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A two-stage analytical approach to assess sustainable energy efficiency

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ABSTRACT

Administrators and policymakers at regional, national and global level are well aware of the necessity and undeniable benefits of renewable energy for long-term sustainability. In this study, we developed a two-stage analytical methodology to assess the efficiency of energy sources (a combination of various energy sources, mostly based on renewable sources), and Turkey, a country with a variety of renewable energy potential because of its favorable geographic and climatic conditions, was used as an illustrative case. Specifically, in the first stage, we utilized a nonparametric method and a powerful benchmarking tool—Data Envelopment Analysis (DEA)—to analyze energy efficiencies for each province. In the second stage, we employed the Ordinary Least Square (OLS) regression and Tobit regression models to investigate the environmental factors affecting energy efficiency. And then, we used the Charnes-Cooper-Rhodes (CCR) DEA and Tobit regression combination to perform a validation of the findings. The tandem utilization of DEA, OLS, and Tobit regression models allowed us to overcome some of the shortcomings of these methods when they are utilized individually. The results revealed the factors that have direct and positive influence/effect on the efficiencies, which included gross domestic product per-capita, population size, and the amount of energy production from renewable energy sources. The findings also suggested that starting the investments at the less-efficient provinces result in a better overall nationwide technical efficiency. These results can potentially help decision makers to develop and manage energy investment strategies.

1. Introduction

In the midst of global energy marketplace, dependence on foreign energy sources is a major challenge for many governments to sustain long-term energy security and uninterrupted energy flow with an affordable/stable cost. The over-dependence on oil and gas as the primary energy source with fluctuating cost structures is causing long-term economic problems [1]. For this reason, investments in renewable energy sources (RES) have been increasing at a substantial rate, with the hope to provide reliable/sustainable energy, and thereby obtaining economic independence [2]. Energy authorities and decision makers are trying to replace conventional fossil-fuel-based energy sources with RES because of the numerous advantages including them being environment-friendly and domestically sourceable [3]. In order to achieve this goal, decision makers are experimenting with and implementing various renewable energy investment projects [4]. Most developing countries have plenty of renewable energy resources, including solar energy, wind power, hydropower, geothermal energy, and biomass. To meet the increasing energy demand, the most effective long-term policy deemed to be increasing investment in renewable energy resources and related technologies. The issue of sustainable energy assessment has gained much attention and significance from both researchers and practitioners over the past couple of decades. Regional efficiency measurement is believed to be one of the crucial steps in achieving sustainable and efficient energy policies [5]. Regional or provincial energy cooperation and

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integration activities provide a more efficient use of resources for the best keeping of environmental, social and economic benefits under energy infrastructure projects and long-term development plans [6].

Data envelopment analysis (DEA) has been a commonly used benchmarking tool to measure the productive efficiency of decision-making units (DMU) to show their performances in many managerial problems. DEA is a nonparametric method which was first introduced by Farrell [7] then further developed by Charnes, Cooper and Rhodes in 1978. DEA is a relatively easy method to use/apply, largely because it does not require any restricting assumptions of the related function and it can handle multiple input and output variables of various units [8]. Due to its several advantages, it has built an impressive footprint (i.e., an extensive application area) in analyzing the efficiency level of the organizations/companies [9]. In the literature, DEA analysis has been broadly used in the energy field to evaluate the performance of energy power companies, and alternative renewable energy projects and technologies [3,10–17].

Despite its advantages and ease of use, DEA is not a perfect method. According to Nahra et al. [18]; the usual usage of DEA has some significant drawbacks. After obtaining efficiency scores from DEA approach, the related scores are regressed on environmental/managerial variables to find out the identifiers of the efficiency rates. DEA assigns a score of 1 to the efficient DMUs and there is no information about ranking among themselves to see efficiency levels in details. Therefore, with the second stage analysis by operating a censored data such as Tobit regression is conducted to obtain knowledge that is more representative [19]. Nevertheless, some inconsistent measurements may occur when the efficient number of DMU is too high, and eventually, it may lead to some serious problems [18,20].

Super-efficiency analysis was developed by Anderson and Peterson [57] to mitigate the inadequacy of the classic DEA approach by relaxing the upper limit of "1" for efficient DMUs. It is based on basic DEA principles, and in some studies, super-efficiency analysis has been employed as an alternative or as an additional approach to classical DEA [21,22]. Therefore, this study proposes a two-stage analytical approach to efficiency assessment based on super-efficiency analysis along with a comparison with the traditional DEA-Tobit regression approach. In this study, in the first stage, the CCR (named after Charnes, Cooper, and Rhodes)-DEA and super-efficiency DEA scores were used as dependent variables in a comparative evaluation of the methods to calculate the technical efficiency outcomes in energy assessment of the provinces. In the second stage, initially, Tobit regression model has been constructed based on CCR-DEA scores, and then depending on the super-efficiency DEA scores Ordinary Least Square (OLS) regression model was built to identify the environmental factors affecting energy efficiency. Since the DEA scores are censored at one, there were some drawbacks in reflecting some of the detailed and important information for ranking. Hence, additionally, a super-efficiency DEA was employed to offer some advantages over the Tobit regression.

We structured the analyses within the context of energy efficiency of Turkey's provinces. Turkey is divided into 81 provinces and 7 regional areas based on several factors such as industrial characteristics, energy consumption rates, natural resource affluence, and geo-climate factors. This study aimed at conducting an extensive investigation from the provincial and regional perspective. In fact, it is very difficult to access all of the unique characteristics that exist at granular levels in developing countries, such as Turkey. Therefore, DEA, Tobit and OLS models are used to handle such complexities that researchers and policy-makers face while performing such a complex, multidimensional and substantially large national/provincial strategic planning projects. The collective use of multiple data/information sources was an added enabler f this study.

Although there have been a number of studies on this topic, there still is ample opportunities to contribute to the extant literature. Hence, this study aims to make contributions to the existing literature in the following ways. First, this study uses a novel two-stage DEA approach to assess the energy efficiency from a variety of sources (mostly from renewable energy sources) and to identify the influential environmental/managerial factors at provincial and regional level using the example of Turkey. Second, the study investigates the changing (i.e., time-varying) tendencies of energy efficiency in different geographic parts/regions of Turkey, and make local/regional comparisons about the prospect of energy efficiency. Lastly, the study takes into consideration the existing utilization rates of the renewable energy alternatives as it assesses the potential for different regions. As such, this paper contributes to the extant literature by offering a methodology and insights to formulate an impactful energy efficiency strategy for new and improved energy investments alternatives. Thus, energy resource planning activities can be planned and implemented realistically by considering and satisfying provincial/regional level characteristics and conditions.

