallic mineral products	1.49	1.59	1.27	1.37	1.37	1.32	1.29	1.23	1.09	0.94	0.86	0.99	0.98
Manufacture of motor vehicles, trailers and bodies	1.52	1.64	1.26	1.42	1.40	1.17	1.21	0.93	0.73	0.65	0.87	0.93	0.91
Activities to support mineral extraction	1.50	1.81	1.67	1.60	1.69	1.62	1.30	1.50	1.60	0.99	1.03	1.01	0.89
Mineral coal extraction	1.24	1.26	1.40	1.29	1.27	1.07	1.13	1.31	1.31	1.16	0.99	0.93	0.77
Manufacture of other transport equipment, except motor vehicles	1.56	1.60	1.25	1.29	1.25	1.14	1.17	1.14	0.90	0.87	0.96	0.80	0.67
Total	1.33	1.40	1.21	1.32	1.30	1.21	1.16	1.10	0.99	1.02	1.05	1.13	1.12

Also, the total factor productivity of the "Manufacture of other transport equipment, except motor vehicles," which includes part of the shipbuilding industry, plummeted from 7th place in 2007 to 26th place in 2019[5]. The collapse of the Brazilian shipbuilding industry from 2014, with the deactivation of a significant number of shipyards, mass layoffs, and activity levels well below installed capacity, is a factor that helps explain the sector's loss of efficiency.

Taking the industry as a whole, we can observe that over these 12 years, the factors of production employed in the Brazilian industry became approximately 12% less productive. Of the 29 industrial sectors, only 3 had gains in TFP: oil and gas extraction, manufacturing of food products, and metallurgy. A significant portion of the productivity decline occurred until 2016. From 2016 to 2018, there was an improvement in the TFP of the Brazilian industry of approximately 14%. During this period, TFP remained almost constant in 4 industrial sectors, increased in 19 sectors, and decreased in the other 6 sectors.

4.1. Stochastic Production Frontier Model

In this section, we present the results of the stochastic production frontier model for the Brazilian industrial sector estimated based on the Bayesian approach, as described in section 4.

[5] According to the CNAE, this sector includes the construction of vessels and floating structures, railway vehicles, aircraft, motorcycles, bicycles and other transport equipment and also the manufacture of military combat vehicles, wheelchairs and similar vehicles for disabled people, and parts for them.

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The stochastic production frontier, like the DEA model, its non-parametric counterpart, has also been employed to evaluate efficiency and productivity in various contexts of the oil industry. Managi et al. [29] analyzed, based on the stochastic production frontier, the impact of technological change on oil and gas production in the Gulf of Mexico. Forman et al. [30] used the stochastic frontier to assess the impact of environmental policies on the efficiency of oil refineries in the United States. The data are sourced from the PIA, with activities classified at the division level of the CNAE 2.0 (two digits). The sample is structured in panel form for 29 sectors. The same variables used in the TFP calculation are also used in the estimation of the stochastic production frontier—namely, output, capital, and labor.

The table presents the estimates of the coefficients of equation 5 along with their respective standard errors and Bayesian confident intervals. Note that the coefficients are significant and have signs in line with expectations. It is interesting to observe that the hypothesis of constant returns to scale for the production function is confirmed, as the mean for the sum of the coefficients is 0.99, with a 95% credibility interval between 0.965 and 1.036.

Additionally, Table 2 presents the distribution of the sum of the coefficients, and the results indicate the confirmation of this hypothesis. Also, the share of capital in income is slightly different from that used in the TFP analysis, averaging 0.37%.

This Bayesian stochastic production frontier model allows for a comprehensive understanding of the relationships between inputs and outputs in the Brazilian industrial sector. The confirmed hypothesis of constant returns to scale suggests that, on average, the industry operates at an optimal scale. The participation of capital in income, although slightly different from the TFP analysis, gives insights into the capital-labor dynamics within the sector.

These results contribute to a more nuanced understanding of the efficiency and productivity dynamics in the Brazilian industrial landscape, paving the way for more targeted policy interventions and strategic industry planning. The next section may delve into specific sectoral implications and policy recommendations based on the findings.

Table 2. Results of Estimated Parameters.

