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Oil windfalls and tax inefficiency: evidence from Brazil

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Abstract:

This paper investigates whether Brazilian municipalities are losing efficiency when collecting local taxes in response to oil windfalls. A two-stage procedure was adopted. First, we calculate the efficiency scores for tax collection using the Data Envelopment Analysis (DEA) method. In the second stage, the efficiency scores are used as the dependent variable in a quantile regression model to assess whether oil rents affect this indicator. The results reveal that the municipalities benefitting from oil revenues (royalties) reduce their efficiency in collecting taxes in response to such grants, which signals that they generate some type of X-inefficiency in municipal public management. Using a Cost-Minimization DEA, it is possible to avoid the problem of mixing technical efficiency with unobservable preferences on public goods. It is also possible to decompose efficiency within three components: technical, allocative and economic.

Keywords: Data envelopment analysis, quantile regression, oil royalties, public sector.

JEL Codes: H21, H71, Q33.

Oil windfalls and tax inefficiency: evidence from Brazil

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1. Introduction

The current regulatory framework for the oil and gas industry in Brazil was defined in 1997 with Law 9478/97, which is also known as the "Oil Law". According to this act, 10% of the gross value of the production of oil and natural gas should be collected by the National Treasury as royalty revenues. Beyond royalties, there is also a "Special Tax" – a resource rent tax levied on highly productive projects. A significant portion of both revenues is distributed to a set of states and municipalities that meet certain criteria related to their proximity to producing areas. There are some legal guidelines that must be followed by local governments in the use of these financial resources, directing them toward certain types of investment. These revenues exhibited a strong growth trend after 2000, when international oil prices climbed and the Brazilian exchange rate (Real/US dollar) started to float.

The opening of the pre-salt exploratory frontier significantly increased the prospects for these rents. To adapt the regulatory framework to the new exploratory conditions, the Brazilian government approved, in late 2010, a new law introducing substantive changes in the legal regime governing the exploitation of oil and natural gas in pre-salt areas.[1] Among the developments, important changes in the sharing of royalties[2] between the Brazilian subnational governments were approved (Law 12.734/2012), which favored non-producing municipalities at the expense of current beneficiaries.

The sudden availability of oil royalties in local budgets after 1997 has brought concerns about the appropriate use of these revenues. Many researchers have devoted attention to the local socioeconomic effects based on paradigmatic case studies. One aspect that has been much less studied is whether oil windfalls have affected the economic behavior of the municipalities that enjoy them in terms of both maximizing their tax effort and minimizing administrative costs.

This paper investigates whether oil royalties in Brazil have increased X-inefficiency in the collection of local taxes. In particular, the paper aims to analyze the hypothesis that these grants lead the benefiting municipalities to collect taxes with an excess of human and capital resources. Thus, we performed a Data Envelopment Analysis (DEA), from which we extracted

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[1] Loosely speaking, the lease regime was replaced by the sharing contract system in the new areas, whereby the Union is the owner of the resource extracted, paying the producer according to the volume produced (cost oil). A new state owned company, Pre-Sal Petroleo SA, was created, aimed at guiding the new sharing contracts. The new law also created a Sovereign Fund to manage rents from oil; this is an attempt to generate financial resources for investments in areas such as education, social programs, technological development and anti-poverty initiatives.

[2] From now on, by 'royalties', we mean 'royalties plus special tax'.

the three components of efficiency (technical, allocative and economic). In a second stage, the efficiency scores generated by the DEA were regressed against oil revenues and other control variables. In addition to the ordinary least squares estimator, we employed a quantile regression model, aiming to assess whether oil windfalls have different impacts according to the percentile of the score.

The advantage of DEA over econometric procedures, such as stochastic frontier, is its non-parametric profile, which allows some flexibility in the composition of inputs and outputs. This profile is particularly useful when the assumptions of profit maximization and/or cost minimization fail. Unlike the efficient frontiers, there is no need to assume an optimizing behavior because the envelopment is constructed based on an output-input ratio of decision units. Moreover, the problem of defining functional forms, which is typical of econometric models, is also avoided.

Although there is a solid body of literature concerned with the relationship between federal grants and fiscal effort[3], the potential adverse impact of financial transfers on the efficiency of the local administrative machine is rarely studied. The fundamental hypothesis to be investigated is whether these resources contribute to a rise in the cost of the machine, i.e., whether there would be an excess of administrative costs to collect the tax. The relaxation of an optimizing behavior is known in the literature as X-inefficiency, and many subsequent studies have sought to investigate the phenomenon and its explanatory factors.

Leibenstein (1966) is the pioneer in obtaining evidence of X-inefficiencies and was the first to link them to technical failures. Until his work, economists tended to be concerned only with allocative inefficiency (Frantz, 1992). The author reports data from diverse industries, noting significant variations in the outputs under very similar conditions for capital, labor and technology. The allocative inefficiencies are not significant for explaining X-inefficiencies because the likelihood of consistent price imbalances across several economic sectors is small. The causes of X-inefficiencies were attributed to motivational issues, the absence of complete contracts in the labor market, lack of knowledge about the production function and lack of competitive pressure in some sectors.

Stigler (1976) is the primary critic of the notion of X-inefficiency, especially regarding its motivational factor. According to him, the concept of X-inefficiency assumes a predetermined product because its maximization is the result of multiple objective functions of the agents involved in the firm (e.g., leisure/labor). The supposed inefficiency would be due to the preference of leisure over income because working generates disutility. Leibenstein (1978) counters such criticism by arguing that effort is a highly discretionary variable for firms due to agency problems and incomplete contracts. Additionally, according to him, lower market competitive pressure causes the constraints to have less of an effect on decision making, so that there would always be an opportunity to replace cost-minimizing behavior with effort-reducing activities.