The rest of the paper is organized as follows. Section 2 provides a literature review from the perspective of the studies dedicated to analyzing energy efficiency. Section 3 presents the background information on the proposed two-stage analytical methodology that combines DEA and Tobit models. Section 4 provides the specifics about the empirical analysis (the case study) conducted for Turkey. Section 5 illustrates and discusses the results while section 6 provides concluding remarks and future research directions.

2. Literature review

Assessment of renewable energy sources/alternatives is an extremely critical and strategic issue followed by countries all over the world to identify and implement the right energy policy under the sustainable development concept and low-carbon economy. A number of studies have taken into account the evaluation of renewable energy sources in order to show their substantial contributions from diverse aspects of human life and to help the governments deliver on a range of policy objectives—economic, environmental, and social. In this regard, some studies in the literature analyze renewable energy portfolio utilizing from various decision making and optimization tools while other studies just consider the energy efficiency issue to provide a comprehensive insight of renewable energy assessment [4,23–26]. Neves et al. [27] proposed a multi-criteria decision analysis model, initially utilizing soft systems methodology then, Keeney's Value-Focused Thinking approach to evaluating energy efficiency attempts. Boomsma et al. [2] analyzed renewable energy investments using real options approach under various support schemes. Siddiqui et al. [5] assessed renewable portfolio standards to limit greenhouse gas emissions according to bi-level model they developed by incentivizing renewable energy production.

In the literature, a majority of DEA studies dedicated to the area of energy have focused on energy efficiency [28,29]. According to Kim et al. [30]; DEA studies in the energy sector can be categorized into two themes: efficiency analysis of renewable energy sources, and efficiency analysis of energy generation plants/companies [31,32]. Under these two categories, the studies are generally constructed according to the provincial level, regional level, or country level to present a comparative analysis. For instance, Mou [33] investigated the efficiency of China's coal-fired power plants applying DEA-Slack based measure methodology according to three levels namely, groups, provinces, and plants. The results show that there are some disparities across groups, provinces and also plant level. Xie et al. [34]; Iftikhar et al. [35]; Ignatius et al. [10] and Zhou et al. [17] examined a country level energy efficiency using DEA model. Wang et al. [13]; Wu et al. [36]; Zeng et al. [37]; Zha et al. [38]; Meng et al. [12] and Zhang et al. [16] applied DEA models at regional level to evaluate the energy and environmental efficiency of China's regions. Wang et al. [39] and Du et al. [40] investigated energy efficiency using DEA approach at the provincial level. There have been a few studies analyzing the efficiency of Turkey's energy sector by utilizing DEA. Bagdadioglu [41]; Bagdadioglu et al. [42]; Sarica and Or [43] and Sözen et al. [44] investigated Turkish electricity distribution sector to analyze performances of the publicly operated organizations utilizing DEA tool.

There are some studies in the literature that employed two-stage DEA-based applications where they used DEA in the first stage and Tobit regression model in the second. Some of the recent studies in this domain are summarized here. Sağlam [45] developed a two-stage DEA to assess the relative efficiency of the 39 state's wind power performances in the USA for the electricity production. Both input- and output-oriented CCR and BCC models have been applied and then Tobit regression was conducted by utilizing DEA results for the second stage analysis. The DEA results showed that more than half of the states operate wind energy efficiently. And the Tobit regression revealed that previously established wind power was both less effective and more expensive. Chen et al. [81] applied a super-efficiency DEA and Malmquist index methods to measure static and dynamic environmental efficiency of 131 cities in China between 2003 and 2014. The influential factors were explored by a panel Tobit model. The results showed that there are significant differences among the cities' environmental efficiency.

In a recent study, Jebali et al. [46] investigated the energy efficiency factors in Mediterranean countries for the period of 2009–2012. In the first stage, a specific bootstrap procedure was applied to get a corrected DEA efficiency estimator. In the second stage, a parametric bootstrap procedure was applied to the truncated regression of DEA on environmental variables. According to first stage results, energy efficiency levels in Mediterranean countries were high and the second stage results show that the gross national income per capita, the population density and the renewable energy use affected energy efficiency. Using a more constraint scope, Sağlam [47] utilized DEA-based approach to evaluate the relative efficiencies of 236 wind farms. Input and output-oriented CCR and BCC models were applied in the first stage, and then the Tobit regression model was developed to investigate the effects of the specification of the wind turbine technologies. DEA results showed that two-thirds of the wind farms were operated efficiently, and the Tobit regression model showed that the brand choice of the wind turbine had a significant impact on the productive efficiency of wind farms. Similarly, Wu et al. [48] used DEA methodology to obtain the efficiency scores of wind farms in China in the first stage and then used the Tobit regression model to examine the relationship between the efficiency scores and environment variables in the second stage.

Feng et al. [49] aimed to develop a green development performance index based on DEA which would be used in the evaluation of the global change/evolution of the green development. DEA and then the Tobit models are used to analyze the potentially influencing factors on green development performance. Niu et al. [50] proposed two-stage (two-sub-process) DEA model to better evaluate the wind turbines micro-siting of wind farms in China. The efficiency scores obtained by the two sub-process of DEA were taken as the dependent variables, and Tobit regression model was used to investigate the relationship between the efficiency scores and the environment variables. Çelen [51] discussed efficiency and productivity of the Turkish electricity distribution companies applying a two-stage (DEA & Tobit) analysis. Çelen [51] did not however used the super efficiency approach for OLS regression to eliminate insufficiencies of Tobit regression.

