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TWO-STAGE RESEARCH PERFORMANCE ASSESSMENT OF TURKISH HEI USING DEA AND BETA REGRESSION

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Abstract:
In this paper, we study the research efficiency of the Turkish higher education sector in a two-stage DEA model with variable returns to scale. The aim of this paper is to benchmark or rank universities according to their research performance and to identify exogenous factors that may affect an institution's efficiency score. DEA scores are a prime example of fractional data - a fact that has been disregarded by many previous DEA models which used popular Tobit regression for censored data in the second stage. Using a sample of 50 private and public universities, the first stage of our model calculates the efficiency scores and determines the efficient reference set for inefficient universities. In the second stage, we use beta regression and bootstrapped hypothesis testing to estimate the effects that external factors (age, size and ownership status) have on efficiency scores. We find that 27 universities in our sample are research efficient. Beta regression summary statistics suggest that extra-large universities tend to be less research efficient than large universities (p=0.1), while both age and ownership status of the university do not have a statistically significant impact on an institution's efficiency score.

Keywords:
Higher education institutions; Research efficiency, Two-stage DEA, Beta regression, Bootstrapped hypothesis testing

JEL Codes:
C12, C14, L25, L33

1. Introduction
The higher education sector in Turkey has experienced tremendous growth in recent years. Among the 208 universities currently accredited by the Turkish Council of Higher Education (YÖK), over 70 were founded in the last 10 years and over 130 universities in the last 20 years (Council of Higher Education, 2019). At the same time, the number of students registered in an undergraduate programme has more than tripled, from around 1.2 million in 2000 to around 4.4 million in 2018, while in the same period, the number of foreign students increased from 16,000 to more than 125,000. Due to population structure, the important role (higher) education plays in the development of the Turkish economy (Mercan, 2013; Mercan and Sezer, 2014; Yurtkuran and Terzi, 2015). Since Turkey's expenditures per student from primary to tertiary education are one of the lowest among OECD countries (Organization for Economic Co-operation and Development, 2018), the Turkish educational sector still has strong potential to grow further in the future. Turkey's current sector of higher education can best be described as highly dynamic mass education, and recent policy changes implemented by the Turkish Council of Higher Education have placed an emphasis on the financial support of classified research universities. Hence, it is crucial for Turkish universities to assess their research performance, not only to manage the scarce monetary and educational resources but also to succeed in this extraordinarily competitive environment. Accordingly, this paper aims to study the research performance of Turkish universities and higher education institutions and attempts to examine the effects

that various exogenous variables that are not under the direct control of the university might have on the institutions' research efficiency.
Traditional performance measures and university rankings, such as the Academic Ranking of World Universities (ARWU), published by the Shanghai Ranking Consultancy or the Times Higher Education World University Ranking, are disadvantaged in that they use arbitrarily chosen and fixed weights for different variables to calculate a global score. Therefore, they provide little insights for identifying both internal and external key variables to improve the efficiency of the institution. In this paper, we therefore use a two-stage analysis in which we combine a classical output-orientated data envelopment analysis (DEA) model with beta regression. DEA has become a popular tool in recent years mostly due to its advantage of being a non-parametric method which aims to compare and benchmark different but nevertheless comparable homogeneous decision-making units (DMUs) in terms of their performance and efficiency based on a chosen set of inputs and outputs. The method was first established by Charnes et al. (1978, 1981) who advanced the earlier work of Farrell (1957) and has since been extensively used to assess the performance and efficiency of DMUs in many sectors and industries, such as sea- and airports (Barros and Dieke, 2007; Koçak, 2011; Odeck and Brathen, 2012), the energy sector (Mardani et al., 2017; Sueyoshi et al., 2017; Zhou et al., 2008), the financial and banking sector (Bak and Gölcükcü, 2002; Berger and Humphrey, 1997; Özkan-Günay and Tektas, 2006) or hospitals and health care (Balkan, 2021; Harrison and Meyer, 2014; Ilgün et al., 2021; Kohl et al., 2019; Kücük et al., 2020), among others. Unsurprisingly, there also exists a large body of literature on using DEA to evaluate and compare universities and institutions of higher education either within one country (Abbott and Doucouliagos, 2003; Agasisti and Bianco, 2006; Athanassopoulos and Shale, 1997; Avkiran, 2001; Casu and Thanassoulis, 2006; Eckles, 2010; Fandel, 2007; Leitner et al. 2007; Mousa and Ghulam, 2019; Shamohammadi and Oh, 2019) or across different countries (Agasisti and Johnes, 2009; Agasisti and Pohl, 2012; Agasisti and Pérez-Esparrells, 2010; Agasisti and Wolszczak-Derlacz, 2016; Daraio et al., 2015). Moreover, Liu et al. (2013) list over 180 articles that apply DEA to the educational sector, and obviously, a complete review of all this literature would be beyond the scope of this introduction. More closely related to our current paper, however, is the recent paper by Koçak and Örkcü (2021) who analyse the graduate education performance and the scientific and technological research competency of 50 Turkish state universities in a two-stage DEA model. A select and more detailed overview of further international DEA studies focused on research efficiency is also presented in Table 1.
Although DEA is a useful tool to compare and benchmark DMUs based on a chosen set of inputs and outputs, the analysis usually fails to assess the influence of external factors, which are exogenously given and, hence, uncontrollable from the point of view of the DMUs, on efficiency. Two-stage analysis is a common adjustment to address this shortcoming. The first stage is then to calculate the efficiency scores of each DMU via the traditional DEA approach, while in the second stage these efficiency scores are used as the dependent variable in a simple linear regression model to estimate the impact the external factors have on efficiency. Due to its simplicity, two-stage DEA is very popular, and many papers use either Tobit regression for censored or truncated data (Ilgün et al. 2021; Bang and Sahay, 2014; Celen, 2013; Grmanova and Strunz, 2017; Kutlar et al., 2013; Latruffe et al., 2004; Sağlam, 2018; Selim and Bursalıoğlu, 2013; Turner et al., 2004; Wu et al., 2016) or bootstrapped truncated regression (Assaf et al., 2011; Barros and Peypoch, 2009; Du et al., 2018; Fernandes et al., 2018; Wanke and Barros, 2014; Wolszczak-Derlacz, 2017) in the second stage. However, as McDonald (2009) points out, DEA scores are neither censored nor truncated but rather fractional. Hence, Tobit regression is not an appropriate choice for a valid second-stage analysis of the efficiency scores.