Frantz (1992) highlights the relationship between rent seeking and X-inefficiency, arguing that both activities are substitutes for each other. Under the rationality hypothesis, the presence of X-inefficiency reduces the resources available for opportunistic behavior. The relationship between rent seeking and X-inefficiency is also exploited by McNutt (1993) in the context of the social cost of monopoly. The author concludes that there is an overlap between both measures and proposes a review of the fundamentals of rent seeking.

[3] See, for instance, Inman (2008), Shah (1994) and Gamkhar and Shah (2006).

Button and Weynan-Jones (1992) try to distinguish between technical inefficiency and X-inefficiency, which is absent in Leibenstein (1966): while the former would be linked to potential technological factors, the latter would result from organizational and/or behavioral elements. Hence, X-inefficiency should be linked to problems of economic inefficiency.

Applying these optimizing principles and X-inefficiency to the public sector is relatively straightforward, with potential implications for rent seeking and public choice issues (Buchanan et al., 1980). According to Button and Weynan-Jones (1992), the concept of X-inefficiency has become essential for assessing privatization policies and designing regulatory mechanisms to encourage cost reduction (price cap, for example). Using some measures of efficiency, the authors gather evidence that private firms operating in competitive markets and not subject to regulatory policies are more efficient than state-owned companies.

Hence, the microeconomic rationality of inefficiencies in the public sector is related to the concepts of X-inefficiency and rent seeking. To some extent, although the theories compete with each other, their predictions are observationally equivalent (Button and Weynan-Jones, 1994). Moreover, the first concept has its origins in the study of private agents (firms), while the second has greater analytical linkages with the public sector.

Returning to the subject of this paper, the aforementioned literature allows the following hypothesis to be formulated: oil windfalls relieve the pressure to fund the public sector. Under incomplete labor contracts, this budgetary relief results in agency problems (or moral hazard) because public managers lose the incentive to adopt efficient managerial practices; this, in turn, leads to X-inefficiency and/or rent-seeking opportunities. Notwithstanding the studies conducted to date on the impact of oil royalties, this hypothesis has not been studied in Brazil.

This paper is divided into four sections in addition to this introduction. Section 2 presents a summary of the literature employing non-parametric methods for studying inefficiencies, and Section 3 presents the DEA. Section 4 describes the data and discusses the selection of inputs, and Section 5 presents the results. Section 6 concludes the paper.

2. Measuring inefficiencies in the public sector

The empirical literature has tried to develop measures to assess inefficiencies around the world, whose microeconomic foundations, although not consensual, are as described in the previous section.

Maital and Leibenstein (1992) first present the relationship between Data Envelopment Analysis (DEA) and X-inefficiencies, with the aim of validating it as a tool for measuring these inefficiencies. The methodology is used to assess the performance of a hockey team from Boston, whose players were treated as the Decision Making Units (DMUs). The goals per match are defined as the output, and the opportunities for shots and wages are considered inputs. The authors conclude that the DEA is an appropriate instrument for measuring efficiencies for cases where inputs and/or outputs are not market variables.

Deller and Nelson (1991) use a Cost-Minimization DEA (DEA Cost) to investigate the efficiency of American rural towns in providing services for local roads. The inputs used are machinery and equipment maintenance, and the output is the length of highway under the town's responsibility. The authors find evidence of scale effects to the extent that the largest cities are more efficient at providing such services. Deller (1992) presents a similar study for educational data in Maine. Borger and Kerstens (1996) compare the use of DEA with deterministic and stochastic parametric procedures with the aim of studying the efficiency of local governments in Belgium. Efficiency ratios are compared under different methodological procedures, and there has been little observed correlation between them. For the non-parametric procedure, the efficiency scores estimated by DEA and FDH[4] are explained in a second stage by the political, economic and social characteristics of municipalities. It is concluded that the local tax rates and the level of education positively affect efficiency and that financial grants and the average level of income affect it negatively.

Worthington (2000) presents a study on the efficiency of the public sector in Australia by comparing DEA with the cost stochastic frontier. Little variation in technical and allocative efficiencies across counties is observed, but allocative factors explain most of the local performance. In a second stage, the DEA Cost efficiencies are used as the dependent variable in a regression model, whose results show that they are positively correlated with debt service and assets and negatively correlated with the size of the labor force. However, under the cost stochastic frontier, the signs of the assets are reversed, showing that the impacts of explanatory variables on the efficiency scores are not robust to the chosen method.

Similarly, Balaguer-Coll et al. (2007) use a two-stage nonparametric procedure to study efficiency in the provision of public services by local governments in Spain. The inputs are current expenditures and grants, whereas non-parametric frontiers are estimated using the DEA and FDH methodologies. In the second stage, a non-parametric regression is estimated to investigate the impact of fiscal and political variables on the efficiency scores. The authors conclude that larger and more populous counties have better performance in the provision of public services and that the efficiencies are affected by the variables mentioned. The estimated signs have proven to be robust to the chosen method.