Parameters	Average (1)	Standard Error (2)	2.5% (3)	97.5% (7)
CTE	1.5432	0.3253	0.9237	2.1790
CAPITAL	0.3693	0.0181	0.3332	0.4047
LABOR	0.6306	0.0245	0.5829	0.6786
$\boldsymbol{\beta_1 + \beta_2}$	0.999	0.019	0.965	1.036
τ^2	0.0436	0.0051	0.0345	0.0547
ϕ	0.8700	0.0375	0.7827	0.9314
$\boldsymbol{\sigma_u^2}$	0.8279	0.1202	0.6238	1.1010

In Table 3, we show the evolution of efficiency over time. To facilitate understanding, the benchmark ranking is that of the year 2019, so that the estimated series of efficiencies illustrate the temporal evolution of this variable. The efficiency values are shown in Table 3. It is also observed in Table 4 that, although there are no significant changes in the ranking of efficiencies concerning the TFP, we must emphasize that TFP and efficiency are distinct concepts. As mentioned earlier, efficiency estimated through the stochastic production frontier measures how far the use of production factors deviates from its optimal employment, while TFP measures technological progress. Regarding the sector of oil and natural gas extraction, similar to the TFP case, it showed poor performance in the first three years of the series, starting to show improvement from 2010 onwards, assuming a trend of significant improvement and reaching the first position in 2019 for the reasons already mentioned.

Table 3. Efficiencies of Industrial Sectors.

Sectors	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Extraction of oil and natural gas	0.39	0.63	0.68	2.57	4.95	1.56	1.42	2.28	1.28	1.24	2.03	2.28	1.98
Maintenance, repair and installation of machinery and equipment	2.29	2.51	2.13	2.12	2.03	1.96	2.02	2.06	2.02	1.96	1.96	1.96	1.98
Manufacture of clothing items and accessories	2.11	1.86	1.81	1.88	2.12	2.08	1.96	1.74	1.59	1.69	1.78	1.81	1.84
Manufacture of computer equipment, electronic and optical products	2.27	1.98	1.12	1.43	1.58	1.55	1.73	1.56	1.61	1.61	1.79	1.72	1.72
Manufacture of tobacco products	2.22	2.50	3.02	2.45	2.49	2.78	2.66	2.43	2.35	1.62	1.46	1.59	1.70
Manufacture of pharmaceutical products	1.70	1.61	1.34	1.49	1.39	1.38	1.45	1.44	1.40	1.45	1.55	1.62	1.63
Other manufacture products	1.63	1.73	1.64	1.69	1.70	1.79	1.84	1.70	1.56	1.52	1.53	1.50	1.60
Preparation of leather and manufacture of leather goods, travel articles and footwear	1.53	1.62	1.44	1.60	1.49	1.62	1.62	1.59	1.47	1.53	1.61	1.60	1.54
Manufacture of coke, petroleum products and biofuels	1.50	1.49	1.27	1.20	1.08	0.83	0.85	0.95	0.58	0.91	0.83	1.11	1.39
Manufacture of metal products, except machinery and equipment	1.76	1.80	1.54	1.49	1.52	1.43	1.42	1.32	1.22	1.23	1.20	1.32	1.36
Manufacture of electrical machines, apparatus and materials	1.45	1.56	1.31	1.43	1.36	1.37	1.46	1.28	1.21	1.21	1.17	1.27	1.36
Manufacture of machinery and equipment	1.63	1.67	1.24	1.48	1.50	1.40	1.45	1.40	1.24	1.22	1.18	1.34	1.34
Chemical manufacturing	1.55	1.46	1.09	1.24	1.31	1.27	1.32	1.25	1.39	1.38	1.34	1.37	1.34
Manufacture of wooden products	1.51	1.56	1.25	1.36	1.23	1.32	1.35	1.24	1.17	1.14	1.25	1.36	1.34
Beverage manufacturing	1.58	1.70	1.74	1.73	1.67	1.71	1.41	1.39	1.44	1.31	1.25	1.28	1.33
Printing and playing back recordings	1.49	1.46	1.18	1.31	1.42	1.28	1.38	1.47	1.25	1.26	1.18	1.25	1.25
Furniture manufacturing	1.34	1.37	1.26	1.51	1.47	1.50	1.43	1.42	1.17	1.23	1.22	1.19	1.23
Metallurgy	1.59	1.78	0.97	1.13	0.99	0.99	1.07	1.07	1.04	0.96	1.04	1.41	1.21
Manufacture of textile products	1.33	1.38	1.25	1.29	1.27	1.29	1.26	1.22	1.13	1.11	1.27	1.20	1.18
Manufacture of pulp, paper and paper products	1.22	1.15	1.02	1.05	1.13	1.06	1.10	1.05	1.19	1.15	1.16	1.28	1.15
Extraction of non-metallic minerals	1.41	1.61	1.64	1.73	1.68	1.59	1.45	1.59	1.48	1.19	1.16	1.16	1.13
Manufacturing of food products	0.96	1.09	1.03	1.17	1.18	1.20	1.15	1.14	1.19	1.17	1.21	1.17	1.12
Manufacture of rubber and plastic products	1.21	1.15	1.11	1.17	1.11	1.07	1.10	1.11	1.03	1.04	1.04	0.99	1.06
Extraction of metallic minerals	2.75	3.10	1.85	3.05	3.84	3.20	2.76	2.05	1.90	1.54	2.01	2.04	1.05
Manufacture of non-metallic mineral products	1.49	1.59	1.27	1.37	1.37	1.32	1.29	1.23	1.09	0.94	0.86	0.99	0.98
Manufacture of motor vehicles, trailers and bodies	1.52	1.64	1.26	1.42	1.40	1.17	1.21	0.93	0.73	0.65	0.87	0.93	0.91
Activities to support mineral extraction	1.50	1.81	1.67	1.60	1.69	1.62	1.30	1.50	1.60	0.99	1.03	1.01	0.89
Mineral coal extraction	1.24	1.26	1.40	1.29	1.27	1.07	1.13	1.31	1.31	1.16	0.99	0.93	0.77
Manufacture of other transport equipment, except motor vehicles	1.56	1.60	1.25	1.29	1.25	1.14	1.17	1.14	0.90	0.87	0.96	0.80	0.67
Total	1.33	1.40	1.21	1.32	1.30	1.21	1.16	1.10	0.99	1.02	1.05	1.13	1.12