In this study, we concentrated on the energy efficiency of various sources (mostly based on renewable sources), at provincial and regional level (using Turkey as an illustrative case), designing and executing a two-stage analytical methodology that combines DEA, Tobit and OLS regression models. Most of the previous studies have employed one or more parametric or non-parametric decision-making tools somewhat arbitrarily without ample justification. Furthermore, in the previous studies, assessment of energy efficiency has been widely investigated at the level of a power plant or an energy company for a given region or the entire country, to compare against other studies or to assess their performance over time. In this study, we have evaluated the energy efficiency of provinces exploiting a thorough analytical approach—a two-stage synergistic methodology relying on the complementary features of the tools employed. Influencing environmental factors have been incorporated in the second stage to provide a more realistic information. Different from other studies in the literature, we have also considered the renewable energy potentials of the regions as inputs and the gross energy generation from renewable sources as an output variable. We used an input-oriented model due to the nature of Turkish electricity sector in a similar manner to the other countries. Contrary to companies, the governments are responsible for serving to all consumers, hence making the outputs as external [51].

3. Background information

3.1. DEA models

DEA has been a prominent method for evaluating the productivity of organizations with multiple incomparable inputs and outputs. DEA was first proposed by Charnes et al. [52] based on the seminal work of Farrell [7] on the measurement of productive efficiency. The objective function of that model was to maximize the ratio of weighted outputs to weighted inputs for a particular organizational unit (or in DEA terminology, decision-making units, DMUs). DEA is a linear programming-based technique for measuring the relative efficiency of DMUs, which has gained considerable interest in recent years due to its advantages over the traditional methods [53]. DEA provides a peer group comparison using a frontier in order to determine efficient and inefficient units. DEA can incorporate multiple inputs and multiple outputs, which can be expressed in different units of measurement.

Another advantage of DEA that significantly contributed to its popularity among researchers and analysts is its ability to help identify the potential improvements for inefficient units. To do so, DEA compares a unit with a convex combination of other units located on the frontier and thereby enables the analyst to identify the sources and the level of inefficiency for each of its inputs and outputs [54].

3.1.1. The CCR model

DEA has two common models, which are CCR [52] and BCC [55] models. CCR model considers the overall efficiency and assumes constant returns to scale. BCC model provides more details about the model, which thinks pure technical efficiency, and assume variable returns to scale.

DEA models can be constructed in two formats, which are called as an input orientation model or an output orientation model. An input orientation models try to find out how to improve input levels while keeping the current levels of outputs for an inefficient organization to become DEA-efficient. On the other hand, an output orientation analysis provides information on how much enhancement of outputs of an inefficient firm is necessary while saving the present levels of inputs for it to become DEA-efficient. An input-oriented DEA model initially developed by Charnes et al. [52], and referred as CCR, can be expressed below for s outputs, m inputs and n number of organizations in the following Eqs. (1)–(4):

$$MinZ_0 = \theta \tag{1}$$

subject to

$$\theta x_{i0} - \sum_{j=1}^{n} \lambda_j x_{ij} - s_i^- = 0 \quad i = 1, \dots, m \tag{2}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{r0} \quad r = 1, \dots, s \tag{3}$$

$$\lambda, s^+, s^- \geq 0 \quad \text{for all } i,\ j,\ r \tag{4}$$

where θ is efficiency score for organization o under investigation; x_{io} and y_{ro} are observed values of input m consumed and output s generated by organization o respectively; s_r^+ and s_i^- are the amounts of excess input i and deficit output s for organization o; λ_j' s are the dual variables utilized to construct a composite ideal organization to dominate organization n.

The objective function above assesses the efficiency score (θ) of the organization under consideration. Within the same objective function, in case the organization is efficient ($\theta = 1$), all-zero slack values (output deficits and input excesses) are also provided for full-efficiency. Constraint (2) maintains that the input level for input i is a linear combination of the inputs and the excess input of i. Constraint (3) points that the optimal output of r is a linear combination of the outputs minus its slacks. In the optimal solution of model (1–4), organization o is efficient if $\theta = 1$ and $s_r^+ = s_i^- = 0$ for all *i* and *r*. The organizations found efficient in the solution of the model (1–4) for organization *o*, form the efficiency frontier, which is called as reference set.

3.1.2. The BCC model

The efficiency frontier defined by the above CCR model reveals constant returns to scale (CRS) [56]. As an extension of CCR- DEA model, Banker et al. [55] offer the BCC model which adds the constraint, $\Sigma \lambda_j = 1$, for variable returns to scale (VRS). The variable λ presented convexity constraint also produces the value of increasing or decreasing returns to scale. An input oriented BCC model with s outputs, m inputs and n number of organizations can be defined as follows in Eqs. (5)–(9):

$$MinZ_0 = \theta \tag{5}$$

subject to

$$\theta x_{i0} - \sum_{j=1}^{n} \lambda_j x_{ij} - s_i^- = 0 \quad i = 1, \dots, m \tag{6}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_i^+ = y_{r0} \quad r = 1, \dots, s \tag{7}$$

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{8}$$

$$\lambda, s^+, s^- \geq 0 \quad \text{for all } i, j,\ r \tag{9}$$

3.1.3. Super-efficiency model

In the previous section, we have identified the CCR-DEA and BCC-DEA models using input or output-oriented versions. According to CCR or BCC results, we can just obtain that which decision-making DMU is efficient or not efficient based on efficiency scores. Additionally, these models do not provide the actual ranking of the efficient DMUs among themselves extensively. The main point behind the developing super-efficiency DEA is to show sorting of 100% relative efficiency of these DMUs. In order to eliminate the insufficiencies of the mentioned models and to assess DMUs' efficiencies realistically and comprehensively, the super-efficiency model was developed by Andersen and Petersen [57]. The DMU is compared with the linear combination of all other units in the model. The investigated DMU is removed from the reference set. Thus, the maximum rate of increase in the inputs of efficient decision-making units is obtained while maintaining the effectiveness of the efficient DMUs. All DMUs are sorted from large to small according to the efficiency scores.