For the Brazilian case, Sousa and Ramos (1999) offer a pioneering study on the use of nonparametric methods for assessing municipal efficiency that investigates the effects of decentralization on the performance of municipalities in the Southeast and Northeast of Brazil, using information from the 1991 Census. They obtain evidence that the financial decentralization implemented by the 1988 Constitution succeeded in favoring the efficient use of public resources. Sousa and Stosic (2005) employ DEA and FDH methods with resampling procedures to treat outlier problems, with the aim of evaluating the efficiency of Brazilian municipalities. Inputs are given by municipal spending, whereas a combination of social indicators for 2001 is used as output. The authors conclude that there is a direct relationship between municipality size and efficiency; they also observe that dependence on oil rents is a common feature of inefficient municipalities. Similar evidence is found in Sousa, Cribari-Neto and Stosic (2005), which, in a second stage, obtains econometric evidence of scale effects on municipal efficiency.

Under the same methodology, Araujo (2007) uses a two-stage DEA to estimate the tax efficiency of the Brazilian municipalities with cross-sectional data from 2004. The inputs are given by the administrative costs and the number of active employees, while the outputs are defined by the number of registered taxpayers and the municipal tax revenue. In a second stage, a quantile regression model is estimated to identify the explanatory factors of efficiency scores; the author obtains evidence that income inequality and inter-governmental grants

[4] FDH - Free Disposal Hull - is also a non-parametric procedure whose rationale is analogous to DEA's, but it allows the convexity assumption to be relaxed.

both have a negative impact on the scores, whereas population and urbanization level have positive impact.

In a study on the flypaper effect, Mattos et al. (2011) construct tax efficiency scores for municipalities in 2004 using the Free Disposal Hull methodology, in which the output is composed of tax revenue and the size of the informal economy. In a second stage, the FDH scores are regressed against some explanatory variables, yielding evidence that federal grants negatively affect the efficiency of tax collection.

3. Methodology

Data Envelopment Analysis (DEA)[5] uses mathematical programming methods to construct a convex sectional surface to envelop the observed data (Coelli et al., 2005). The distance of each decision making unit (DMU) from this surface is the basis for building measures that aim to mimic the concepts of efficiency: the farther from the frontier, the greater the DMU's relative inefficiency. Thus, the DMUs can be ranked according to their performance in relation to the output under study.

Figure 1: Data envelopment and efficiency scores

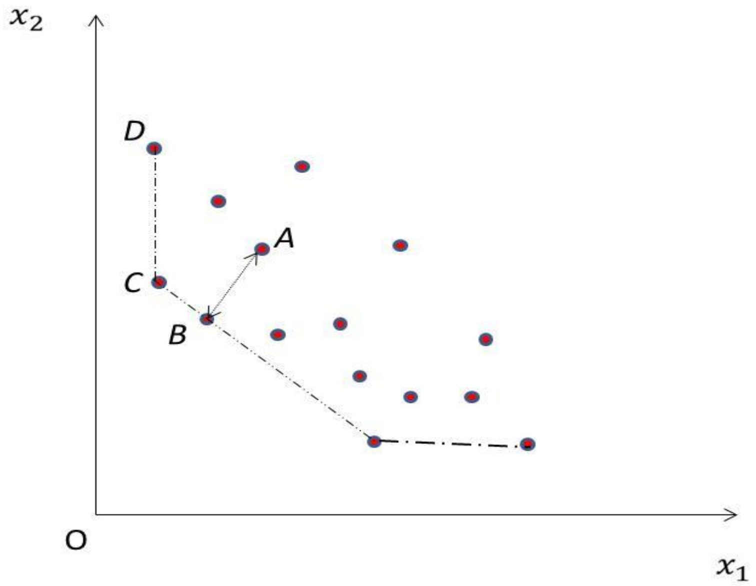


Figure 1 shows the general idea behind the envelopment analysis. The linear programming algorithm selects the most efficient units and traces a convex surface around them. Point A represents an inefficient unit, whereas *B* and *C* are efficient because they are located on the surface. The inefficiency measure is a function of the distance *AB*. Point *D*, despite being located on the border, is not efficient because the CD stretch of the envelope is parallel to the y-axis, i.e., there is an excess of input (x_2). This problem is known as *slack* or excess inputs[6] and arises from the non-imposition of a functional form for the envelope.

[5] For a survey about the method, see Cooper et al. (2011).

[6] The number of slacks is decreasing as the sample size tends to infinity. The maximization algorithms used to estimate the DEA usually treat the slacks in a second stage of programming. See Coelli (1996) for the case under analysis.

The advantage of DEA (and non-parametric procedures, in general) is that it dispenses with the assumption of economic optimizing behavior (Balaguer-Coll et al., 2007). Thus, DEA is free of the fundamental econometric problem of defining a functional form for the optimal frontier. Under the hypothesis that at least some units are efficient by an ad hoc criterion, the other units are compared to these. The linear programming algorithm aims to find the coefficients that define a convex combination of these efficient units. This process allows good flexibility in defining inputs and outputs. However, the absence of functional form allows a certain arbitrariness in the composition of these variables, which ultimately constitutes a drawback of the method.

The general algorithm of DEA can be expressed as follows: there is a set of I decision-making units, each one producing M products $y_1, \cdots, y_M$ from N inputs $x_1, \cdots, x_N$. For each DMU $i = 1, \cdots, I$, one must solve the following optimization problem: [7]

$$\min_{\lambda_k, \theta} \theta \tag{1}$$

subject to

$$\sum_{k=1}^{I} \lambda_{km} y_{km} - y_m \geq 0, m = 1, \cdots, M \tag{2}$$

$$\boldsymbol{\theta x_n - \sum_{k=1}^{I} \lambda_{kn} x_{kn} \geq 0, n = 1, \cdots, N} \tag{3}$$

$$\boldsymbol{\lambda_k \geq 0, \qquad k = 1, \cdots, I} \tag{4}$$

$\theta \leq 1$ measures the efficiency of decision unit i, representing the factor by which the inputs can be scaled down without decreasing the product. [8] Thus, as $\theta \to 1$, the more efficient the DMU. $\lambda_1, \cdots, \lambda_I$ are constants to be calculated jointly with θ through linear programming. y_m and x_n are the product and the input observed in unit i.

