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Using data envelopment analysis and the bootstrap method to evaluate organ transplantation efficiency in Brazil

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Abstract
Brazil has the most extensive public program for organ transplantation in the world, and the Brazilian National Health System (SUS) provides full coverage of all costs involved in organ donation, transplants, and post-transplant. Despite the relevance of the subject and the shortage of organs for transplants, transplantation process efficiency assessments are still uncommon in Brazil and abroad. This study aims to evaluate the efficiency of the Brazilian states and the Federal District in transforming potential organ donors into actual donations. We applied data envelopment analysis (DEA) in conjunction with the bootstrap technique, using organ transplantation data from 2018. The bootstrap methods applied (bootstrap technique, the bootstrap-biased scores of efficiency, and the bootstrap bias–corrected scores of efficiency) allow to obtain a confidence interval for DEA scores and provide greater robustness to studies based on DEA methodology. The bootstrap bias–corrected model indicates that there is significant room for improvement in terms of converting potential donors into actual donors. The mean corrected score is 0.55, signalizing that altogether the Brazilian states could maximize in 45% the number of transplanted organs without necessarily increasing the pool of potential donors. The study provides insights into the Brazilian processes of organ donation and transplantation, helping to identify locations in need of resource allocation improvements. Given the scarcity of studies with a joint application of DEA and bootstrap techniques in this crucial health activity, we also intend to methodologically contribute to this type of benchmark analysis, emphasizing the importance of considering measurement errors, randomness, and bias at DEA models.

Keywords Bootstrapping · Brazil · Data envelopment analysis · Efficiency analysis · Organ donation-transplantation process

Highlights

- This study provides new empirical evidence on the efficiency of the organ donation–transplantation process in Brazil, a key component of the Brazilian National Health System.
- It is applied a methodological approach not yet explored in this field—it was computed bootstrap bias–corrected efficiency scores, through bootstrap, to overcome the inherent bias present in the DEA score.
- This research shows that it is important to correct the scores of conventional data envelopment analysis (DEA) models through bootstrap since it provides greater robustness to the studies based on DEA and changes the efficiency scores and the results of the benchmarking analysis.
- The benchmarking approach applied in this study helps managers, practitioners, and policymakers in the healthcare sector to compare healthcare units at different locations, to identify those in need of better public attention, and to prioritize key resources and activities.
- The results indicate policymakers that there is room for improvement in transforming potential donors into actual donors in all Brazilian states and the Federal District.

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1 Introduction

Organ donation and transplantation activities have relevance in the health sector because they represent the only therapeutic alternative for patients with chronic diseases and terminal organ failure [1]. In addition, the growing and aging of the global population and prevalence of unhealthy living habits increase the need for government planning of policy and health programs and increase the pressure for organ transplantation [2].

Brazil has the most extensive public transplant program globally and ranks second in the number of transplants performed, after the USA. The retrieval process begins with the identification of a potential donor at a hospital, following a protocol established by the Brazilian Federal Medical Council for diagnosing brain death. In the case of brain death, the potential donor's notification is compulsory and must be forwarded to the Organ Notification, Retrieval and Distribution Centers in each Brazilian state [3]. In Brazil, brain death is legally defined as death, characterized by the complete and irreversible absence of all neurological functions [4].

Over 90% of transplants performed in Brazil are financed by the Unified Health System (SUS)—one of the largest public health systems in the world and with one the most inclusive coverage to all citizens [5]—since most private health plans do not cover this type of treatment, which involves high costs and high level of surgical complexity [3]. Nationally, the amount of public resources spent on these activities has increased significantly over time. Spending on activities related to organ donations and transplantation totaled USD 315 million in 2015 alone, up 75% from 2008 (including surgery, organ donation and procurement activities, testing, medications, and all the ancillary steps of a transplantation process) [1].

A significant problem in Brazil is the discrepancy between the number of potential donors and the number of transplants performed [6–9]. According to the Brazilian National Transplantation System—SNT, in 2018, Brazil performed 23,226 organ/tissue transplantations, and there were more than 38,000 people on the waiting list for a transplant. In the absence of official public statistics of transplant waiting times in Brazil, the articles of Marinho [6] and Marinho et al. [7] evaluate some economic aspects of the waiting lists and present a set of estimates related to waiting times for several solid organs (heart, cornea, liver, lung, kidney, and pancreas, and simultaneous kidney and pancreas transplantation). They found that in an optimistic model, wait times almost always exceeded a year and that in a less optimistic model, wait times could reach as much as 9 years for a liver and more than 11 years for the kidney. Although Brazil has evolved in legal and organizational terms in recent years, especially since the creation of the transplant law and SNT in 1997 [8], one of the factors contributing to the growing waiting lists is the inefficient management of available organs supply [9–11].

Despite the relevance of efficiency measurement in organ donation and transplantation services, the academic endeavors in this field are still scarce. In the USA, Stogis et al. [12] evaluated the performance of the Organ Procurement Organizations (OPOs) using a measure derived from the numbers of potential organ donors in the population in relation to the observed donations, while Ozcan et al. [13] analyzed the efficiency of the OPOs using data envelopment analysis (DEA) models; Misiunas et al. [14] combined DEA and artificial neural networks for the prediction of organ recipient functional status in the USA; and Ahmadvand and Pishvaee [15] applied DEA to evaluate the efficiency of possible patient-organ pairs for kidney allocation in order to enhance the fitness of organ allocation under inherent uncertainty. In Brazil, Marinho et al. [16] evaluated the technical efficiency of the organs and tissues transplantation using DEA models; and more recently, Costa et al. [17] used DEA and Malmquist index models, and Siqueira and Araujo [15] applied DEA to evaluate the efficiency of kidney transplantation in Brazil.