Super-efficiency DEA model has the identical function formula with CCR model used for assigning the most productive scale size in the traditional DEA framework and it can be defined in Eqs. (10)–(13) as follows:

$$MinZ_0 = \theta \tag{10}$$

subject to

$$\sum_{\substack{j=1 \\ j \neq o}} \lambda_j x_{ij} \leq \theta x_{io} \quad i = 1, \dots, m \tag{11}$$

$$\sum_{\substack{j=1 \\ j \neq o}}^{n} \lambda_j y_{rj} \geq y_{ro} \quad r = 1, \dots, s \tag{12}$$

$$\theta, \lambda_j \geq 0 \quad j \neq o \tag{13}$$

3.2. Tobit regression model

To identify the determinants of efficiency, the Tobit model is employed in the second stage of the analysis. Tobit model was proposed by James Tobin in 1958 to describe the relationship between a non-negative dependent variable (y) and independent variable (x). Tobit model is also known as a truncated or censored regression model to provide technical efficiency scores of DMUs under a restricted range of values of the dependent variable [58,59]. The efficiency scores computed from CCR-DEA receive values between 0 and 1 and used as dependent variable in Tobit regression.

The calculated efficiency score in the first stage (y_i) will be validated by environmental variables (z_i) in the second step. A latent (unobserved) variable in the Tobit model can be calculated as in Eq. (14):

$$y_i^* = z_i\beta + \varepsilon_i \text{ with } \varepsilon_i \approx N\left(0, \sigma^2\right) \tag{14}$$

where, z_i is an (r × 1) vector of environmental variables and β is an (r × 1) vector of parameters to be estimated.

Employing this latent variable (y^*), the calculated efficiency score (y_i) can be defined in such a way that is censored at less than 0 and more than 1, as seen in Eq. (15):

$$y_i = \begin{cases} y_i^* & \text{if } 0 < y_i^* < 1 \\ 0 & \text{for other values of } y_i^* \end{cases} \tag{15}$$

The Tobit model employed the Newton Raphson method based on maximum likelihood function. The parameters are also predicted by maximum likelihood utilizing the Newton Raphson method. Although Tobit model is often used to clarify environmental variables in the two or three stage analysis, Tobit models have some limitations as mentioned by Simar and Wilson [20].

Estimation with OLS regression brings about a biased parameter estimate problem owing to the assumption of a normal and homoscedastic distribution of OLS. The most significant problem has occurred when the utilized environmental variables in the Tobit model are correlated with the efficiency scores obtained from the first stage with the Tobit models that causes the inconsistency problem of estimators (2013a). To remove these drawbacks, Simar and Wilson [20] proposed a bootstrapping approach.

4. Empirical analysis: an application for Turkey

A graphical depiction of the proposed two-stage analytic methodology (for the assessment of energy efficiency) is given in Fig. 1.

As mentioned before and as shown in Fig. 1, this study employs a two-stage methodology. In the first stage, CCR-DEA and super-efficiency DEA were used to analyze the energy efficiencies of each province in Turkey. In the second stage, based on the CCR-DEA scores, a Tobit regression model was constructed and depending on the super-efficiency scores, an OLS regression model was built to investigate the environmental factors. Finally, after completing all of the assessments, a strategic renewable energy policy for Turkey was identified.

4.1. Data

Turkey, one of the largest countries in Eastern Europe—located between Europe and Asia like a bridge, is situated on 780,576 km^2 of total land. The country is subdivided into 7 main regions, 21 sub-regions, and 81 provinces/cities (see Fig. 2), according to geographic, demographic, and economic characteristics.

In this study, all 81 provinces in the 7 regions of Turkey are considered. The data used in the study was obtained from multiple

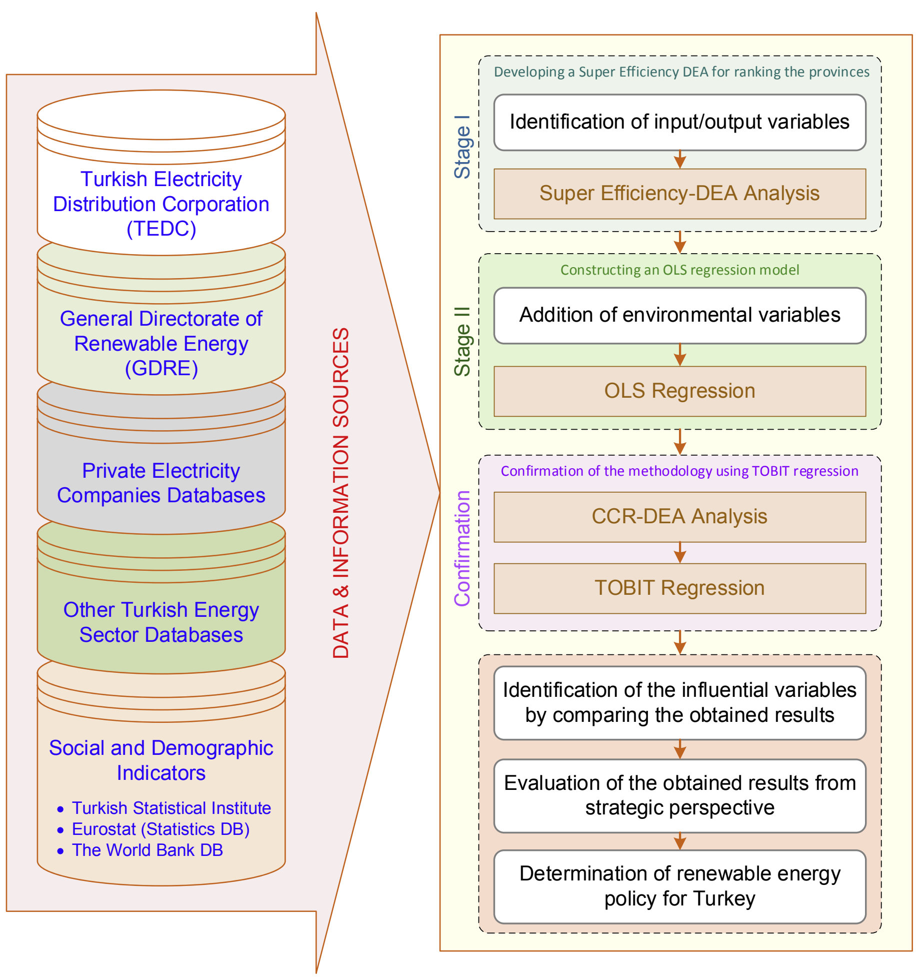

Fig. 1. A graphical depiction of the proposed two-stage analytical methodology.