Constraint (2) states that the envelope to be built surrounding the decision-making units by the weights $\lambda_1, \cdots, \lambda_I$ should represent an upper bound for any observed production y_m, $m = 1, \ldots, M$; equation (3) is analogous to the inputs, indicating that the envelope should represent a lower bound for each observation $x_n, n = 1, \cdots, N$.

The formulation defined in (1) – (4) assumes constant returns to scale (CTS). This assumption is appropriate only when the DMU operates at optimal scale. If the scale is not optimal, the scale effects can mix with issues of technical efficiency and both measures can be confusing

[7] Subscripts i were omitted to simplify notation.

[8] Problem (1) assumes an input-oriented efficiency measure. It is also possible to formulate the same problem through an output-oriented measure, but as Coelli et al. (2005, p. 181) point out, both formulations generate the same efficient frontier and hence identify the same set of efficient DMUs. The difference lies in the efficiency measures associated with the inefficient units.

(Worthington, 2000). To avoid this problem, there is the alternative of estimating an envelope with variable returns to scale (VRS) simply by adding the following restriction of convexity:

$$\sum_{k=1}^{I} \lambda_k = 1 \tag{5}$$

Equation (5) imposes a restriction forming a convex hull in the intersection of the hyper planes that envelop the data. The goal is to ensure that the decision units are only compared with peers of similar size, which does not happen under constant returns.

The calculated coefficients θ represent a measure of technical efficiency of the DMU. To obtain a measure of allocative efficiency, it is necessary to introduce input prices. The economic efficiency can be decomposed within their technical and allocative components by performing a second stage of programming, which consists of extending the DEA to incorporate the costs of production to solve the following problem:

$$\min_{x_k^*,\lambda_k} \sum_{k=1}^{N} w_k x_k^* \tag{6}$$

subject to the same constraints (2) to (5). $\boldsymbol{w_1}, \cdots, \boldsymbol{w_N}$ are the input prices the i[th] DMU faces, and $\boldsymbol{x_{kn}^*}, \boldsymbol{n} = \mathbf{1}, \cdots, \boldsymbol{N}$ is the optimal level of input that meets the criterion of allocative efficiency. Thus, the cost efficiency is given by the following:

$$CE_i = \frac{\sum_{k=1}^{N} w_k x_k^*}{\sum_{k=1}^{N} w_k x_k} \tag{7}$$

By construction, $\boldsymbol{CE_i} \in (\mathbf{0}, \mathbf{1}]$, and as $\boldsymbol{CE_i} \to \mathbf{1}$, the decision-making unit becomes more efficient.

The calculation of the score based on a Cost Minimization DEA (hereinafter DEA Cost) allows its allocative efficiency component to be incorporated in addition to the technical element estimated in the first stage. Technical inefficiency $\boldsymbol{TE_i}$ corresponds to $\boldsymbol{\theta_i}$. The allocative efficiency (AE) is calculated as a residual:

$$AE_i = \frac{CE_i}{TE_i} \tag{8}$$

The three efficiency measures – technical, allocative and economic – vary in the interval (0,1], and as they become closer to the upper bound, the DMU becomes more efficient. Another advantage of this extension is that the *slacks* can be interpreted as an allocative inefficiency, as Ferrier and Lovell (1990) *apud* Coelli (2005) argue, which reduces the need for their treatment from the technical point of view.

4. Inputs, outputs and data

This paper employs DEA Cost to investigate whether oil windfalls affect the economic efficiencies of the benefiting municipalities related to tax collection. The underlying assumption is that this methodology allows the X-inefficiencies described previously to be measured. The natural candidates for outputs are the tax revenues under local responsibility according to the Brazilian law, namely, the Urban Property Tax (IPTU), the Tax on Services of Any Nature (ISSQN), the Tax on Donations to Individuals (ITBI) and municipal fees (FEE), which are all expressed in per capita terms to establish a control for the size of the municipality.

The inputs should be proxies for capital and labor. The measure of capital adopted here is the total value of municipal assets per capita. The ideal would be to obtain a measure of physical assets and facilities for the collection of taxes, but this breakdown is not available for the Brazilian data. The measure of labor refers to the number of employees of the municipal executive per thousand inhabitants. Again, the ideal would be to include only the workers assigned to collect taxes, but this database does not contain this information.

The measures for input prices were inspired by Worthington (2000). Unlike firms in competitive markets (where input prices are given), each municipality is faced with its own price, given by local conditions. Therefore, input prices must be constructed from observable variables. In the present study, the price of labor was obtained by the average personnel expense, i.e., the ratio of personnel expenses to the number of employees of the municipal executive. Similarly, the price of capital was defined by the average capital expenditure, i.e., the ratio of capital expenditure to assets.[9]

Before continuing, it is important to outline some insights on the reason for choosing DEA Cost instead of the conventional one-stage DEA. The former has the advantage of building scores for economic efficiency decomposed into its two elements – allocative and technical. Typically, the nonparametric estimates for the public sector are only concerned with the technical component, which implicitly assumes that municipalities always see advantage in maximizing taxes given the available resources. However, the decision to tax citizens is an implicit representation of local preferences on the size of the public budget; these preferences are endogenous to economic factors, including the relative price of labor required to "produce" tax. Thus, although the measure of input price is subject to imperfections and weaknesses coming from a limited database, it more accurately reflects the local choices regarding tax funds, given allocative and economic constraints. In other words, the (unobservable) municipal preference on the size of the public sector can "contaminate" the estimates of technical efficiency; hence, economic efficiency is more suitable for measuring incentives because it requires reaching a given amount of tax revenue at the lowest cost.