Since the 1980s, efficiency studies have been increasingly applied in the healthcare sector, and DEA models figure as one of the most popular tools in this field [18]. DEA models have been applied to measure the efficiency of many different health-care settings and services, as hospitals [18–24], accountable care organizations [25, 26], ambulatory ophthalmic surgery centers [27], health-care systems [19], radiology services [28], primary care practices for diabetic patients [29], cancer centers [30], dialysis facilities [31], nursing homes [32], to name a few. However, very few studies applied DEA to measure the efficiency of the Organ Donation and Transplantation process (ODT) [13, 16, 17, 33], as previously mentioned. A recent systematic literature review in health and management databases revealed that the efficiency of ODT activities is mostly assessed using indicators—ratios of a single input to a single output [34].

Given the absence of research dedicated to the measurement of the efficiency of the organ and tissue transplantation process in Brazil, this research aims to evaluate, for the year 2018, the technical efficiency of the Brazilian states and the Federal District in converting potential donors (number of notifications of brain death) into transplants (number of organs and tissues transplanted), in line with the previously cited work of Stogis et al. [12], applying a DEA model. By this, we aim to discuss the proportion and impact of notifications wasted because of inefficiencies located at any stage of the Brazilian processes of organ and tissue donation and transplantation. The wastage signalizes that more transplants could be performed, given the number of notifications in the system, and is related to problems regarding the non-availability or inefficient employment of available resources.

This lack of resources may represent, for example, underreporting brain deaths because the machinery required for confirming the diagnosis is broken in the healthcare unit. Also, a family refusal to donate the organs of a deceased relative may be due to health professionals' wrong approach at the family interview. Altogether, to assess the conversion of material, human and financial resources—as professionals, equipment, intensive care units, human resources training programs, health investments, public campaigns focused on organ transplantation, among others—into expected health outcomes bring valuable information for the Brazilian reality [33].

The assessment translates into recognizing the less prepared health units, health regions, or health systems, thus benefiting a larger number of patients on the waiting list without increasing the number of resources spent. This health-efficiency rationale can also be applied to other healthcare realities, leading to improvements started from identifying wastes in the use of resources. One example is the identification of efficient units in the sample that can serve as a reference, allowing future investigation of successful managerial practices that could be adapted and spread in the remaining inefficient units [35].

Given the scarce literature applying mathematical or statistical methods to assess the efficiency of organ and tissue transplantation processes, as previously mentioned, this study aims to enrich academic evidence on the topic, also encouraging new empirical research. It aims to contribute to the healthcare performance literature in two ways: providing new empirical evidence on ODT' efficiency, and bringing a methodological approach not yet explored in this field—we computed bootstrap bias–corrected efficiency scores, through bootstrap, to overcome the inherent bias present in the DEA score [29]. Additionally, in the Brazilian transplantation system—whose computerized systems contain incomplete, non-up-to-date, or non-integrated data among states and regions [36]—we aim to emphasize the importance of information sharing and also of replicable procedures for performance assessments. This benchmarking approach also intends to help managers, practitioners, and policymakers in the healthcare sector to study and plan improvements reflecting a better resource allocation [37]. This is particularly relevant in countries like Brazil, facing severe budgetary constraints and high socioeconomic heterogeneity among health units, states, and regions [33]. In short, this scenario highlights the academic and managerial relevance of applying systematic tools to compare healthcare units at different locations, to identify those in need of better public attention and efficient prioritization of key resources and activities.

This paper's structure is as follows: "section 2" presents the relevant theoretical and empirical literature on organ donation and transplantation process, and the method applied in this article. "Section 3" provides detail on the research method. "Section 4" describes and discusses the results, and the "sections 5 and 6" present the final remarks.

2 Research method

2.1 DEA methodology

To evaluate, for the year 2018, the efficiency of the Brazilian states and the Federal District in converting potential donors (number of brain death notifications) into transplants (number of organs and tissues transplanted), we applied DEA efficiency model. Thus, the state-level activities of organ transplantation in Brazil constitute the analyzed productive process that allows the processing of potential donors into effective donors whose organs are transplanted.

DEA is a nonparametric method used to estimate the relative efficiency of peer decision-making units (DMUs) that apply similar production factors [38]. The DMUs are compared concerning their analogous processes, in which the same type of key resources (or inputs) is applied to generate the same type of key results (outputs), even though at different amounts [38].

DEA uses linear programming to compute input-output combinations of the selected units, rank DMUs according to their relative efficiency scores, and estimate the frontier of production possibilities. The relative efficiency is based on the notion that an inefficient DMU could maximize its output production (given the number of inputs applied) or minimize its input consumption (given the actual output level). Efficient DMUs (score = 1) form the frontier of best production practices, while the remaining DMUs ($0 \leq \text{score} < 1$) are located below the frontier. For example, an efficiency score of 0.8 entails an inefficiency level of 20% in converting inputs into outputs compared to the other units in the sample. In turn, the inefficiency level portrays the distance of each DMU to the frontier of production possibilities [39].

Unlike linear regression techniques, which represent the sample mean and evaluate trends around the central average, and not the relationship between inefficient and efficient units [40], DEA benchmark and rank the performance of each DMU in the sample [23, 39]. By allowing the identification of best-performing units, the benchmarking approach favors the identification of successful practices to be adapted for the worst performing units, in order to tackle inefficiency points and generate quality and process improvements [25]. In turn, by signaling the worst-performing units, it may draw the attention of managers, public policymakers, and practitioners to the DMUs in need of more significant resources and managerial attention [39].

We say that a DMU is technically efficient if the reduction of one input would result in the decrease of its outputs or the increase in the consumption of another input; or if the increase of one output would result in the increase of its inputs or in the reduction of another of its outputs [38]. This means that, compared to the other DMUs in the sample, there is no resource wastes and no space for productivity improvements. It is worth noting that the conversion process analyzed generates relative efficiency scores, only benchmarking the units included in the sample of analysis [38].