6. Conclusions

In this study, we analyzed the performance of the Brazilian oil and natural gas exploration industry based on productivity and efficiency indicators, comparing its performance with other industrial sectors. Productivity or total factor productivity (TFP) and efficiency were evaluated using the stochastic production frontier model.

Results from both methods indicate that policies stemming from the Pre-Salt significantly boosted the oil and natural gas extraction sector in terms of technological progress and efficiency. Between 2007 and 2009, the sector ranked among the least efficient, at the 29th position. However, in 2019, it reached the first position in terms of efficiency. This structural change that began in 2010 was driven by technological innovations resulting from investments in R&D, reflecting an upward trend

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in Pre-Salt exploration promoted by Petrobras, as well as the new regulatory framework and government incentives for oil exploration in Brazil.

Unfortunately, these productivity gains were not exported to other industrial branches connected with the oil industry, such as the shipbuilding sector, whose efficiency and productivity scores were low throughout the analyzed period. However, it is worth noting that the Brazilian economy experienced a severe crisis between 2015 and 2017, which may have hindered industrial sectors linked to the oil exploration sector from incorporating technological gains during that period.

Author Contributions: Conceptualization and methodology, Mario Jorge Cardoso de Mendonça; Validation, Amaro Olimpio Pereira Jr and Julian David Hunt; Data preparation, Rodrigo Mendes Pereira; Formal Analysis, José Francisco Moreira Pessanha.

Funding: This research received no external funding.

Acknowledgments: The authors thank to Prof. Alexandre Szklo for valuable must and CNPq and FAPERJ for financial support.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. A Posteriori Distribution.

Complete conditional distribution of β

$$(\beta|\ldots)\sim N(b_*,H_*^{-1}) \quad \text{Eq. (A.1)}$$

where:

$$b_*=\left(\frac{(y+u)^{'}x}{\tau^2}+\mu_0\Sigma_0^{-1}\right)\left(\frac{x^{'}x}{\tau^2}+\Sigma_0^{-1}\right) \quad \text{Eq. (A.2)}$$

$$H_*=\left(\frac{x^{'}x}{\tau^2}+\Sigma_0^{-1}\right)^{-1} \quad \text{Eq. (A.3)}$$

Complete conditional distribution of τ^2

$$(\tau^2\,|\ldots)\sim IG(c_*,d_*) \quad \text{Eq. (A.4)}$$

where

$$c_*=\alpha_0+\frac{NT}{2} \quad \text{Eq. (A.5)}$$

$$d_*=\gamma_0+\frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{N}\left(y_{it}-x_{it}\beta+\log u_{it}\right)^2 \quad \text{Eq. (A.6)}$$

Complete conditional distribution of σ^2

$$(\sigma_u^2\,|\ldots)\sim IG\left(c_{**},d_{**}\right) \quad \text{Eq. (A.7)}$$

$$c_{**}=\alpha_1+\frac{NT}{2} \quad \text{Eq. (A.8)}$$

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$$d_{**} = \gamma_1 + \frac{\sum_{i=1}^{N}\sum_{t=2}^{T}(\log u_{it} - \phi \log u_{i,t-1})^2}{2} \quad \text{Eq. (A.9)}$$

For the paremeter ϕ and, therefore for the technical inefficiency u_{it}, it is not possible to find a known conditional distribution. In this case, it is necessary to use the Metropolis -Hastings (Shaby e Wells, 2010).

$$p(u_{it} \mid ...) \infty \exp\left(\frac{(y_{it} - x_{it}\beta - \log u_{it-1})^2}{2\tau^2}\right)\exp\left(\frac{(\log u_{it} + \phi \log u_{it-1})^2}{2\sigma^2}\right) \quad \text{Eq. (A.10)}$$

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