Furthermore, the X-inefficiency is defined as a deviation from the cost optimizing behavior. Such deviation is the result of economic factors affecting the agent's motivation, as outlined in section 2. To the extent that the DEA Cost allows calculating economic efficiency as a whole

[9] Worthington (2000) constructs a similar measure for studying the public sector in Australia but only uses physical capital expenditure.

(not just technical), it is a more comprehensive tool for empirically assessing this type of inefficiency than the one-stage DEA.

Table 1 summarizes the variables used in the estimation of cost efficiencies.

Table 1: Variables used in DEA-Cost estimation

Variable	Description	Source
Outputs		
IPTU	Municipal revenue per capita	Finbra/STN
ISSQN		
ITBI		
Fees		
Inputs		
Labor	Employees of executive power/thousand inhab.	RAIS
Capital	Asset value per capita	FINBRA/STN
Labor price	Personnel expenditures/employees	Constructed
Capital price	Capital expenditures/asset	

The data on oil revenues were obtained from the National Petroleum Agency (ANP), which contains information on the total royalties and special tax distributed to states and municipalities. These data comprise the following: i) collection of royalties up to 5% on the gross value of oil production, concerning the compensation to the affected municipalities (Law 7.990/89, cl. 7º); ii) collection of royalties above 5% of oil production (Law 9.478/97, cl. 49, I and II); and iii) collection of special participation tax (Law 9.478/97, cl. 50).

Data on municipal revenues and expenditures were extracted from the Brazilian National Treasury/FINBRA[10]. This database organizes information from the accounting and financial reporting of Brazilian states and municipalities. The municipal product (GDP) and population, which are control variables in the second stage, were obtained from IBGE – Brazilian Institute of Geography and Statistics. Data on the level of municipal public employment were extracted from RAIS – the Annual Report of Social Information, from the Labor and Employment Secretariat.

These four databases resulted in a panel of municipalities observed from 2002 to 2009. The estimation of economic efficiency scores was performed using the DEAP software – Data Envelopment Analysis Program – developed by Timothy Coelli (Coelli, 1996). For this analysis, it was necessary to produce a rigorously balanced panel with local observations between 2002 and 2009. Thus, only municipalities that had information for these eight years were considered for the estimation, which resulted in panel of 3454 DMUs observed over eight years. Table 2 presents descriptive statistics of the variables used in DEA.

[10] Finanças Brasileiras/STN.

Table 2: Descriptive statistics I: DEA

Variable	Mean	Standard Deviation	Min	Max
Population	34112.57	203542	804	11037593
Personnel Expenditures*	14900.00	112000	14.71	6786994.45
Capital Expenditures*	4448.68	37400	2.16	3129066.13
Tax Revenue*	6766.63	126000	0	10857777.53
IPTU Revenue*	1994.92	39600	0	3226271.06
ISSQN Revenue*	2881.97	63200	0	5954568.06
ITBI Revenue*	485.37	8097.42	0	706246.96
Fees*	589.23	5759.53	0	365801.88
Assets*	60978.23	1620049	0	16577762.80
# Employees of Executive	725.25	2660.73	1	141108
# Observations	40249			

Source: Elaborated by the author. (*) Thousands of Reais. The exchange rate Real/US$ is approximately 2.30 in January 2014.

5. Results

The economic efficiencies and their technical and allocative components were estimated through the steps of equations (1) to (8). The overall statistics are shown in Table 3. Among the 3454 municipalities, 19 proved to be economically efficient ($CE = 1$), 37 met the criteria for full technical efficiency ($TE = 1$) and 23 proved to possess allocative efficiency ($AE = 1$).