Fig. 2. A schematics illustration of Turkey's 7 regions and 81 provinces.

sources, including Turkish Electricity Distribution Corporation (TEDC), General Directorate of Renewable Energy (GDRE), related data from energy sector databases, private electricity companies, and the basic social and demographic indicators (which are collected and consolidated from Turkish Statistical Institute, Eurostat and World Bank statistics).

The determination of input and output variables is a very critical issue in DEA practices, where the aim is to evaluate the efficiencies of decision-making units. Obtaining such a comprehensive data set provided us the opportunity to represent the problem in the richest way. In identifying the proper set of input and output variables, we considered the previous energy efficiency studies [51; 60], the professional opinions of relevant individuals, and the detailed review conducted by Jamasb and Pollitt [60]. In the light of these information sources, for the current study, we chose four input variables and two output variables for the DEA, and six variables were considered as the environmental factors for the Tobit and OLS regression models. In the related literature, the most widely used output variables were gross energy generation in MWh and the number of customers. We have utilized these two factors as output variables, which are symbolized by y_1 and y_2, respectively.

The total renewable energy potential has been taken as a ratio, x_1, the network length in km, x_2, total installed power of renewable energy in MW, x_3 and the transformer capacity in MVA, x_4 are employed as input variables. Transformer capacity [51; 60; 61], network length [61,62] and total installed power [51,63] are widely used input variables in various studies [64; 60]. Unlike other studies, we included the renewable energy potential as an input variable. It is noted that this study focuses on particularly the renewable energy efficiency of the provinces in Turkey. Thus, the related variables of energy efficiency have been investigated, and finally considered as total installed power of renewable energy (input), total renewable energy potential (input) and gross energy generation from renewable energy sources (output).

Energy efficiency of the provinces in Turkey can be affected by several factors in addition to the aforementioned technical variables. We have used six independent environmental variables (z_i), namely, total exports, gross domestic product per capita, humanity development index, total energy generation, population, area in order to apply Tobit regression analysis. These environmental variables have been utilized in different Tobit regression studies [65–67].

4.2. Measurement of input and output variables

Mostly in-line with the extant literature, brief definitions of the input and output variables used in the analysis are presented as follows:

x_1: Total renewable energy potential-All the renewable energy resources have been analyzed according to climatic conditions of the provinces and the abundance of sources in the regions. The intensity of wind, solar, hydro, geothermal and biomass energy sources in the regions are identified and the total renewable energy potential has been identified as a ratio by using multi criteria decision making tools. Wind speed, sunshine duration, river regimes, percentages of the biomass waste and thermal power of locations obtained from TEDAS are considered for the evaluation of overall potential rate while the renewable energy potentials are assessed (%).

x_2: Network length- Electricity distribution line measured in (km) per province.

x_3: Total installed power of renewable energy- Total installed power means the theoretical capacity of the generators if working at maximum output (MW).

x_4: Transformer capacity- The maximum capacity of transformers which is loaded electricity in order to connect to the distribution system (MVA).

y_1: Gross energy generation from renewable sources- The energy production obtained from the renewable energy power plants throughout the year (MWh).

y_2: Number of consumers- Measured as the total number of customers for the electricity service delivered.

Several external factors, which are beyond the controllable scope of the problem definition, can affect the energy efficiency scores of the districts. This study mainly considers the following six factors as environmental variables:

z_1: Total exports- It is widely known that exports matter for economic growth and development [68] and that differential export performance may contribute to spatial inequality [66] and thus, energy efficiencies of the provinces can show different behaviour because the energy consumption is closely related to economic development (million dollars per provinces).

z_2: GDP per capita- Gross domestic product (GDP) per capita is the most important indicator of the economic strength and prosperity level of the citizens living in the province and measured by million dollars per capita [67,69].

z_3: Human development index- Human development index (HDI) is a composite statistic of life expectancy, education, and per capita income indicators, which are generally used to rank countries into four stages of human development. According to different analysis, human development is closely related to energy usage [70].

z_4: Total energy production- Total energy production which consists of all kind of energy sources, such as fossil fuel, coal, thermal, natural gas etc., to supply electricity need and measure in MWh [71].

z_5: Population- The variable of the population defined as the number of citizens living involved side, measured by million [80].

z_6: Area- Area is expressed in the region of the city area, and measured by km^2 [48; 72].

According to the established practices, the number of DMU's should be at least twice the number of inputs and outputs [73]. In this study, the number of DMU was eighty-one, which is higher than total input and output variables. The descriptive statistics of the variables adopted in the analysis are shown in Table 1. The correlations between input and output variables were statistically verified, which are given in Table 2.

In this study, classic CCR and super-efficiency DEA scores were taken as dependent variables in a comparative evaluation of methods for identifying technical efficiency in the energy efficiency of the provinces. In the first stage of the study, the DEA Solver software was utilized to determine efficiency performances of the provinces. In the second stage, to identify the influencers of the energy efficiency, the Tobit and OLS models are constructed using EViews 9 software. Based on the obtained outcomes, we assert that super-efficiency DEA scores provide a better dependent variable than the CCR–DEA scores in the second stage regression.

All of the correlation coefficients between input and output items exhibit positive correlation, as shown in Table 2. Thus, the input and output items well comply with the prerequisite condition of the DEA model.

5. Results and discussion

A commercial package called DEA-Solver Professional Release 13.0 was used for input-oriented CCR, BCC and super-efficiency models. In this study, we have adopted the input minimization assumption, since the purpose of the study was to measure the input usage efficiency of provinces. In the recent years, it has been widely accepted as a strategic issue in the energy sector that companies in competitive markets are increasingly in need of minimizing their inputs or fit among their strategies, environmental and organizational contingencies, in order to be in the competitive environment. Decision makers, energy authorities in the country or managers of power plants for investment planning can only decrease inputs to promote the efficiency. The following subsections detail the data analyses used in this study.

5.1. Efficiencies of the provinces

We used (Eqs. (1)–(4)) to derive the efficiency index for each of the provinces and the reference sets in which all DMUs' efficiency equals to one. A total of 11 provinces appeared in the reference set as efficient units, as shown in Table 3. Additionally, the total count of occurrence was obtained as 212 in the DEA analysis.