Table 1. Summary of selected DEA literature on research efficiency of universities and other higher education institutions

Authors	DMUs	Inputs	Outputs
Xiong et al. (2018)	17 Chinese research institutes	2 (R&D labour, R&D expenditures)	3 (number of patents, number of published papers, income from licences)
Lee and Worthington (2016)	37 Australian Universities	2 (academic staff, number of PhD students)	2 (publication, grants)

Moncayo-Martínez et al. (2020)	40 Mexican universities	3 (full and part-time teachers, money received by federal or local government, researchers in Researchers' National System)	3 (number of indexed journal papers, number of patents granted in Mexico, number of accredited postgraduate programs)
Abramo et al. (2011)	78 Italian universities (divided into subgroups according to research fields)	3 (staff-years of full professors, staff-years of associate professors, staff-years of assistant professors)	1 (scientific strength)
Johnes and Yu (2008)	109 Chinese universities	6 (staff time, staff quality, proportion of postgraduates, research expenditures, library books, area of buildings)	3 (prestige of university, total number of publications, publications per member of academic staff)
Sagarra et al. (2017)	55 Mexican universities	3 (full-time faculty, total enrolment, first joining graduates)	3 (publications in SCOPUS, graduates)
Navas et al. (2020)	157 Colombian universities and institutions of higher education	4 (Saber 11 test results, number of professors with PhD, number of professors with master degrees, number of undergraduate students)	1 (number of articles)
Tekneci (2014)	94 Turkish universities	3 (number of faculty members, number of research assistants, 3-year sum of research investment funds)	4 (number of indexed publications, number of citations, number of PhD graduates, number of projects funded by the Scientific and Technological Research Council of Turkey)
Johnes and Johnes (1993)	36 economics departments at British universities	2 (staff time of personnel performing only research, staff time of personnel performing teaching and research)	2 (publications, grants)

Due to these shortcomings, Hoff (2007) and Ramalho et al. (2010) proposed logit fractional regression models (Papke and Wooldridge, 1996) as an alternative to traditional linear and Tobit regression models in the second-stage DEA. The use of fractional regression models in second-stage DEA has gained momentum in recent years, and many researchers now begin to use fractional regression to estimate the effects of external factors on DEA scores (Almeida et al., 2020; Gelan and Nuriithi, 2012; Gutiérrez et al., 2017; Gutiérrez and Lozano, 2020; Martins, 2018; Moutinho and Madaleno, 2021; Moutinho et al., 2020, 2021; Pérez-Reyes and Tovar, 2021; Raheli et al., 2017; Tran et al., 2021).

In this paper, however, we will follow an alternative strand of research and contribute to the existing literature by using beta regression in the second stage of our efficiency analysis. Beta regression was introduced by Ferrari and Cribari-Neto (2004) as a flexible tool for regressing fractional data, such as rates and proportions. We consider it a natural choice to analyse the relationship between the fractional (output-oriented) DEA efficiency scores and exogenous factors, such as age, size and ownership status of the university. To the best of our knowledge, Andrews (2021), Pirani et al. (2018), Wohlgemuth et al. (2020) and Türkan and Özel (2017) are the only other authors who have applied beta regression in second-stage DEA so far. In particular, the latter also study the efficiency of Turkish universities in the 2014-2015 academic year by focusing on public universities. However, our approach is different, in that we not only focus on the research efficiency of Turkish HEIs but also use a much wider data set including data for both private and public universities between 2014 and 2019. This allows us to calculate the efficiency scores for a

broader range of years, and to investigate whether, besides other external factors, there also exists a relationship between the status (private vs public) of the university and its research efficiency.
The remainder of this paper is organised as follows. In section one, we describe the data and the first stage of the DEA methodology used. In this stage, five input and three output variables are used to estimate the relative research efficiency scores for each university within our sample. The second stage of our analysis is then outlined in sections two and three, in which we use beta regression and bootstrapped hypothesis testing to evaluate the effects that external environmental factors, not being under the direct control of the university, might have on these DEA efficiency scores. The last section includes a brief discussion and summary of our main results, and concludes.