Table 3: Descriptive statistics of inefficiencies - DEA Cost

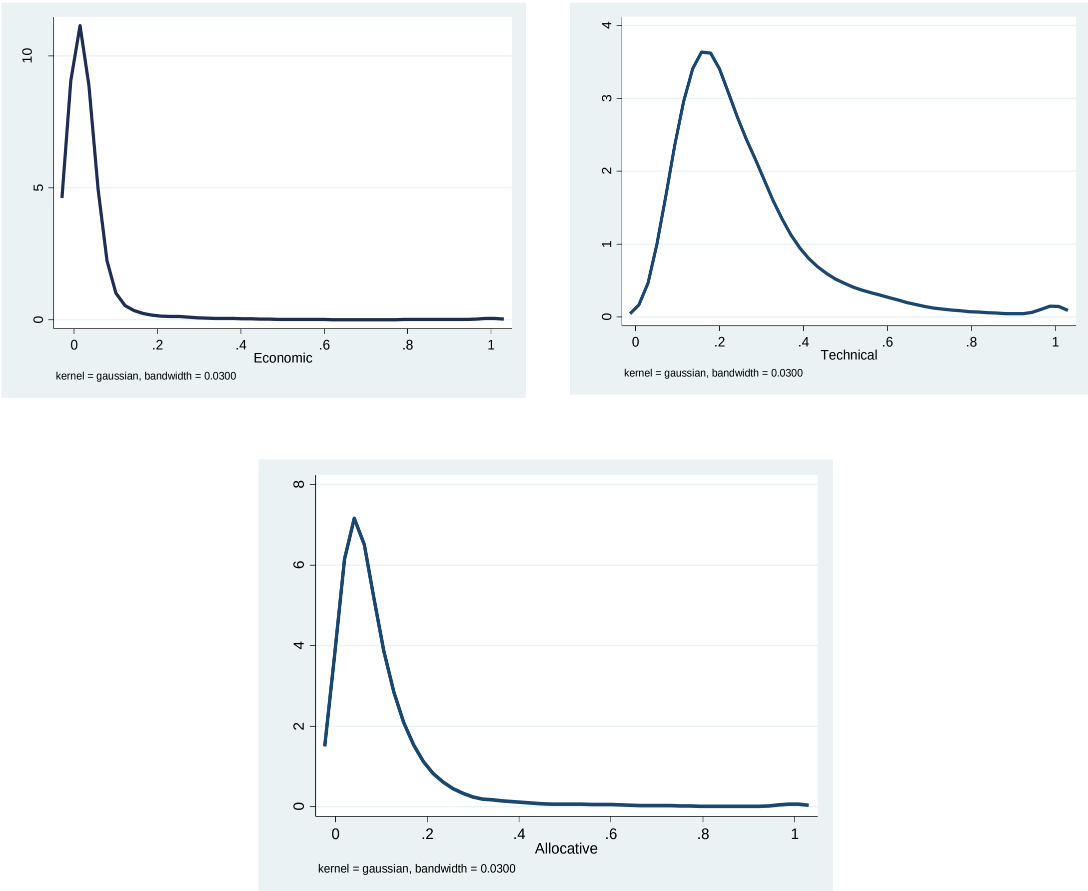
Efficiency	Mean	St. Dev.	1st quartile	Median	3rd quartile
Economic	0.033	0.09	0.005	0.011	0.026
Allocative	0.096	0.121	0.03	0.061	0.113
Technical	0.258	0.169	0.146	0.212	0.315

Source: Elaborated by the author

The data shown in Table 3 suggest a fairly high concentration of municipalities with a low degree of economic efficiency. The three components exhibit average efficiency higher than the median. Only the technical efficiency has a coefficient of variation (ratio standard deviation to mean) less than unity. These results suggest large data dispersion and the presence of outliers related to input prices. Figure 2 presents a nonparametric estimation of the distributions of economic efficiencies and their components using a Gaussian kernel estimator and a bandwidth of 0.03. [11]

[11] This nonparametric procedure consists of estimating the density of a set of data from the function $f(x) = \frac{1}{n}\sum_{k=1}^{n} K\left(\frac{x-x(k)}{h}\right)$, where n is the number of observations, $K(.)$ is a Kernel function such that $\int K(t)dt = 1$ and h is the chosen bandwidth, which determines the degree of smoothness of the curve. The Gaussian kernel is given by $(2\pi)^{-1/2}\exp(-u^2/2)$, where $u = (x - x(k))/h$. Here, we used an arbitrary bandwidth, but as warned by Li and Racine (2007), it is an important parameter because it involves a tradeoff between bias and variance. If h is too small, the estimation bias will be low, but the variance will be large, whereas the choice of a very high h will increase the smoothness of the curve (reducing variance) but imply a potential bias. For details about the procedure, as well as techniques for choosing the bandwidth, see Li and Racine (2007).

Figure 2: Estimated distribution of inefficiencies – Gaussian Kernel



As observed, the distributions of the three components are strongly asymmetric to the right, so that there is a large concentration of economically inefficient municipalities in tax collection. [12]

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[12] This large concentration of inefficient municipalities may be a consequence of the strong presence of outliers in input prices because the technical component offers better results. Sousa, Cribari-Neto and Stosic (2005) propose a technique that combines bootstrap resampling with Jacknife to delete outliers. As we are more interested in ranking inefficiencies (and the impact of royalties on them) than in the value itself, it was decided to keep the outliers in the sample. The quantile regression in the second stage aims to address the asymmetry arising from these outliers.

Table 4: Estimated efficiency scores for the top 20 beneficiaries of oil revenues per capita, according to DEA-Costs

		Efficiency			
State	Municipality	Technical	Allocative	Economic	R$
RJ	Quissamã	0.063	0.144	0.009	5309.49
RJ	Rio das Ostras	0.087	0.641	0.056	4064.55
ES	Presidente Kennedy	0.186	0.070	0.013	2745.93
RJ	Macaé	0.938	0.886	0.831	2081.36
RJ	Casimiro de Abreu	0.101	0.158	0.016	2033.51
RJ	Armação dos Búzios	0.388	0.652	0.253	1878.30
BA	Madre de Deus	0.551	0.492	0.271	1276.45
SE	Carmópolis	0.973	0.239	0.232	1265.53
SE	Pirambu	0.174	0.038	0.007	1037.92
RJ	Macuco	0.066	0.079	0.005	602.62
AM	Coari	0.365	0.049	0.018	599.60
SP	São Sebastião	0.517	0.538	0.278	583.95
SE	Japaratuba	0.181	0.035	0.006	576.90
RJ	Parati	0.587	0.137	0.080	558.99
SE	Rosário do Catete	0.339	0.168	0.057	495.08
RJ	Mangaratiba	1.000	1.000	1.000	444.18
BA	Pojuca	0.191	0.072	0.014	437.18
RJ	São José de Ubá	0.107	0.068	0.007	434.83
RN	Areia Branca	0.179	0.039	0.007	424.45
SC	São Francisco do Sul	0.503	0.579	0.291	416.87
SP	Bertioga	1.000	1.000	1.000	400.56
	Average Brazil	0.258	0.096	0.033	12.54

Source: Calculated by the author. Top 20 calculated as an average from 2002 to 2009.