Norman and Stoker [74] classified the DMUs into four categories according to the perceived efficiency levels:

(1) The robustly efficient units. The DMU is efficient and also it appears in many reference sets as their benchmarks.
(2) The marginal efficient units. The DMU is efficient but it is not other DMU's benchmark in that the DMU may have different characteristics from others in the same category.

Table 1
Descriptive statistic of inputs and outputs.

	Unit	Max	Min	Mean	SD
T. Renewable Energy Potential	Ratio, %	0.0721	0.0004	0.0123	0.012
Network Length	Km	67642	1783	13381.950	11134.211
T. Installed Power of Renew. Energy	MW	3128.251	0	390.383	558.933
Transformer Capacity	MVA	21546	103	1660.777	2791.645
G. Energy Generation from Renewables	MWh	3128000	0	280950.991	471181.996
Number of Consumer	Person	542435	813	25154.283	67713.269
Ln (Total exports)	Million dollar	20.253	5.814	13.896	2.407
Ln (GDP per capita)	$M per capita	3.008	0.469	1.925	0.555
Human development index	Index, %	1	0	0.079	0.121
Ln (Total energy production)	MWh	10.089	0.113	6.526	2.682
Ln (Population)	Million	16.481	11.297	13.219	0.950
Ln (Area)	Km^2	10.621	6.745	8.982	0.651

Unit: the measurement unit; Max: the maximum value; Min: the minimum value; Mean: the average value; SD: the standard deviation. Note: Ln denotes the natural logarithm of the related variable.

Table 2
Correlation coefficient between input and output variables.

	Total Renewable Energy Potential (x_1)	Network Length (x_2)	Total Installed Power of Renew. Energy (x_3)	Transf. Capacity (x_4)	Energy Generation from Renewable Sources (y_1)	Number of Consumer (y_2)
Total Renewable Energy Potential (x_1)	1	–	–	–	–	–
Network Length(km) (x_2)	0.56216	1	–	–	–	–
Total Installed Power of Renew. Energy(MW) (x_3)	0.81655	0.2939	1	–	–	–
Transformer Capacity (x_4)	0.418871	0.8489	0.2996	1	–	–
Energy Generation from Renewable Sources (y_1)	0.72015	0.3126	0.8478	0.2898	1	–
Number of Consumer (y_2)	0.46064	0.3876	0.2612	0.2852	0.1609	1

Table 3
The count of occurrence of efficient provinces in the reference sets.

Province	Count of occurrence
BATMAN	38
ELAZIG	1
GAZIANTEP	30
GUMUSHANE	34
IGDIR	46
IZMIR	16
KAHRAMANMARAS	16
KIRIKKALE	5
KUTAHYA	11
SANLIURFA	4
YALOVA	11
Total	212

(3) The marginal inefficient units. These will have an efficiency rating, between 0.9 and 1, and if they adjust their inputs or outputs, they could soon raise their score towards 1.0
(4) The distinctly inefficient units. With an efficiency score of less than 0.9, these units would have difficulty in making themselves efficient in the short term.

Based on the above criteria, we then regrouped the total sample of 81 provinces into four categories as noted above. Table 4 shows the number and percentage of cities included in the four categories, which can then be used for the different investment origins.

As it is shown in Table 4, 13.5% of provinces belonged to the robustly efficient unit, while only 3.7% of the DMUs fit in the marginal inefficient units. Also, nearly 82.71% of the provinces were classified into the distinctly inefficient unit. These results suggest that most of the provinces are inefficient when compare to the efficient units in Turkey.

Table 4
Number and percentage of provinces for each efficiency category.

	All Provinces	
	Number	Percent
Robustly efficient units	11	13.50
Marginal efficient units	0	0.00
Marginal inefficient units	3	3.70
Distinctly inefficient units	67	82.71
Total	81	100.00

Table 5
Categories of scale returns for each group of provinces.

	Provinces	
	Number	Percent
IRS	60	74.074
DRS	4	4.938
CRS	17	20.987
Total	81	100

5.2. Comparison of return to scale

DEA method may be utilized with the assumption of constant or variable returns to scale. Banker et al. [55] classified the scale efficiency of DMUs into three categories: (i) increasing returns to scale (IRS); (ii) constant returns to scale (CRS); and (iii) decreasing returns to scale (DRS).

Increasing return scale means that increase in the input will result in a greater than proportionate increase in output, whereas decreasing return scale is the case where the result is less than the proportionate increase in output. Constant return scale is exhibited where the result is the proportionate increase in output [75]. Table 5 shows that there were 60 DMUs in the condition of increasing return scale, and there were 4 DMUs in the condition of decreasing return scale, and there were 17 DMUs in the condition of constant return scale.

When we evaluated 81 provinces according to the regions, we obtained the following results in Table 6.

i. The percentage of regions in the IRS category, The Black Sea Region (16.04) had the highest percentage among all.
ii. The Marmara Region, The Black Sea Region, The Central Anatolia Region and The Southeastern Anatolia Region (1.23%) were similar and greater than the other regions in the DRS category.
iii. The percentage of regions classified into CRS, The Aegean Region and The South Eastern Anatolia Region (4.94%) had similar behaviour in CRS category and they were greater than the others.

The implication drawn from item (i) is that The Black Sea Region tend to perceive the need to create more fit by enhancing their outputs, renewable energy generation and number of customers, as compared to other regions. Our results from item (ii) indicate that The Marmara Region, The Black Sea Region, The Central Anatolia Region and The Southeastern Anatolia Region expend more input to obtain the same level of output compared to the other regions. Item (iii) also points that The Aegean Region and The South Eastern Anatolia Region tend to have higher efficiency than other regions.

CCR and BCC models were utilized to obtain overall technical and pure technical efficiencies, besides the super-efficiency model to rank the efficient DMUs. According to Table 7, if the efficiency value equals 1, the DMU is efficient; if it is less than 1, the evaluated region is deemed inefficient. When we look at the overall efficiency scores in CCR model, 11 cities were efficient (100%). Besides that, pure efficiency scores were obtained from BCC model, which indicated that about 18 cities were efficient (100%)—these cities used their inputs efficiently. Scale efficiency score was obtained by calculating the ratio of overall technical efficiency to the pure technical efficiency, and it indicates the potential productivity achieved from maintaining the optimal size of an economy. For instance, a large economy exhibits economies of scale at various levels. For a scale efficient province, the input and output oriented efficiencies equal each other. Indeed, if pure technical efficiency is not high enough, this may cause a managerial problem in the direction of inputs and consequently of RES (renewable energy

Table 6
Categories of scale returns for each region of Turkey.