2. First Stage: Data Envelopment Analysis & DEA Scores
DEA is a deterministic non-parametric linear programming technique that evaluates the relative efficiency of functionally homogeneous DMUs. Using DEA, the relative efficiency of an arbitrary decision-making unit is defined as the ratio of virtual outputs to virtual inputs. The efficiency of this DMU k is then given by the weighted sum of unit k's m factors of output, divided by the weighted sum of its n factors of input, i.e the efficiency of DMU k is given by

$$\frac{\sum_{j=1}^{m}\lambda_j y_{j,k}}{\sum_{i=1}^{n}\mu_i x_{i,k}}. \quad (1)$$

The objective of the linear programming problem is then to determine those unknown weights or decision variables that maximise the efficiency of the k-th DMU for all k={1...s} DMUs in the sample.
There are two types of DEA models: the CCR model and the BCC model. The basic CCR model was initially developed by Charnes et al. (1978) and measures the technical efficiency scores by assuming constant returns to scale (CRS), while the BCC model, as proposed by Banker et al. (1984), allows for variable returns to scale (VRS). Obviously, in most applications, these different assumptions on the returns to scale can yield significantly different estimates for the DEA scores. However, the literature offers mixed suggestions and findings on which specification to select in which application, as the appropriate choice depends on various factors, such as the industry structure or the variation of the inputs and outputs in the sample itself. In this paper, and in line with previous research on the efficiency of higher education institutions (HEIs) (Avkiran, 2001; Xiong et al., 2018; Johnes and Yu, 2008; Selim and Bursalıoğlu, 2013), we use the output-orientated BCC model, reflecting the fact that the universities in our sample are largely heterogeneous in three exogenous key-variables (size, age and ownership status) and may therefore exhibit increasing, constant or decreasing returns to scale. Moreover, the output-orientated approach was chosen because the inputs might be fixed and not controllable from the institution's point of view, at least in the short term. Another reason for using a BCC model with VRS is that CCR models are only appropriate if all institutions are fairly homogeneous and operate at an optimal level of scale (Martínez-Campillo and Fernández-Santos, 2019). In the BCC model, the linear optimisation problem can then be rewritten as

$$\max_{\lambda_j} \sum_{j=1}^{m} \lambda_j y_{j,k} \quad (2)$$

$$subject to \sum_{j=1}^{m} \lambda_j y_{j,k} - \sum_{i=1}^{n} \mu_i x_{i,k} \geq 0 \forall k = \{1...s\} \quad (3)$$

$$\sum_{i=1}^{n} \mu_i x_{i,k} = 1, \quad (4)$$

$$\lambda_j, \mu_i \geq 0, \quad (5)$$

where $x_{i,k}$ represents the value of DMU k's i-th unit of input, $y_{j,k}$ represents the value of DMU k's j-th unit of output, i and j are the weights assigned to those $i = \{1...n\}$ inputs and $j = \{1...m\}$ outputs, and s denotes the total number of DMUs in the sample.

The selection of appropriate inputs and outputs is crucial in the application of DEA as selecting too many or the wrong inputs and outputs could have an immediate effect on both the DEA scores and the discriminatory power of the model. However, the literature on how to choose an appropriate set of inputs and outputs is sparse at best, and it is a well-accepted consensus to choose those inputs and outputs that are not only considered to conform to the purpose of the institution but also positively correlated (Duan and Deng 2016; Kao et al., 1993). Moreover, there exist several rules of thumb to choose the minimum number of DMUs necessary to ensure good discriminatory power of the DEA model. Golany and Roll (1989) suggest that the minimum number of DMUs used should be at least twice the number of inputs and outputs considered. Bowlin (1998) recommends having at least three times the number of DMUs, as there are inputs and outputs. Banker et al. (1989), in turn, propose a more intricate rule of thumb, in which the sample size n should at least satisfy max(pq,p+q), where p is the number of inputs and q the number of outputs used in the analysis, while Dyson et al. (2001) advise that the number of DMUs should exceed twice the product of inputs and outputs.

Since we are interested in measuring and comparing the research efficiency of Turkish HEIs, our inputs and outputs are chosen following the previously mentioned established literature on research efficiency and reflect the particular aspects of the Turkish higher education system. Currently, the Council of Higher Education lists 208 universities and institutions of higher education, 129 of which are public and 79 of which are private foundation-based non-profit organisations. In Turkey, all universities and higher education institutions are required by law to be nationally accredited and are, moreover, supervised and annually audited for their academic and professional standards by the Council of Higher Education. Universities tend to be heterogeneous in both size and programmes offered, i.e., while public universities tend to be large in terms of the number of programmes offered, the number of professors hired, and the number of buildings and the size of the campus, private universities tend to be smaller, as they typically offer fewer programmes that are more focused on current job market demands. Accordingly, private universities have smaller campuses with fewer professors and buildings. However, academic activity in all universities is organised in faculties and departments, each department consisting of several professors at the assistant, associate and full professorship levels and at least two research assistants. For universities that do not offer doctoral programmes, research assistants are typically PhD students studying at a different Turkish university but usually publish their research in the name of the university they are employed at. Moreover, in Turkey there exist no teaching-only universities, and both professors at all levels as well as research assistants are expected to do research, and the number of published articles in established journals is one of the main criteria for contract renewal and promotion in private universities. In this competitive environment, grants from the Scientific and Technological Research Council of Turkey (TÜBITAK) play an important role in so far as many smaller universities are short of funding. Grants are subject to a thorough review process and, after a successful application, funds are paid for specific research projects with a minimum duration of at least 6 months to a maximum of three years. The grant usually finances all research activities related to the funded project such as additional laboratory equipment, travel costs for the researchers or any additional costs to third parties, and the project should yield a minimum of one research paper published in an established national or international journal. Unlike in many other countries, however, the grant cannot be used by the department or university to hire additional full-time or part-time academics or by the researchers to buy themselves out of their teaching obligation.