Table 4 exhibits the components of inefficiencies for the top 20 beneficiaries of oil revenues (royalties and special tax) per capita in average terms from 2002 to 2009.[13] Some major beneficiaries such as Macaé (RJ), Carmópolis (SE) and Rio das Ostras (RJ) have coefficients above the national average. Moreover, Bertioga (SP) and Mangaratiba (RJ) meet both criteria of efficiency (technical and allocative), and therefore, they are economically efficient municipalities. However, there are major beneficiaries with values well below average, such as Quissamã (RJ), Pirambu (SE) and Macuco (RJ). Thus, a merely visual look does not infer any relationship between oil windfalls and economic efficiency in tax collection.

Because DEA is a nonparametric methodology that uses mathematical programming to calculate efficiency scores, its fundamental purpose is to generate an ordering of municipalities according to these measures. It does not provide further information about the cause of these inefficiencies. To advance this investigation and following analogous procedures from the aforementioned papers, a second-stage of estimation was performed: the estimated scores were included as the dependent variable in a regression model. Revenues from oil royalties and special tax, in mean values, were used as independent variables

[13] It is important to highlight two aspects: First, the rank of municipalities is almost the same, either in gross or in per capita terms; second, Campos dos Goyatcazes (RJ), the largest beneficiary in Brazil, is not included in the basis used for the DEA-Cost because, as stated earlier, it is necessarily a rigorously balanced panel and the tax information for this county is discontinued in FINBRA.

($\log ROY$), along with some controls for the observable characteristics of municipalities, namely the following:

a) GDP per capita ($\log$ GDPPC): refers to the municipal economic product per capita, with data from IBGE. This variable establishes a control for the fiscal capacity under the hypothesis that richer municipalities are more efficient;
b) Population ($\log POP$): the projected population (source: IBGE), to control for scale effects, under the assumption that the most populous municipalities would find it easier to be efficient;
c) Financial grants from the federal and state levels ($\log$ UNION and $\log$ STATE): obtained from FINBRA/National Treasury. These variables control for possible decreasing fiscal effort resulting from additional revenues in the municipal budget, with an effect similar to the one we are investigating for oil revenues.
d) Human Development Index – Education (HDI_ED), calculated by IPEA[14] with data from the 2000 Census. This variable aims to control for the educational characteristics of the municipality. It is expected that when this index is higher, the tax collection efficiency is greater.
e) Capital Revenues ($\log$ CAPREV), obtained in FINBRA, to control for other sources of revenue in city hall.
f) Share of agricultural product in the local economic product ($AGRIC$), calculated with data from IBGE. This variable is intended to be a proxy for the profile of the local tax base to control for possible inefficiencies resulting from rural counties, which have greater difficulty collecting taxes. In other words, the hypothesis being tested is that the more urbanized the city is, the greater the economic efficiency.

The estimation in the first stage (DEA Cost) used input and output data for eight years (2002-2009) to generate efficiency scores for 3454 decision-making units (municipalities) across the country. Thus, in this second stage, we have a cross section of 3454 localities, so that the independent variables listed above, including oil revenues, refer to their average for the 2002-2009 period (except for HDI_ED, whose values were extracted from the 2000 Census).

Table 5 reports the descriptive statistics of the variables used in the second stage.

[14] Institute of Applied Economics Research

Table 5: Descriptive statistics II: Quantile regression

Variable	Mean	St. Deviation	Min	Max
Oil Royalties (thousands of Reais[#])	487.05	7675.38	0	340000.00
Oil Royalties per capita (Reais)	12.54	146.14	0	5309.48
GDP per capita (thousands of Reais)	6.83	6.7	1.22	115.92
Population (thousands)	40.63	243.92	0.89	10900.00
HDI – Education	0.794	0.087	0.483	0.978
Assets (Millions of Reais)	81.60	1860.00	0.30	10600.00
Grants from federal government (millions of Reais)	12.10	39.10	2.54	1070.00
Grants from state government (millions of Reais)	11.50	90.00	0.55	4550.00
Share of agricultural product (%)	22.78	15.62	0	74.71
# Observations	3454			

Source: Calculated by the author. [#]Real is the Brazilian currency. The exchange rate Real/US$ was approximately 2.30 in January 2014.

Because the estimated scores are limited to the interval (0,1] by construction, an estimator with limited dependent variables (e.g., Tobit) would be more efficient than a traditional least squares. An alternative procedure adopted here is to construct a dependent variable through a standardized measure that preserves the ranking of economic efficiencies. This variable was calculated from the scores as follows:

$$y = \log CE - \log \overline{CE} \tag{9}$$

where $\overline{CE}$ is the average score of efficiency. Thus, $y \gtrless 0$ as $CE \gtrless \overline{CE}$.

As reported previously (Figure 2) the distribution of the calculated efficiency scores is highly asymmetric. Therefore, it is interesting to model not only their conditional mean but also other quantiles. Thus, a *quantile regression* (Koenker and Basset Jr., 1978; Koenker and Hallock, 2001) was estimated to identify how the dependent variable responds to the explanatory variables at different points of the distribution such as the median and other quantiles. While a classical regression model estimates a conditional mean function, the quantile regression allows estimating functions for any conditional quantile given a set of covariates. As argued by Koenker and Basset Jr. (1978), when the errors have a Gaussian distribution, the least squares estimator meets the minimum variance criterion of Cramer–Rao, but when this assumption does not hold, the quantile regression estimator is more robust, especially in the presence of distributions with very long tails.[15]

[15] Assuming a linear model $y_i = X_i\beta + \varepsilon_i$, in a quantile regression, the estimated parameters are obtained by minimizing the sum of the weighted absolute deviations, according to the following expression:

$$\min_{\beta} \left[\sum_{y_i \geq X_i\beta} \tau |y_i - X_i\beta| + \sum_{y_i < X_i\beta} (1-\tau)|y_i - X_i\beta| \right]$$

where τ is the quantile of reference (for example, for median $\tau = .5$). For the properties of this estimator, see Koenker and Basset, Jr. (1978).