	Marmara	Black Sea	Aegean	Central Anatolia	Eastern Anatolia	Mediterranean	South eastern Anatolia	Total Percent
IRS	12.34	16.04	4.94	14.81	12.34	7.41	6.17	74.074
DRS	1.23	1.23	0	1.23	0	0	1.23	4.938
CRS	1.23	3.70	4.94	0	3.70	2.47	4.94	20.987

Table 7
Input oriented DEA model results.

DMU	Overall Efficiency (CCR)	CCR Rank	Pure Efficiency (BCC)	BCC Rank	Scale Efficiency	Super- Efficiency	Super- Efficiency Rank	Returns to Scale
ADANA	0.1658	67	0.1783	79	0.9298	0.1658	66	Increasing
ADIYAMAN	0.5506	36	0.5816	43	0.9466	0.5505	35	Increasing
AFYON	0.2329	64	0.2662	71	0.8749	0.2329	63	Increasing
AGRI	0.4480	42	1.0000	1	0.4480	0.4480	41	Increasing
AKSARAY	0.0854	79	0.1978	76	0.4317	0.0854	79	Increasing
AMASYA	0.5749	33	0.6379	38	0.9010	0.5748	33	Increasing
ANKARA	0.3922	49	0.4028	61	0.9733	0.3921	48	Decreasing
ANTALYA	0.6335	28	0.6734	35	0.9406	0.6334	28	Constant
ARDAHAN	0.1529	71	1.0000	1	0.1528	0.1528	70	Increasing
ARTVIN	0.1265	76	0.4317	58	0.2931	0.1265	75	Increasing
AYDIN	0.4901	40	0.4919	48	0.9961	0.4900	39	Constant
BALIKESIR	0.1635	69	0.1796	78	0.9104	0.1635	68	Increasing
BARTIN	0.1540	70	0.4610	52	0.3339	0.1539	69	Increasing
BATMAN	1.0000	1	1.0000	1	1.0000	1.3704	8	Constant
BAYBURT	0.4209	46	1.0000	1	0.4208	0.4208	45	Increasing
BILECIK	0.0871	78	0.5402	46	0.1612	0.0871	78	Increasing
BINGOL	0.8326	18	0.9832	19	0.8468	0.8325	18	Increasing
BITLIS	0.2383	63	0.6684	36	0.3563	0.2382	62	Increasing
BOLU	0.3805	51	0.4580	53	0.8307	0.3805	50	Increasing
BURDUR	0.3870	50	0.4726	50	0.8187	0.3870	49	Increasing
BURSA	0.2074	65	0.2207	74	0.9394	0.2074	64	Increasing
CANAKKALE	0.1359	73	0.1969	77	0.6897	0.1358	72	Increasing
CANKIRI	0.2593	60	0.6807	34	0.3808	0.2592	59	Increasing
CORUM	0.4216	45	0.4406	57	0.9568	0.4215	44	Increasing
DENIZLI	0.5432	38	0.5457	45	0.9952	0.5431	37	Constant
DIYARBAKIR	0.8561	15	1.0000	1	0.8561	0.8561	15	Decreasing
DUZCE	0.4440	43	0.6613	37	0.6713	0.4440	42	Increasing
EDIRNE	0.1170	77	0.2798	70	0.4180	0.1169	76	Increasing
ELAZIG	1.0000	1	1.0000	1	1.0000	1.1264	10	Constant
ERZINCAN	0.3691	54	0.4453	54	0.8288	0.3691	53	Increasing
ERZURUM	0.6207	30	0.6284	40	0.9877	0.6207	30	Constant
ESKISEHIR	0.4236	44	0.4862	49	0.8711	0.4235	43	Increasing
GAZIANTEP	1.0000	1	1.0000	1	1.0000	1.3512	9	Constant
GIRESUN	0.9348	12	0.9786	20	0.9551	0.9348	12	Decreasing
GUMUSHAN	1.0000	1	1.0000	1	1.0000	1.5889	5	Constant
HAKKARI	0.3741	52	0.7771	27	0.4813	0.3740	51	Increasing
HATAY	0.3992	48	0.4155	59	0.9607	0.3992	47	Increasing
IGDIR	1.0000	1	1.0000	1	1.0000	2.3100	3	Constant
ISPARTA	0.2565	62	0.4054	60	0.6325	0.2564	61	Increasing
ISTANBUL	0.1909	66	0.2125	75	0.8981	0.1908	65	Decreasing
IZMIR	1.0000	1	1.0000	1	1.0000	1.8359	4	Constant
K.MARAS	1.0000	1	1.0000	1	1.0000	1.3815	7	Constant
KARABUK	0.9329	13	1.0000	1	0.9328	0.9328	13	Increasing
KARAMAN	0.7754	20	0.8110	23	0.9559	0.7753	20	Increasing
KARS	0.6321	29	0.7188	30	0.8793	0.6321	29	Increasing
KASTAMON	0.1646	68	0.3599	65	0.4572	0.1646	67	Increasing
KAYSERI	0.2964	58	0.3031	69	0.9778	0.2963	57	Increasing
KILIS	0.8390	1	1.0000	1	1.0000	10.5113	2	Constant
KIRIKKALE	1.0000	81	0.3913	62	0.0927	0.0362	80	Increasing
KIRKLARELI	0.0363	21	0.7912	25	0.9580	0.7580	21	Increasing
KIRSEHIR	0.7581	17	1.0000	1	0.8390	0.8390	17	Increasing
KOCAELI	0.5640	35	0.6291	39	0.8964	0.1047	77	Increasing
KONYA	0.1396	72	0.1426	80	0.9784	0.1396	71	Increasing
KUTAHYA	1.0000	1	1.0000	1	1.0000	1.5126	6	Constant
MALATYA	0.2975	57	0.3563	66	0.8346	0.2974	56	Increasing
MANISA	0.0645	80	0.1214	81	0.5315	0.0311	81	Increasing
MARDIN	0.5075	39	0.5138	47	0.9875	0.5075	38	Increasing
MERSIN	0.4536	41	0.4642	51	0.9770	0.4535	40	Increasing
MUGLA	0.6007	31	0.6072	41	0.9891	0.6007	31	Increasing
MUS	0.6901	25	0.7795	26	0.8852	0.6900	25	Increasing
NEVSEHIR	0.4044	47	0.4411	56	0.9166	0.4043	46	Increasing
NIGDE	0.1350	74	0.2343	73	0.5758	0.1349	73	Increasing
ORDU	0.7077	24	0.7297	29	0.9697	0.7076	24	Increasing
OSMANIYE	0.6349	27	0.7143	31	0.8887	0.6349	27	Increasing
RIZE	0.6829	26	0.6908	32	0.9884	0.6828	26	Increasing
SAKARYA	0.3255	55	0.3409	67	0.9548	0.3255	54	Increasing
SAMSUN	0.3724	53	0.3751	63	0.9926	0.3724	52	Constant
SANLIURFA	1.0000	16	0.9089	21	0.9348	0.8497	16	Increasing
SIIRT	0.8498	14	0.9036	22	0.9971	0.9010	14	Increasing
SINOP	0.9011	32	0.5928	42	0.9974	0.5913	32	Constant
SIRNAK	0.7227	1	1.0000	1	1.0000	1.1080	11	Constant
SIVAS	0.5913	22	0.7562	28	0.9555	0.7226	22	Increasing
TEKIRDAG	0.1319	75	0.2617	72	0.5036	0.1318	74	Increasing
TOKAT	0.5735	34	0.5765	44	0.9947	0.5735	34	Increasing