Regarding the DEA model orientation choice, this study applies an output-oriented DEA model, where the technical efficiency scores are estimated considering the extent that outputs could be maximized while maintaining constant the input levels. Differently, an input-oriented model would estimate scores as the extent to which inputs could be reduced while maintaining constant the output levels. There is a perception that when it comes to public health services, managers should prioritize the maximization of outputs rather than the minimization of inputs (focusing on the improvement of health results that will benefit healthcare users). The output considered in this research—the number of transplants performed—represents a health demand not fully met worldwide. The expressive waiting list for organs and tissue transplants in Brazil [5–7] signals the relevance of focusing on output maximization. Additionally, an output orientation model's choice follows previous research on the subject [13, 16, 17, 22].

Another model specification, in line with previous research [16, 17, 20, 25, 29], is the adoption of variable returns to scale (BCC model, based on Banker et al. [41]). The alternative, constant returns to scale (CCR model, based on Charnes, Cooper and Rhodes [42]), assume that there is no economies or diseconomies of scale due to the size of operation (size of the unit of analysis) because an increase or decrease in the input levels would generate a proportional increase or decrease in the output levels [38]. However, there is no reason to suppose that Brazil's organ transplantation process follows constant returns to scale, with no impact due to underdimensioned or sub-dimensioned units.

As a linear programming technique, the DEA model objectives (e.g., the maximization in the number of transplants) are linked to requirements that are represented by linear mathematical relationships. For demonstration purposes, consider the existence of n DMUs, where each DMUj ($j = 1,...n$) uses m inputs to generate s outputs (Table 1). The xij and yrj nomenclatures represent respectively the ith input and the rth output in the DMUj, and DMU0 represents one of the units analyzed.

In this representation of the output-oriented model, a non-Archimedean infinitesimal and the Si– and Sr + elements represent the input and output slacks, respectively. The outputs slacks indicate an insufficient output production, while the inputs slacks signal idle capacity, or resources being consumed in excess [43]. In turn, α_j and are the parameters to be calculated, where α_j is the feasible DMUj production set and is the technical efficiency of the DMUj0. Since the BCC

Table 1 DEA output-oriented envelopment models

Frontier type		DEA envelopment model
CCR		$\text{Max } \theta_o + \varepsilon\left(\sum_{i=1}^{m} S_i^- + \sum_{r=1}^{s} S_r^+\right)$
	subject to:	
		$\sum_{j=1}^{n} \lambda_j x_{ij} + S_i^- = x_{io} \quad \forall i$
		$\sum_{j=1}^{n} \lambda_j y_{rj} - S_r^+ = \theta_o y_{ro} \quad \forall r$
BCC		(1) $\lambda_j \geq 0, \ \forall j$
		Add $\sum_{j=1}^{n} \lambda_j = 1$

model assumes that an increase or decrease in the input variables can lead to a more than proportional or less than proportional change in the outputs, the impact of the scale on the DMU's productivity is assessed by the scale efficiency (SE =) [38, 44].

As a nonparametric technique, DEA presents less a priori restrictions when compared to parametric approaches. Only a large class of functions or production sets with broadly defined properties is assumed, estimated through data available. To exemplify, DEA requires minimal assumptions about how the production factors of the aimed process relate to each other [38]. Additionally, DEA does not rely on a priori information on which inputs and outputs are most important in setting the efficiency scores. It also requires little or no information on prices and preferences [45]. Thus, it represents a flexible model compared to parametric methods, relying more on the data used than theoretical assumptions [38].

2.2 DEA-bootstrap methodology

As a mathematical method, DEA presents some inherent statistical limitations. All inefficiency estimated at DEA scores is attributed to resource allocation management problems, not accounting for randomness, measurement errors, and bias. As a data-driven method, it relies on the quality of the dataset used and presents a high sensitivity to units with extreme values as input(s) or output(s) [38].

Another critical point is that DEA estimators are naturally positively biased because the relative efficiency frontier is estimated based on one sample. This means that if other units were included in the analysis, the present DMUs could only obtain equal or lower scores. There is no guarantee that the benchmarks (efficient DMUs) have made their best effort possible since they can achieve efficient scores only when compared to the sampled DMUs. Thus, the estimated frontier is below the "real" frontier, which is not observed. In the best scenario, the estimated frontier coincides with the "real" frontier [38]. This means that DEA estimators of efficiency are benevolent or biased upward (in favor of DMUs). Kneip et al. [46 , p. 405] state that *"The problem comes mainly from the bias of the individual efficiency estimates, and the fact that the bias does not vanish at an appropriate rate, except in case involving small dimensions*." In our case, we have the smallest possible dimension (one input and one output). Our sample also has adequate size, according to Wilson [47]. Following this paper, it can be calculated that a sample size equal to 13 DMUs would be enough to mitigate the bias problem in our DEA-VRS model.

Because the actual frontier is not observed, the additional problem arises that DEA estimators' actual probability distribution is not known. To tackle those shortcomings, we combined DEA with the statistical resampling technique known as bootstrap [48]. More specifically, we applied the smoothed bootstrap technique, as pioneered by Simar and Wilson [49], and previously applied by DePuccio and Ozcan [20] to investigate the linkage between medical home programs and hospital efficiency, and by Testi et al. [29], to assess the primary care practice performance for diabetic patients.

The objective is to use the statistics of interest of each resampling to know the parameters' distribution to be estimated and to calculate statistics of interest on the original sample. The bootstrap resampling allows computing the scores' variance even under an unknown data distribution, thus enabling to obtain confidence intervals for each DMU's estimated efficiency [49].

This computational statistical technique randomly generates new samples of the same size from the original dataset. This means that each new sample created via bootstrap may have some original observations selected more than once, while other original observations may not be chosen, and if *n* is small, it will even contain values repeated several times. This may cause spikes in the distribution. In this scenario, performing a small number of resamples can lead to different statistics on different runs, even when identical standards are employed. However, if the number of replications is huge (> 1000), then each time we repeat the bootstrap series of replications, the variance will be almost the same [38]. Thus, many replications are desirable to reduce the differences in variance between different rounds [38]. In the present study, we applied 10,000 replications, and the result was stable.