Traditionally, the primary role and purpose of universities has been to contribute to the well-being and advancement of societies and markets by being key in creating, preserving and distributing knowledge. However, the discussion on how this aim can be achieved best and most efficiently has been going on for decades if not centuries and to a large extent not only depends on cultural aspects but also changes over time (Carter, 1972; Brennan et al., 2004; Moscardini et al., 2022). It is, hence, clearly beyond the scope of this paper to give a concise summary and overview of all aspects of this discussion. However, the underlying plethora of approaches to higher education objectives and how to evaluate and measure the efficiency of institutions of higher education can be divided into the two following groups (Kupriyanova et al., 2018; Estermann and Kupriyanova, 2019):

1) Resource-based/performance-based approaches that focus on the productivity of universities, i.e. to the extent to which universities can create and distribute a maximum of knowledge with a minimum of resources.

2) Value-based approaches which also consider the extent to which universities contribute to the progress and advancement of a civil society and desirable cultural values such as equality, diversity and social justice, the promotion of democracy or sustainability, or the inclusion and empowerment of minorities, among others.

While it may be correctly criticised that the first approach might be too technical and certainly too narrow to truly understand the social benefits of universities and academic research, the latter approach is more unified but harder to capture and to measure from an empirical point of view. Moreover, resource-based approaches, despite their narrowness and shortcomings, are still useful and key in providing valuable information and actionable insights for the strategic development of universities (Lynch and Baines, 2004). For that reason, our paper will follow the resource-based view.

Based on these considerations and following the literature on DEA and research efficiency of HEIs, a select overview of which was presented in the previous section, we choose inputs that reflect both physical and human capital, while our outputs are related to established research metrics, such as the Hirsch-index and the number of publications for which the university received funding from the supervising Council of Higher Education.

To be precise, our model includes inputs that take into account both monetary and human capital, while our outputs are related to established research metrics, such as the H-index and the number of published articles in indexed journals. In detail, our set includes the following five inputs:

1) The average yearly research funding and grants allocated by the Scientific and Technological Research Council of Turkey for projects between 2014-2018.
2) The average number of full professors between 2014-2019.
3) The average number of associate professors between 2014-2019.
4) The average number of assistant professors between 2014-2019.
5) The average number of research assistants between 2014-2019.

and the following three outputs:

1) The H-index which, based on the number of cited articles, quantifies the impact and research productivity of the HEI between 2015-2019 measuring the impact and quality of the research articles.
2) The number of articles published between 2014 and 2018, and for which the HEI received funding from TÜBITAK as a proxy for both the quantity (absolute number of research articles) and the quality of the research (as funded research has gone through an internal review process and publication in indexed journals is an obligation for receiving the research fund). A similar idea was followed by Agasisti and Ricca (2016).
3) The number of graduate degree programmes offered by the HEI in 2019 as a proxy for the extent and variety of the university to promote and facilitate research and disseminate knowledge. An alternative variable would be to consider the number of students registered for the graduate programmes offered. However, unlike the number of graduate programmes offered, this number is not under the direct control of the HEI.

Table 2. Pearson correlation coefficients for inputs and outputs in our DEA model.

Outputs	H-Index	TÜBITAK Articles	Graduate Programmes
Inputs			
Project Grants	0.5396***	0.8388***	0.236*
Full Professors	0.5193***	0.4279***	0.9094***
Assoc. Professor	0.4378***	0.3917***	0.9398***
Asst. Professors	0.2215	0.1195	0.7600***

Research Assistants	0.4372***	0.3388**	0.8946***

Note: *p<0.1, **p<0.05, ***p<0.01

Table 2 presents the Pearson correlation coefficients for the inputs and outputs. The results show that a moderate to strong positive correlation exists between most inputs and the research outputs. This further corroborates the choice of inputs in our BCC model to assess the ability of each HEI to produce research outputs most efficiently with those inputs at hand. Data for the above inputs and outputs were collected for a sample of 50 of the 138 more established Turkish universities, i.e. which were older than 10 years and located in different regions in Turkey. Sources included the websites of TÜBITAK and YÖK, the Web of Science, Scopus, and the individual websites of the universities in our sample.

DEA scores were estimated using the deaR package in the statistical software R, and Table 3 summarises the estimated research-efficiency scores and reference sets for the inefficient universities using the BCC model. For comparison and to determine the technical and scale efficiencies of the DMUs, and whether the data exhibits constant (CRS), decreasing (DRS) or increasing (IRS) returns to scale, the table also includes the scores of the CCR model. Moreover, we report the bootstrapped 99% confidence intervals for the BCC scores to provide some inference. Confidence intervals were calculated using the bootstrap procedure proposed by Simar and Wilson (1998) with 12.000 bootstrap repetitions.