The results are summarized in Table 6. For comparison, we also included estimates from Ordinary Least Squares (OLS). Because the dependent variable was constructed, the standard deviations were calculated using bootstrap. As observed, oil royalties have a negative impact on economic efficiencies regarding the administration of tax resources. This conclusion is valid for the three quantiles studied. The coefficients are significant at 1% for the first quartile and for the median, whereas they are significant at 5% for the third quartile and for the OLS estimates. In other words, the oil windfalls generate a more deleterious impact on inefficient municipalities.

The economic explanation is straightforward: these types of rents relax the municipal budget constraint, reducing the pressure to increase resources to fund the public sector. Thus, there is a negative impact not only on the technical efficiency (i.e., on the incentive to produce tax) but also on the administration of tax revenues at the lowest cost as possible (economic efficiency). Therefore, the benefiting municipalities could extract the same amount of taxes per capita at a lower cost in terms of physical inputs and personnel.

Table 6: Results of quantile regression. Dependent variable: Standardized Economic Efficiency

Variable	OLS	Quantile		
		0.25	**0.50**	**0.75**
$\log ROY$	-0.00944**	-0.0227***	-0.0217***	-0.0134**
	(0.00372)	(0.00318)	(0.00351)	(0.00560)
log GDPPC	0.579***	0.465***	0.505***	0.687***
	(0.0618)	(0.0639)	(0.0444)	(0.0792)
$\log POP$	-0.0683	0.0643	0.0138	-0.255***
	(0.0540)	(0.0609)	(0.0503)	(0.0770)
$\log UNION$	-0.297***	-0.384***	-0.427***	-0.306***
	(0.0686)	(0.0804)	(0.0899)	(0.0779)
$\log STATE$	0.0311	0.0519	0.127***	0.121*
	(0.0451)	(0.0464)	(0.0381)	(0.0639)
HDI_ED	3.234***	3.174***	2.924***	1.943***
	(0.280)	(0.365)	(0.227)	(0.473)
$\log CAPREV$	0.0322*	0.0417***	0.0457***	0.0549**
	(0.0182)	(0.0187)	(0.0130)	(0.0202)
$AGRIC$	-0.0853	-0.128	-0.147	-0.179
	(0.118)	(0.127)	(0.100)	(0.134)
Constant	-5.470***	-4.929***	-4.773***	-4.981***
	(0.695)	(0.864)	(0.933)	(0.723)
# Obs.	3.454	3.454	3.454	3.454
Pseudo-R^2	0.54	-	-	-

Significant at ***1%; ** 5%; and * 10%. Bootstrap standard deviations in parentheses.

Regarding the other controls, as expected, the local fiscal capacity, which is expressed by the economic product per capita, positively impacts economic efficiency. The effect of population is significant only for DMU located in the third quartile. Federal grants have a negative impact on economic efficiency under the same argument as oil revenues, whereas grants from state governments only proved to be 1% positively significant in the median efficiencies.

HDI–Education proved to be positive and significant at 1% for all estimates. Confirming the hypothesis, the higher the educational level of the municipality is, the more efficient it is in managing tax resources. Capital revenues are positive and significant only in the quartiles, signaling that this additional revenue helps increase economic efficiency. However, the effect on the conditional mean, as revealed by the OLS estimate, is significant at only a 10% level.

Finally, the proportion of agricultural product in relation to municipal GDP has no impact on economic efficiency, indicating that the county's profile (urban or rural) does not affect its eventual willingness to raise taxes at the lowest cost as possible.

6. Concluding remarks

This study aimed to investigate the hypothesis that Brazilian oil windfalls may be generating inefficiencies in the management of tax revenues of the benefiting municipalities. To fulfill this goal, we used a nonparametric methodology, whose main advantage is that it avoids defining a functional form for the tax production function.

We estimated a Cost Minimizing DEA, which allowed us to assess not only the technical inefficiency but also the allocative component. The outputs were local taxes, while the inputs used were capital expenditures and personnel expenditures. Relative prices were calculated from their respective average costs. In a second stage, a quantile regression was performed to assess possible different impacts of oil windfalls according to the point of the distribution of scores. The procedure is justified by the evidence for the strongly asymmetric distribution of the calculated economic efficiencies from DEA Cost.

The results suggest an inverse relationship between oil revenues and the degree of economic efficiency in municipal tax management. The benefiting localities would be able to produce the same amounts of tax per capita at a lower cost than is currently done. This potential cost reduction is higher for the major beneficiaries of oil royalties and special taxes.

This study has several possible extensions. First, the estimated distributions of efficiency scores suggest the presence of outliers, whose treatment could produce a more accurate result. Second, parametric procedures such as stochastic frontiers could be tested, aiming to assign a theoretical explanation to the observed inefficiency in terms of X- inefficiency in the public sector. Despite the limitations, this paper took an important step toward investigating the impact of oil revenues on the administrative management of municipalities, particularly in light of the current discussions about the redistribution of these resources among federal units in the context of pre-salt discoveries, which can put Brazil among the top players in the world oil market.

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