For demonstration purposes, consider a sample (× 1, × 2, ..., xk), where $r = 1, 2, \ldots, k$. The smoothed-bootstrap sample is generated as follows:

(1) *K* samples are selected randomly and with the replacement of {1, 2, ..., *K*}.
(2) A random variable ∈ is generated with standard normal distribution.
(3) A Zr = xk + h∈ is estimated, in which *h* is a bandwidth.

This procedure imitates the continuous distribution function of the inputs. The new sample (z1, z2, ..., zk) is used to calculate the efficiency, having a normal distribution of variance h2 and symmetric over the observed data.

The combination of DEA and bootstrap in measurements of efficiency in the health sector is incipient-applied, for instance, in Araújo et al. [50], to assess private hospitals, in Testi et al. [29], to evaluate primary care performance for diabetic patients, and in DePuccio and Ozcan [20], to compare the efficiency of medical and non-medical home hospitals—but, to the best of our knowledge, has not yet been applied to organ donation and transplantation process.

Besides contributing to the literature on the efficiency of the organ transplantation processes, the use of the bootstrap can bring methodological improvements by revealing the need to correct the scores of conventional DEA models [40]. The joint application of these two methodologies in organ transplant data provides greater robustness to the studies based on this methodology and can reveal a significant change in results obtained in this body of literature.

2.3 Variables and data source

This research uses secondary data obtained from official documents and available for public consultation on the Internet—the Brazilian Transplantation Registry of the Brazilian Organ Transplant Association (ABTO), edition of 2018 (Table 2). Therefore, ethics approval was not needed, in accordance with the policies of our institution. The units of analysis (DMUS) are the Brazilian states. Since there are no records of transplants for the state of Amapá, this state was removed from the sample, resulting in 26 DMUs analyzed.

The operation of the SNT supports the choice of the Brazilian states and the Federal District as DMUs. By law, each state is responsible for the organ and tissue donation and transplantation process. Each state manages its queue, but in the absence of recipients in a given state, an organ can be transplanted in a patient from another region. In this sense, the states are not entirely isolated from each other in performing transplants, although they have full autonomy. However, as there are long lines in all states, this is an exception and hardly ever happens (Marinho et al. 2010). To remedy this problem, we decided to apply a variable return to scale model because it allows convex combinations between states, as they can choose to cooperate and sometimes divide the tasks. If the data available on a given state aggregate data on the processes used in different states, the convex combination can approximate alternative but non-observed aggregations.

Therefore, the Brazilian States' selection as DMUs was based on the administrative role that each federative unit plays in the focused process. States fully control the resources they

Table 2 Potential donors and donors whose organs were transplanted in 2018, in the Brazilian states and the Federal District

State	Number of brain death notifications (potential donors)	Number of transplanted organs
Acre (AC)	51	5
Alagoas (AL)	65	18
Amazonas (AM)	96	12
Bahia (BA)	541	133
Ceará (CE)	516	194
Distrito Federal (DF)	245	47
Espírito Santo (ES)	166	80
Goiás (GO)	391	26
Maranhão (MA)	108	11
Mato Grosso (MT)	90	2
Mato Grosso do Sul (MS)	190	43
Minas Gerais (MG)	691	197
Pará (PA)	124	20
Paraiba (PB)	118	6
Paraná (PR)	1227	428
Pernambuco (PE)	522	178
Piauí (PI)	172	14
Rio de Janeiro (RJ)	846	220
Rio Grande do Norte (RN)	159	32
Rio Grande do Sul (RS)	683	186
Rondônia (RO)	93	12
Roraima (RR)	32	3
Santa Catarina (SC)	581	219
São Paulo (SP)	2957	923
Sergipe (SE)	75	10
Tocantins (TO)	29	4
Brazil	10,768	3023
Mean	414	116
Minimum	29	2
Maximum	2957	923

The Brazilian Transplantation Registry of the Brazilian Organ Transplant Association (ABTO, 2018)

have to transplant organs and also can decide how to pick-up organs. Some states (e.g., São Paulo) follow the model of organ procurement organizations (OPOS), and others (e.g., Rio de Janeiro) prefer to use internal hospital commissions.

In Brazil, all donation-transplantation activities are regulated by the SUS state manager (Transplantation Act—Law 9434 of February 5, 1997). The articulation of the donation process (once a brain death notification occurs), the management of the potential donor registry, and the logistics and the distribution of donated organs are performed at the state level by the State Transplant Centers (STC). STCs are also supported by the Organ Procurement Organizations (OPO) and the Intra-Hospital Commission for Organ and Tissue Donation for Transplantation (CIHDOTT) [51].

Although the states cannot directly control the number of transplants and of brain death notifications, they are responsible for managing all available resources to ensure that donor conversion occurs. This represents, for example, an initiative for the awareness and training of donation teams and physicians dealing with brain death cases and family interviews for organ donation, as well as the allocation of material and financial resources for organ donation transplantation among relevant actors and activities.

The performance variability among Brazilian states, regarding the conversion of potential donors into transplants, may indicate asymmetries in the application and management of organ donation–transplantation resources. Although many non-discretionary socioeconomic factors influence the transplant numbers, discretionary management practices present in these states' reality may account for wastes in the donor conversion rates, thus affecting the availability of organs for transplant. Therefore, each state could seek to identify successful practices adopted by its DEA-efficient peers, considering the adaptation to their local realities [35].

Some empirical studies emphasized the relevance of organizational aspects to the performance of Brazilian organ donation and transplantation services at the state level. A case study noted process improvements on ODT activities within a Rio de Janeiro hospital after implementing a quality management program. The program led to improved learning and knowledge capabilities, with an incremental process that detects errors and subsequently corrects behavior or alters organization standards or premises [52].