Table 3. DEA scores for the CCR and BCC models, the bootstrapped 99% confidence intervals of the BCC scores, the reference sets, scale efficiencies and returns to scale of the HEIs in our data set.

		CCR Model	**BCC Model**					
DMU	**University**	**Efficiency Score**	**Efficiency Score**	**Lower CI**	**Upper CI**	**Reference Set**	**Scale Efficiency**	**RTS**
1	Acıbadem	0.758	1	0.699	1	X	0.758	IRS
2	Adnan Menderes	0.753	0.753	0.660	0.753	Bartın (40%), Marmara (38%), Özyeğin (22%)	1	DRS
3	Akdeniz	0.610	0.643	0.557	0.643	Boğaziçi (6%), Gaziantep (18%), TOBB (16%), Marmara (56%), Özyeğin (4%)	0.949	DRS
4	Ankara	1	1	0.753	1	X	1	CRS
5	Atatürk	0.736	0.788	0.652	0.788	Boğaziçi (19%), Gaziantep (10%), Marmara (71%)	0.934	DRS
6	Atılım	0.930	1	0.766	1	X	0.930	IRS
7	Bartın	1	1	0.700	1	X	1	CRS

8	Bilkent	1	1	0.699	1	X	1	CRS
9	Boğaziçi	0.920	1	0.748	1	X	0.919	DRS
10	Bülent Ecevit	0.729	0.842	0.722	0.842	Bartın (71%), Gaziantep (10%), Hitit (9.5%), Marmara (9.5%)	0.866	DRS
11	Canakkale	0.738	0.934	0.883	0.933	Bartın (35%), Marmara (22%), Özyeğin (43%)	0.791	DRS
12	Celal Bayar	0.608	0.804	0.710	0.803	Gaziantep (34%), Hitit (53%), Marmara (8%), Mersin (5%)	0.756	DRS
13	Cukurova	0.993	1	0.831	1	X	0.993	DRS
14	Cumhuriyet	0.706	0.789	0.741	0.789	Bartın (55%), Marmara (32%), Özyeğin (13%)	0.894	DRS
15	Kilis 7 Aralık	1	1	0.698	1	X	1	CRS
16	Dokuz Eylül	0.733	0.759	0.626	0.759	Bilkent (5%), Ege (14%), Marmara (75%), Yeditepe (6%)	0.965	DRS
17	Düzce	0.707	0.870	0.775	0.870	Bartın (67%), Gaziantep (12%), Marmara (7%), Özyeğin (14%)	0.813	DRS
18	Ege	1	1	0.777	1	X	1	CRS
19	Erciyes	1	1	0.897	1	X	1	CRS
20	Fırat	0.611	0.624	0.541	0.624	Gaziantep (31%), Izmir Economics (1%), Marmara (36%), Özyeğin (4%), TOBB (28%)	0.979	DRS
21	Gazi	0.962	0.995	0.842	0.995	Ankara (33%), Izmir Tech. (0.5%), Marmara (37%), Uludağ (29.5%)	0.967	DRS
22	Gaziantep	0.948	1	0.785	1	X	0.948	DRS
23	Gaziosmanpaşa	1	1	0.699	1	X	1	CRS

24	Gebze Technical	0.728	0.830	0.657	0.830	Ankara (2%), Izmir Tech. (54%), Izmir Economics (26%), Sabancı (18%)	0.877	IRS
25	Hacettepe	0.829	1	0.835	1	X	0.829	DRS
26	Hitit	0.910	1	0.745	1	X	0.910	DRS
27	Inönü	0.813	0.813	0.813	0.800	Bartın (50%), Erciyes (19%), Izmir Economics (6%), Marmara (25%)	1	IRS
28	Istanbul Medipol	0.650	0.676	0.605	0.676	Izmir Economics (33%), Özyeğin (42%), Marmara (14%), Sabancı (11%)	0.962	DRS
29	Istanbul Technical	0.716	1	0.731	1	Ankara (29%), Boğaziçi (68%), Hacettepe (3%)	0.716	DRS
30	Istanbul	0.695	1	0.839	1	X	0.695	DRS
31	Izmir Technical	1	1	0.699	1	X	1	CRS
32	Izmir Economics	1	1	0.699	1	X	1	CRS
33	Karabük	0.820	0.871	0.750	0.870	Bartın (47%), Gaziantep (5%), Izmir Economics (3%), Hitit (39%), Marmara (6%)	0.942	DRS
34	Karadeniz Technical	0.516	0.610	0.534	0.610	Boğaziçi (40%), Gaziantep (23%), Marmara (37%)	0.845	DRS
35	Koç	1	1	0.764	1	X	1	CRS
36	Kocaeli	0.488	0.571	0.508	1	Boğaziçi (10%), Gaziantep (14%), Gaziosman (15%), Özyegin (34%), Marmara (27%)	0.854	DRS
37	Marmara	1	1	0.704	1	X	1	CRS
38	Mersin	1	1	0.731	1	X	1	CRS
39	Middle East Technical	0.958	1	0.720	1	Ankara (4%), Boğaziçi (52%), Ege (14%), Marmara (16%), TOBB (14%)	0.958	DRS

40	Ondokuz Mayıs	0.733	0.735	0.608	0.735	Erciyes (6%), Izmir Economics (35%), Marmara (39%), Uludağ (20%)	0.997	IRS
41	Özyeğin	1	1	0.699	1	X	1	CRS
42	Pamukkale	0.626	0.690	0.579	0.690	Bartın (5%), Gaziantep (73%), Marmara (20%), Özyeğin (2%)	0.908	DRS
43	Sabancı	1	1	0.699	1	X	1	CRS
44	Sakarya	0.891	0.996	0.897	0.996	Bartın (65%), Marmara (35%)	0.895	DRS
45	Selçuk	0.819	0.824	0.729	0.824	Bartın (23%), Marmara (61%), Özyeğin (16%)	0.993	DRS
46	Süleyman Demirel	0.667	0.733	0.688	0.733	Bartın (28%), Marmara (41%), Özyeğin (31%)	0.910	DRS
47	TOBB	1	1	0.699	1	X	1	CRS
48	Uludağ	1	1	0.763	1	X	1	CRS
49	Yeditepe	1	1	0.699	1	X	1	CRS
50	Yıldız Technical	0.792	0.915	0.777	0.914	Boğaziçi (27%), Gaziosman (8%), Izmir Tech. (37%), Marmara (28%)	0.866	DRS

The results show that DEA scores range from 0.571 to 1, with an average score of 0.901. Moreover, there are 31 universities whose efficiency scores exceed 0.9, and 27 universities are found to be research efficient under the BCC model with the maximum score of 1. Under the CCR model, however, 17 universities are research efficient, reaching this maximum score. For the CCR model, our results are moreover partially in accordance with Koçak and Örkcü (2021) who found that in a sample of 53 established state universities 15 (Ankara, Atatürk, Boğaziçi, Ege, Gazi, Gebze, Hacettepe, Istanbul, Istanbul Technical, Izmir Tech., Karadeniz Tech., Kahramanmaraş Sütçü Imam, Middle East Tech., Mimar Sinan Fine Arts, Süleyman Demirel, Yıldız Tech.) were efficient in terms of either their research performance or both graduate education and research.

Information regarding scale efficiency and returns to scale can be summarised as follows: 17 universities exhibit constant returns to scale, which implies they are operating at their optimal size for research. As for the 33 scale inefficient universities, 28 exhibit decreasing returns to scale, while only five show increasing returns to scale. This suggests the latter are too small to operate at their most productive scale size, while the former are too large to take full advantage of their scale. Those large universities can improve their scale efficiency by downsizing, i.e. by closing some programmes or by separating their research activities into distinct units. It is worth mentioning that BCC efficiency scores are relative scores and do not indicate absolute efficiency, which has two main important consequences. First, although efficiency in our data set is high, Turkish universities might score lower compared to a different reference group. Second, one institution might have a BCC score of one but may nevertheless be too large or too small in its inputs, and hence exhibit either decreasing or increasing returns to scale (as, for example, Acibadem, Cannakale and Cukurova in our data set).

The question of how and to what extent their resources are effectively and efficiently used may be of particular interest not only for the management of inefficient universities, but also for governmental supervisors in the assessment of scarce financial resources. Using Istanbul Medipol University as an example, we show how the DEA framework can help managers and supervisors get valuable information that can be turned into actionable insights to deal with these questions. According to Table 3, Istanbul Medipol University exhibits decreasing returns to scale and has a BCC efficiency score of 0.676, which means that in order to become (weakly) efficient, this DMU must increase its research output by approximately 47.9% (calculated as the inverse of the efficiency score minus 1), without further adjustment of its inputs. In theory, further output (and hence efficiency gains) can be obtained if the DMU has slacks, i.e. if the DMU can improve its efficiency by reducing its inputs or increasing its outputs in different proportions. Table 4 summarises the slacks for Istanbul Medipol University and shows that this university - compared to its efficient peers - has to increase its outputs, i.e. the H-index by 25% and the number of TÜBITAK articles by 240% to become efficient. Moreover, the input slacks show that Istanbul Medipol University has unused resources and should therefore reduce both its human and physical capital as these excess resources do not sufficiently contribute to research. That is to say, the management of Istanbul Medipol University may reduce the number of assistant professors by 40% and the number of research grants by 10% without affecting the research efficiency of the institution. These technical results have to be taken with a grain of salt as these inputs could contribute to the university's efficiency in other ways that are not captured by the DEA model. Nevertheless, the slacks can provide managers with useful information about the source and nature of their institution's inefficiency, and are therefore key to better decision-making.

Table 4. Slacks and expected efficiency improvement for Istanbul Medipol university.