Additionally, the positive impact of educational and organizational initiatives on ODT rates has been recently reported in the Brazilian States of Rio de Janeiro and Santa Catarina. Rio de Janeiro experienced a sharp increase in the referrals of potential organ donors, donor conversion rates, and donation rates following the implementation of full-time organ donation teams in the structure of selected hospitals [53]. Santa Catarina achieved similar improvements after articulated ODT initiatives in the state's hospitals. The efforts included (a) implementation of a remuneration system for hospital transplant coordinators; (b) development of hospital training programs focused on ODT processes, especially regarding family interview to organ donation, potential donors' identification, brain death diagnosis, and maintenance of deceased donors; (c) implementation of full-time organ donation teams in the hospital structure; (d) involvement of intensive care doctors in transplant coordination [54].

When interpreted with caution, DEA results can signal states that should undergo reassessments concerning the layout of activities and resource allocation for organ donation–transplantation activities, aiming to identify the obstacles that distance these states from their efficient peers. The present effort may be complemented in the future by qualitative research that will help to enrich the benchmarking discussion. This includes case studies and in-depth interviews with the worst- and best-performing DMUs to identify successful practices and management obstacles.

As input, we used the number of notifications of brain death by state (potential donors). The output is the number of transplants performed by state (number of organ and tissue transplant surgeries performed). We used a single input and single output because our primary interest is on the donor utilization rate, represented by the number of notifications of brain death (as input) and the number of transplants (as output). In this sense, if we put more variables, we would lose focus on the process of interest. The selected output sums up the desirable result of the organ donation process. In turn, input—the potential donors—represent the potential capacity of organ donation for each DMU (given that the brain death notification is required for a transplant to occur). By focusing on those variables, the model targets the waste within the process of converting potential donors into transplants. The inefficiency of converting potential donors into transplants leads to a reduced pool of donors and contributes to the insufficient offer of organs for transplantation, being a problem acknowledged by both researchers and practitioners in the area.

It is worth mentioning that although we are using a single input/output model, a simple output/input arithmetic ratio, or the average productivity, would not be adequate to estimate the technical efficiency of the organ donation–transplantation process in Brazil, since we admit the presence of variable returns to scale in this process. The states are not homogenous, and there is no reason to suppose the existence of constant returns to scale. Also, as observed by Sikka, Luke and Ozcan [40], assessing organizational performance using simple ratio analyses, instead of using the DEA, has an important limitation: it does not allow one to assign relative weights to ratios, making it difficult to differentiate efficient from inefficient units. That is why we apply the DEA (VRS model), which allows the presence of variable returns to scale. Moreover, our model is output-oriented, which is an important feature in a transplant system facing long waiting lines [7]. In this context, a simple productivity measure has no orientation.

We also applied a procedure recommended by Kneip et al. [55] and Simar and Wilson [56] to test the null hypothesis of constant returns to scale (CRS) versus variable returns to scale (VRS) and the null hypothesis was rejected. Consequently, this result reinforce that a DEA VRS model is advisable in our sample. Despite this rejection and the other objections discussed above, we also calculated the productivity (output divided by input) that implies constant returns to scale to keep our work in close contact with the more traditional production theory.

The calculation was performed in R 3.0.3 [57]. The use of a single input and single output allow us to exploit R's graphing capabilities. We used the benchmarking program [38] available in R [57] and the FEAR 3.0 (2020) to test the null hypothesis of constant returns (CRS) to scale versus variable returns to scale (VRS).

3 Results

At first, to account for monotonicity, a fundamental assumption in production theory, we have run a regression (OLS). The results indicate that the number of brain death notifications is positively correlated with the number of transplanted organs, and the elasticity of output is positive. We used a log-log model so as the coefficient of NOTIF estimates the elasticity of output as an anonymous referee suggested. As can be seen in the regression (Table 3), the product's elasticity is positive (1.3431), as we expected. The value of this parameter has a significant meaning. An expansion of death notification reports (NOTIF) by 1% would imply expanding transplants by 1.34%. In principle, this may seem like a good result. Still, we have to consider that each donor can donate various organs and tissues (liver, lungs, heart, kidney, pancreas, cornea, etc.) and, in our data, each transplanted organ counts as a transplant performed. Results indicate no use of all transplantable organs in Brazil and elsewhere [6–10], indicating room for improving the number of donated organs.

We also address another important DEA feature: the returns to scale. If the technology admits variable returns to scale, one should consider using a simple model, just dividing output by input, because it implies the assumption of constant returns to scale. As recommended by Kneip et al. [55] and Simar and Wilson [56], two tests were performed. The first test uses the mean of the Kneip et al. [55] test statistic over NSPLIT random sample splits. In this first case, the test statistic is $\tau = 0.6520584$, and the is p value = 0.374. The second test involves a Kolmogorov-Smirnov one-sample test to test whether NSPLIT p values follow a uniform distribution. The second test shows a test statistic $\tau = 0.3929313$; and a p value = 0.380. The null hypothesis (constant returns to scale) is rejected in both tests. Consequently, a DEA-VRS model is advisable in our sample. Despite this result, we also used a

Table 3 OLS regression: NOTIF × transplants

Coefficients:	Estimated	Std. error	T value	Pr (>|t|)
(Intercept)	− 3.6157	0.5788	− 6.247	1.86e-06 ***
log (NOTIF)	1.3431	0.1057	12.708	3.78e-12 ***

Signif. codes: 0 "***" 0.001, "**" 0.01, "*" 0.05; "." 0.1 ""1

Residual standard error: 0.616 on 24 degrees of freedom

Multiple R-squared, 0.8706; adjusted R-squared, 0.8652

F-statistic, 161.5 on 1 and 24 DF; p value, 3.783e-12 simple technology (productivity), although this indicator only admits constant returns to scale for the sake of being directly connected with traditional production theory. Moreover, we recognize that productivity reveals how a producer transforms inputs into outputs, rather than how they could do it, as DEA shows. The tests are available in the package Frontier Efficiency Analysis with R (FEAR 3.1).