Inputs to be lowered	Slacks	Outputs to be raised	Slacks
Project Grants	4.46 (10%)	H-Index	6.01 (25%)
Assistant Professors	123.07 (40%)	TÜBITAK Articles	263.49 (240%)

3. Second Stage: Beta Regression Analysis & Effects of External Factors on DEA Scores

The calculation of the DEA scores in the first stage of our analysis was purely based on the chosen set of inputs and outputs. However, efficiency scores may also be influenced by external factors beyond the direct control of the university, and may therefore represent factors other than efficiency (Fizel and Nunnikhoven, 1992). Our particular choice of those external factors (age, size and ownership status) is motivated by both the theory of the institutional learning curve and the fundamental economic principle of diminishing marginal returns. While the former states that as firms and institutions grow older, they gather experience, and that accumulated experiences enable them to use their inputs more efficiently, the latter principle indicates that larger institutions not only tend to have more overhead and bureaucracy but are also considered less flexible, which clearly should harm their efficiency. Moreover, Agasisti and Ricca (2016) show that there exist differences in the technical efficiency of Italian universities due to their ownership status, i.e. that private universities in Italy are relatively more efficient than public ones. We hypothesise that a similar relationship might also hold for Turkey.

To assess the impact these three main uncontrollable external factors age, size and ownership of the university have on research efficiency, we now use the DEA scores we obtained in the previous section as a dependent variable in the following regression model specification with a logit link function

$$logit(DEA) = ln\left(\frac{DEA}{1-DEA}\right) = \beta_0 + \beta_1 AGE + \beta_2 SZE + \beta_3 OWN. \quad (6)$$

The basic idea of the logit link function is to convert the linear combination of the values of the independent variables, which may take any value between minus and plus infinity, to the scale of a probability or proportion, i.e. a value between 0 and 1. We chose the three exogenous factors age (AGE), size (SZE) and ownership status (OWN) of the university as independent variables. Data on these variables were obtained from uniRank and the statistical database provided by YÖK. Measurements of the variables are as follows: AGE in years passed since the HEI was founded; SZE in four categories, S, (fewer than 5,000 students enrolled), M, (more than 5,000 but fewer than 12,000 students enrolled), L, (more than 12,000 but fewer than 30,00 students enrolled) and XL, (more than 30,000 students enrolled); and finally, OWN in the binary categories 0 for private and 1 for public. Please note that the impact of the variable SZE in our regression model differs from the scale efficiency obtained in the previous section. While scale efficiency measures if an organisation performs on the most productive scale or not, and hence, indicates whether one particular institution is too large or too small in terms of its inputs, variable SZE in the regression model quantifies the impact of the size of the institution (as measured in the number of students) on the efficiency scores and can therefore be used to directly compare the effect on the research efficiency of two institutions with the same age and ownership status, but which only differ in their size. Moreover, we expect the size of the HEI to be a relevant variable for its efficiency. Omitting this variable would therefore lead to the well-known omitted variable bias.

As stated previously, DEA scores are a prime example of fractional data. Accordingly, we use the betareg package (Cribari-Neto and Zeileis, 2010), which implements beta regression for fractional data in the statistical software R, to estimate the coefficients. Summary statistics of the estimation results are reported in Table 5 and indicate that the coefficient for extra-large universities is statistically significant at the 10% confidence level, while the remaining coefficients for the age and ownership status of a university are statistically insignificant. That is to say, our results suggest that, as expected, extra-large universities tend to be less research efficient than large universities. These results partially contrast with Türkan and Özel (2017) and Agasisti and Ricca (2016). While the former find that both the size (as measured in the number of students) and the age of public universities had no statistically significant effects on their general research and teaching efficiency, the latter conclude that the type of university (private/public) appears to have an effect on the efficiency of universities in some Italian regions.

Table 5. Summary statistics of the beta regression results using the scores from the BCC model as the dependent variable.

	Dependent Variable
	DEA Score
Age	0.009 (0.008)
Size M	0.060 (0.554)
Size S	0.234 (0.610)
Size XL	-0.828* (0.430)
Status (Public)	0.034 (0.479)
Constant	2.337*** (0.491)
Observations	50
R-Squared	0.2574
Log Likelihood	72.41

Note: *p<0.1, **p<0.05, ***p<0.01

For a more specific interpretation of the coefficients reported in Table 5, we have to remember that, due to the use of the logit link function in the above equation, the estimated coefficients do not run on a linear, but rather on a log-odds scale, a thorough description of which is, for example, given by MacKenzie et al. (2018). In the context of our model, these odds are defined as the ratio of DEA scores, i.e.

$$odds = \frac{DEA}{1-DEA} \tag{7}$$

However, a simple rearrangement of terms in Equation (6) shows the odds to be also equivalent to

$$odds = exp(\beta_0 + \beta_1 AGE + \beta_2 SZE + \beta_3 OWN). \tag{8}$$

In terms of changes in our two statistically significant variables, Equation (8) is then more straightforward and easier to comprehend. For instance, as the coefficient for extra-large universities yields -0.828, we can conclude that increasing the size of the university by one category (from L to XL) decreases the log-odds in the efficiency scores by 0.828 points. This is equivalent to saying that moving from large to extra-large universities decreases the odds of the research efficiency scores by a factor of exp(-0.828)≈0.437 or by about 56.3%.