The expressive difference of magnitude between some scores obtained in the traditional models and those generated in the bootstrap models suggests that conducting a purely deterministic analysis, via traditional DEA models, may result in considerably overestimated scores that hinder the managerial contributions of results. This means a significant influence of factors (as statistical bias, randomness, and measurement errors) that should not be disregarded in this type of efficiency analysis. Moreover, the total mean squared error (MSE = bias squared + variance) in the bootstrap bias–corrected model (2.941) is equal to 71.889% of MSE in the bootstrap biased model (4.091). We show the four models' results, but we believe that the bootstrap bias–corrected model performs slightly better.

The use of a secondary dataset for computing scores, as well as the manifold situations stated in the literature in which non-predictable and external factors may hamper the conversion of potential donors into transplants (as delays in the transportation of organs because of traffic accidents or flooding areas), highlights the importance of comparing productivity of DEA traditional and bootstrap-corrected scores.

As can be seen in Table 4, in the uncorrected model there are five efficient states (score = 1.000) - ES, PR, SC, SP, and TO, and the less efficient states are MT (0.053), PB (0.112), GO (0.167, PI (0,171), and MA (0.230) but in the bootstrap bias–corrected model, there are no efficient states. The traditional DEA and the bootstrap-biased model are both benevolent vis-à-vis the DMUs because they do not consider the estimator's positive bias. Considering the bootstrap bias–corrected model, the most efficient states are CE (0.864), SC (0.861), TO (0.833), ES (0.805), and PE (0.776), and the least efficient ones are GO (0.156), PB (0.239), PI (0.248), MT (0.273), and MA (0.347). Relatively speaking, the states of SC, ES, and TO remain as the most efficient states in both models—traditional and bootstrap bias-corrected—while PA and SP rank in sixth and ninth position, respectively, in terms of efficiency in the ODT process, when we consider the bootstrap bias–corrected model. This result is important because the states of Santa Catarina and São Paulo are often cited as benchmarks of the Brazilian's transplantation process [6, 13, 14]. The productivity indicator, an unlimited quotient (output/input), and not limited to the interval [0, 1], displays a pattern similar to the bootstrap bias–corrected model. The top five states are, respectively, ES (48.193), SC (37.694), CE (37.597), PR (34.882), and SP (31.214). Here, SP appears among the top five, in place of TO, as it occurred in the bootstrap bias-corrected model. Productivity shows, at the bottom of the ranking, in ascending order, the states MT (2.222), PB (5.085), GO (6.650), PI (8.140), and RR (9.375) are placed among the five worst states instead of MA, as it happened in the bootstrap bias–corrected model.

In short, Santa Catarina (SC) and Espírito Santo (ES) are among the best five placed states in all models, including the biased bootstrap model that we did not discuss above, to save space in the text. On the other hand, Goiás (GO), Mato Grosso (MT), Paraíba (PB), and Piauí (PI) are always among the five worst–performing states in all models.

As displayed in Table 5, the four models (non-corrected efficiency, NC; biased bootstrap, BB; bias-corrected bootstrap, BC; and productivity, PR) are highly correlated. Depending on the evaluation's objectives and the availability of software and data, the four models would be substitutes that could, to some extent, be used interchangeably. However, it is worth mentioning the existence of biases in traditional non corrected efficiency and productivity estimators, without the bootstrap's treatment and the possibility of carrying out various reliable statistical tests that the bias-corrected bootstrap offers.

Most Brazilian states (58%) presented a bootstrap bias-corrected efficiency score below 0.600, resulting in a low mean score of 0.550, or an overall inefficiency level of 0.450 (1.000–0.550). This signals that altogether the Brazilian states could maximize in 45% the outputs (number of transplants performed) without necessarily increasing the consumption of inputs (number of potential donors). In contrast, only 15% of states presented bootstrap bias-corrected efficiency scores above 0.800, with a considerably lower inefficiency level.

Regarding the Brazilian regions, those with the highest mean bootstrap bias–corrected scores are South (0.753) and Southeast (0.691), while Midwest has the lowest mean bias–corrected score (0.312). The North and Northeast regions had mean bootstrap bias-corrected scores of 0.560 and 0.518, respectively. The maximum (Ceará, 0.864) and minimum (Goiás, 0.156) bootstrap bias–corrected scores indicate a significant variety of states' efficiency levels. Such heterogeneity highlights the importance of benchmarking analysis as the efficiency obtained considers possible performance levels attained within the sample, comparing the conversion process of each state with other states analyzed.

There are significant economic and social differences between Brazilian states. The choice of considering only the number of notifications of brain death (as input), and the number of transplants (as output), allows the results to be analyzed from an internal management perspective of each state investigated, as a low conversion of brain death notifications into organ procurements, and then into transplants, signalize inefficiency points and human errors. In other words, once brain death is notified, the whole process must be well managed—

Table 4 Non-corrected efficiency, bootstrap biased efficiency, confidence intervals, and bootstrap bias-corrected efficiency for each of the Brazilian States and the Federal District for the year of 2018

State	Brazilian region	Non-corrected efficiency	Bootstrap biased efficiency	2.5%	97.5%	Bootstrap bias-corrected efficiency	Productivity
Acre (AC)	North	0.309	0.604	0.436	0.592	0.514	9.804
Alagoas (AL)	Northeast	0.751	0.834	0.668	0.824	0.753	27.692
Amazonas (AM)	North	0.291	0.452	0.361	0.448	0.409	12.500
Bahia (BA)	Northeast	0.647	0.599	0.451	0.584	0.520	24.584
Ceará (CE)	Northeast	0.984	0.981	0.737	0.969	0.864	37.597
Distrito Federal (DF)	Midwest	0.441	0.435	0.326	0.426	0.37	19.184
Espírito Santo (ES)	Southeast	1.000	1.000	0.716	0.970	0.805	48.193
Goiás (GO)	Midwest	0.167	0.176	0.138	0.173	0.156	6.650
Maranhão (MA)	Northeast	0.230	0.385	0.306	0.380	0.347	10.185
Mato Grosso (MT)	Midwest	0.053	0.322	0.228	0.319	0.273	2.222
Mato Grosso do Sul (MS)	Midwest	0.488	0.523	0.395	0.516	0.449	22.632
Minas Gerais (MG)	Southeast	0.774	0.746	0.558	0.735	0.655	28.509
Pará (PA)	North	0.353	0.466	0.372	0.460	0.420	16.129
Paraiba (PB)	Northeast	0.112	0.276	0.204	0.272	0.239	5.085
Paraná (PR)	South	1.000	1.000	0.617	0.968	0.774	34.882
Pernambuco (PE)	Northeast	0.893	0.879	0.663	0.866	0.776	34.100
Piauí (PI)	Northeast	0.171	0.273	0.219	0.270	0.248	8.140
Rio de Janeiro (RJ)	Southeast	0.722	0.690	0.504	0.679	0.594	26.005
Rio Grande do Norte (RN)	Northeast	0.420	0.500	0.387	0.493	0.439	20.126
Rio Grande do Sul (RS)	Southeast	0.738	0.706	0.533	0.697	0.624	27.233
Rondônia (RO)	North	0.304	0.906	0.373	0.462	0.422	12.903
Roraima (RR)	North	0.530	0.467	0.641	0.892	0.764	9.375
Santa Catarina (SC)	South	1.000	1.000	0.731	0.985	0.861	37.694
São Paulo (SP)	Southeast	1.000	1.000	0.552	0.973	0.709	31.214
Sergipe (SE)	Northeast	0.339	0.531	0.418	0.523	0.476	13.333
Tocantins (TO)	North	1.000	1.000	0.707	0.970	0.833	13.793
Mean score (Brazil)		0.566	0.644	0.471	0.632	0.550	
Minimum score		0.053	0.176	0.138	0.173	0.156	20.760
Maximum score		1	1.000	0.737	0.985	0.864	2.222

physical and human resources—so that the potential donor's organs are not wasted. In this sense, although the South, Southeast, and Midwest regions have the highest GDP and human development index in Brazil, the first two had the highest efficiency scores. In contrast, the Midwest region had the lowest efficiency bootstrap bias–corrected scores, behind the North and the Northeast, which are the least developed regions of Brazil. Also, Ceará, located in the Northeast region, is the most efficient state of the federation (0.864). Other states from the North and Northeast regions—TO, RR, CE, PE, and Al—had bootstrap bias–corrected efficiency scores higher than 0.700. Therefore, the results represent an initial step for further improvements, pinpointing within the Brazilian reality what states are being successful in the donation-transplantation conversion process and what needs special attention. The maximization of transplants performed may be chased with a thorough analysis of the Brazilian activities of organ donation and transplantation, investigating the best initiatives used in the states considered a reference.

Table 5 Spearman correlation matrix (statistically significant at the 0.01 level)

	NC	BB	BC	PR
NC	1.000	0.892	0.925	0.891
BB	0.892	1.000		0.810
BC	0.925	0.887	1.000	0.791
PR	0.891	0.810	0.791	1.000

In short, the low-efficiency scores and the significant variability among states indicate strong asymmetries in the implementation and management of resources for donation/transplants among the states. This heterogeneity of the Brazilian performance is in line with the results of previous national studies, such as those conducted by Costa et al. [17], Marinho, Cardoso and Almeida [16]; Marinho et al. [58]; and Marinho and Cardoso [59]. Despite the differences among the studies, including variables, method, year, states, they all point out inefficiencies and considerable room for improvements in the ODT process in Brazil.

Figure 1 shows the original efficiency, bias-corrected efficiency, bias-corrected efficiency, and the confidence interval. São Paulo (SP) is the most developed state in Brazil and makes approximately 30% of transplants in this country [60]. It is an important center for technology and workforce training and treats many patients from other states. Thus, the outlier behavior is not due to errors in the data nor to highly atypical observations. In this sense, removing SP from the sample would greatly distance the model from the Brazilian reality. Moreover, looking at Fig. 1, it is observed that removing SP from the sample would not change the boundary. Nevertheless, we performed a model without São Paulo, and the efficiency scores of the other states remained unchanged.

The solid line is the uncorrected (original) DEA frontier, closer to the observations, as expected. Next, from lower to upper, the dotted line (...) is the corrected frontier; the top dashed line (–-) is the upper confidence interval of 95%.

The graph allows us to infer the existence of a frontier with non-increasing returns to scale. There is a slight decrease in the frontiers' slope after 500 notifications (value close to that observed in Santa Catarina).

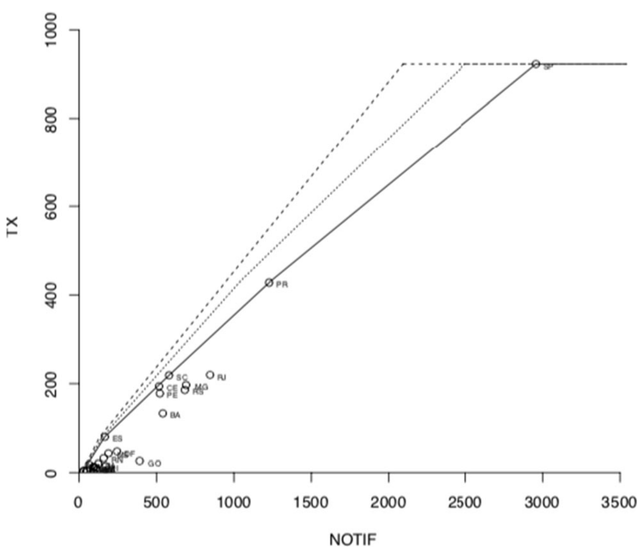

Fig. 1 Uncorrected model, bias-corrected model, and confidence interval. Number of brain death notifications, or potential donors, at the horizontal axis vs. number of effective donors, or transplants performed, at the vertical axis. Bottom to top: uncorrected model (solid line), bias-corrected model (dotted line), and confidence interval (dashed line)

It is noted that the frontiers diverge for high output values (transplants), except for the outlier (SP), but converge for low output values. This is because, for higher transplants (Tx) values, any positive deviation may increase the technology, thus shifting the frontier upwards. For example, if Tx = 1000 belongs to technology, Tx = 1100 can also come to belong. For low Tx values, the small positive deviations would not have much influence. In an output-oriented model, as used in this study, inefficiency is often high for low output values and would not be significantly affected by small deviations of Tx at low production levels.