4. Bootstrapping DEA Scores & A Different View on Hypothesis Testing

Besides simply calculating the confidence intervals of DEA scores, the bootstrap procedure can also be used to test various hypotheses about the efficiency or features of our HEIs and to estimate the p-value of a certain null hypothesis H_0. In our case, we want to give a different view on testing the hypothesis that private universities tend to be more research efficient than public ones. That is to say, we test the null hypothesis $H_0: E[\lambda_1] = E[\lambda_2]$ versus the alternative hypothesis $H_1: E[\lambda_1] > E[\lambda_2]$, where $E[\lambda_1]$ denotes the (expected) average BCC efficiency score of private and $E[\lambda_2]$ the average BCC efficiency score of public universities.

The null H_0 is then typically rejected if the corresponding p-value is considered to be too small or if the ratio

$$\tau_{obs} = \frac{n_1^{-1}\sum_{i\in\chi_1}\lambda_i}{n_2^{-1}\sum_{i\in\chi_2}\lambda_i} \tag{9}$$

of the empirical DEA scores λ_i in the two groups $i \in \{\chi_1, \chi_2\}$ becomes significantly larger than 1. However, there exists no straightforward closed-form solution to either directly calculate the p-value or decide whether the above ratio is significantly larger than 1. Instead, Simar and Wilson (2008) suggest using a bootstrap procedure with B repetitions to calculate the $b = \{1 \dots B\}$ ratios

$$\tau_b^* = \frac{n_1^{-1}\sum_{i\in\chi_1}\lambda_i^*}{n_2^{-1}\sum_{i\in\chi_2}\lambda_i^*} \tag{10}$$

of the bootstrapped DEA efficiency scores in the two groups. The p-value can then be roughly approximated by $p \approx \frac{\#\{\tau_b^* > \tau_{obs}\}}{B}$, i.e. by the percentage of which the ratio of bootstrapped DEA scores exceeds the ratio of the empirical and observable DEA efficiency scores.

With $B = 12000$ repetitions in the bootstrap procedure and denoting by n_1 and n_2 the number of private and public universities in our sample, we get $p \approx 0.845$ as the estimate for the p-value. In other words, we can not reject H_0 and do not find a statistically significant difference between private and public HEIs in terms of research efficiency. This result also corresponds to our previous findings, which we obtained through the beta regression.

5. Results & Conclusion

Assessing the research efficiency among the HEIs in Turkey became crucial after recent policy changes of the Turkish Council of Higher Education aimed to increase the competitiveness of Turkish universities in the international arena and financially support classified research universities according to their performance. Accordingly, this study employed a two-stage DEA model to measure and evaluate the research efficiency in the context of Turkish HEIs. The first stage in our DEA model obtains efficiency scores through output-oriented DEA, while the second stage correlates these scores with various contextual factors, such as age, size and ownership status of the university, using beta regression analysis and bootstrapped hypothesis testing.

Our results in the first stage indicate that research efficiency within the Turkish system of higher education is relatively high, with an average DEA score of 0.901. Results regarding scale efficiency are as follows: 17 universities in our sample exhibit constant return to scale, which implies they are operating at their optimal size for research. As for the remaining 33 scale inefficient universities, 28 exhibit decreasing returns to scale, while only 5 operate under increasing returns to scale. While these results indicate that the latter are too small to operate at their most productive scale size and can increase their average productivity by an expansion in size, the former are too large to take full advantage of their scale. These large universities could possibly improve their scale efficiency by downsizing, i.e. by closing some programmes or by separating their research activities into distinct units. The Beta regression model in the second stage of our analysis suggests that the coefficient for extra-large universities is statistically significant at the 10% confidence level. That is to say, our results indicate that extra-large universities tend to be less research efficient than large universities whereas, for age and ownership status, no statistically significant dependence on research efficiency was detected. Finally, the bootstrap procedure is used to test the hypothesis that private universities tend to be more research efficient than public ones. We confirm the previous result as we do not find a statistically significant difference between private and public HEIs in terms of their average research efficiency.

There are several limitations to this study. First, some data used in this study were taken from the Web of Science and Scopus databases. Although they are the largest academic research databases that cover multidisciplinary, scholarly literature, these databases are far from complete and do not cover all articles published in indexed journals. Second, there are several indicators for measuring the quality of publications. While the Hirsch-index is a well-accepted metric to capture the quality of research, other common metrics and indicators include the field-related impact factor or the number of article downloads and reads. However, the true impact of research should be based on its induced benefits for society and the academic community, which not only is difficult to quantify but can also take a long time to take effect and to materialise. Third, our paper focuses on research efficiency of Turkish universities. Although we find half of the universities in our sample to be research efficient it does mean that those efficient universities are also operating efficiently on an international level as DEA scores are relative scores which are calculated in relation to the other DMUs in the data set. Moreover, besides research the transfer of knowledge through teaching is another important objective of higher education and given the focus of our paper - our model is not designed to distinguish between research and teaching efficiency. Fourth, to evaluate the research efficiency of HEIs we followed a resource-based approach, which may certainly and correctly be criticised as being too technical and too narrow, as it usually does not capture alternative aims and scopes of HEIs such as the development and progress of civil societies through the promotion of equality, diversity, social justice or sustainability. Recent studies in the field of DEA (Puertas and Marti, 2019) try to close this gap, and we leave it open to future research to create appropriate DEA models that can not only capture those alternative objectives of higher education but may also include a complete data set for all 208 currently accredited Turkish universities and higher education institutions.

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