4 Final remarks

This research contributes to the literature on the efficiency of the ODT process. It delivers relevant findings regarding the methodology applied and the performance of the Brazilian National Transplantation System, a key component of the Brazilian National Health System.

To our best knowledge, this is the first study that applies DEA with bootstrap to assess the efficiency of the ODT process, and the results reveal that this is an essential difference concerning the six previous studies that applied DEA do make this type of assessment. This research shows that it is important to correct the scores of conventional data envelopment analysis (DEA) models through bootstrap since it provides greater robustness to the studies based on DEA and changes the efficiency scores and the results of the benchmarking analysis. The joint application of these two methodologies in ODT data for Brazil revealed a change in the efficiency scores that the deterministic estimates, generated by DEA, attributed to major Brazilian states, such as São Paulo (SP) and Santa Catarina (SC), which are often cited as benchmarks of organ transplants in Brazil. In fact, we found that Santa Catarina (SC) and Espírito Santo (ES) are among the best five placed states in all models we performed.

We were also able to show, in a regression model, that the number of transplants is susceptible to the number of brain death reports because the elasticity is equal to 1341. However, this sensitivity should be increased because a donor can potentially donate several organs and tissues (liver, lungs, heart, kidney, pancreas, cornea, etc.), and each transplanted organ counts as a transplant carried out in our data.

In short, the findings of this study advise researchers that it is essential to be aware of the measurement errors, randomness, and bias present in the application of DEA models to perform benchmark analysis. The results also inform policymakers that there is room for improvement in transforming potential donors into actual donors in all Brazilian states and the Federal District, including ES, PR, SC, and TO, that were considered efficient when applied the traditional DEA model without bias correction through bootstrap or even in the productivity model. In addition, the comparison of the findings using graphs made with R facilitates the understanding of the problems addressed.

We are aware of the limitations of our research. First, this study is limited by the sample size that encompasses only one year. We believe this is not a serious shortcoming because we wanted to portray the last year with available and reliable data and avoid dealing with serial correlations and seasonal effects. Moreover, an intertemporal analysis would be almost impossible to be plotted on a graph containing confidence intervals in the same way that was presented in Fig. 1. Additionally, the model had good discrimination capability, marking only 5 out of 26 DMUs as fully efficient in the model without bias correction. We believe that, in the end, the relatively small number of DMUs in the sample caused no problem. The bootstrap also addresses this limitation of the DEA method as it provides the efficiency scores with stochastic properties and eliminates the bias. Finally, Charnes et al. [61] suggest a widely adopted—although with no theoretical support—rule of thumb that the number of DMUs should be at least three times the number of factors (inputs and outputs). We use one output and one input. According to this rule, we should use at least six DMUs but we go much further, since we use 26 DMUS. Moreover, we cannot expand the sample, because there are just 27 states in Brazil (the state of Amapá was excluded because there is no record of transplants there).

Second, our study is not disaggregated by organ type. This occurs for the sake of simplicity and mainly because our focus is on notifications (potential donors) and donors whose organs were transplanted despite the type of organ transplanted. We know that one donor can potentially donate several organs.

Some possible avenues for future research include (a) integrate quality of transplantation indicators (e.g., graft survival after transplant) into efficiency frontiers, and to address the incorporation of undesirable outputs (e.g., graft rejection) and uncontrollable variables (e.g., recipient age/sex) in DEA models; (b) to consider exogenous determinants of efficiency that might affect transplants' performance in the spirit of Simar and Wilson [62], which regress estimates of efficiency on some covariates in a second stage; and (c) improvement of efficiency frontier by improving the data quality with a more extended sample as it becomes available and yet considering other models. Below we present these three points in detail.

In addition to its practical gist, this study aims to serve as an academic stimulus, given ODT's scarce efficiency literature using quantitative methodologies. As a continuation of the current effort, and considering the results found here, we suggest the qualitative investigation of DMUs with worse and better efficiency scores, aiming to identify successful practices and management obstacles. Case studies and in-depth interviews with state transplant-coordinators (professionals responsible for managing the donation-transplantation activities at the state level) are appropriate for such purposes. This may enrich the efficiency discussion and help us understand what main technical and human failures corroborate the non-conversion of potential donors into transplants. Another possibility is to seek the perspective of families that have gone through the decision to donate organs from a loved one.

Additionally, a DEA model covering more extended periods would allow tracking results before and after adopting specific initiatives (such as awareness campaigns and hospital quality programs regarding organ donation and transplantation).

Finally, the use of a two-stage DEA model would allow identifying factors that impact the efficiency of DMUs. It is worth noting that little is known about the type and degree of impact that various contextual factors, non-discretionary in the short and medium-term, can affect the supply and demand of organs for transplantation. The inclusion of variables that distinguish Brazilian states in social and economic terms encourages reflection in this poorly investigated field."

Authors' contributions Both authors contributed to the study conception and design. Alexandre Marinho was responsible mainly for the methodology and statistical analysis; Claudia Araujo was responsible mainly for the literature review. Both authors read and approved the final manuscript.

Data availability This research uses secondary data obtained from official documents—the Brazilian Transplantation Registry of the Brazilian Organ Transplant Association (ABTO), edition of 2018. (available at: http://www.abto.org.br/abtov03/Upload/file/RBT/2018/Lv_RBT-2018.pdf).

Code availability Not applicable.

Declarations

Conflict of interest The authors declare that they have no conflicts of interest.

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