Table 7 (*continued*)

DMU	Overall Efficiency (CCR)	CCR Rank	Pure Efficiency (BCC)	BCC Rank	Scale Efficiency	Super- Efficiency	Super- Efficiency Rank	Returns to Scale
TRABZON	0.7991	19	0.8045	24	0.9933	0.7991	19	Increasing
TUNCELI	0.7110	23	1.0000	1	0.7109	0.7109	23	Increasing
USAK	0.3098	56	0.4413	55	0.7018	0.3097	55	Increasing
VAN	0.2578	61	0.3102	68	0.8310	0.2578	60	Increasing
YALOVA	1.0000	1	1.0000	1	1.0000	30.0598	1	Constant
YOZGAT	0.2643	59	0.3691	64	0.7161	0.2643	58	Increasing
ZONGULDAK	0.5452	37	0.6896	33	0.7905	0.5451	36	Increasing

sources).

Scale efficiency provides more information about the need for efficient usage of the inputs by considering advanced technologies and fast infrastructure services [76]. In this study, 11 provinces had the scale efficiency, which means these locations have had optimal scale size [77]. To elaborate, there were 11 cities with the overall technical efficiency value of 1 among the 81 provinces, which means all of their pure technical efficiency values and scale efficiency values were 1, indicating that the resource utilization of such provinces, whether in technique or scale, reached the fittest. This indicates that the DMU's were in the stage of constant returns to scale (CRTS), an optimal status for the combination of input factors and production scale, and there was no need for improvement [78]. Also, 60 provinces were in the stage of increasing returns to scale (IRTS) among 81 provinces. If they can expand their production scale, they may be able to improve the overall operational efficiency. Furthermore, 4 provinces were in the stage of decreasing returns to scale (DRTS) among 81 provinces. They should decrease their inputs and production scale in order to improve their overall operational efficiency. In brief, 17 provinces (i.e. 20.98% of the total provinces) were in the stage of CRTS; 60 provinces (i.e. 74.07% of the total provinces) were in the stage of IRTS; and the remaining 4 of them (i.e. 4.94% of the total provinces) were in the stage of DRTS.

According to the ranks of the provinces, Yalova, Gaziantep, Elazig, Sanliurfa, Kutahya, Kirikkale, K.maras, Izmir, Igdir, Gumushane, and Batman were efficient cities in terms of the utilizing renewable energy potential. There was no need for any improvement since the proportionate increase in input is exactly equal to the increase in output. After that Giresun, Karabuk, Sinop, Diyarbakir, Siirt and other provinces were coming as top ranks in terms of utilizing domestic renewable energy sources.

The provinces, Adana, Adiyaman, Afyon, Agri, Aksaray, Amasya, Ardahan, Artvin, Balikesir, Bartin, Bayburt, Bilecik, Bingol, Bitlis, Bolu, Burdur, Bursa, Canakkale, Cankiri, Corum, Duzce, Edirne, Erzincan, Eskisehir, Hakkari, Hatay, Isparta, Karabuk, Karaman, Kars, Kastamonu, Kayseri, Kirikkale, Kirklareli, Kirsehir, Kocaeli, Konya, Malatya, Manisa, Mardin, Mersin, Mugla, Mus, Nevsehir, Nigde, Ordu, Osmaniye, Rize, Sakarya, Sanliurfa, Siirt, Sivas, Tekirdag, Tokat, Trabzon, Tunceli, Usak, Van, Yozgat, Zonguldak were in the stage of increasing returns to scale. If they expand their scales, they can improve the overall efficiency. In this respect, investment studies on the network length, transformer capacity, and installed power of renewable energy should be increased in order to improve the efficiency in the related provinces. The obtained results were very consistent and were closely matching the current energy policies and investments of the government. For instance, the new nuclear power plant will be installed in Akkuyu, Mersin to fulfill the energy need. Geographic location and some considerable opportunities of the city ensures ample advantageous to build the new power plants in the city, as realized from DEA analysis. In addition to this, there are several renewable plants, which mostly continue to build and have decided to invest in these provinces. Besides, the majority of these cities (IRS) have either built-in power plants or newly granted power plants to be built in the future.

Ankara, Diyarbakir, Giresun, Istanbul were in the stage of decreasing returns to scale, a situation that occurs when the proportion of output is less than the desired increased input during the production process. At this point, number of consumer and energy generation from renewable energy outputs should be increased to improve efficiency frontier. Istanbul and Ankara are the most important metropolitan provinces of Turkey, and these cities take immigration from other regions at a seriously high rate every year. Many investment plans, which include transportation, healthcare and industrial progress, have been conducted properly to meet the needs of public efficiently. The vast majority of investments in these cities have been made, depending on the ever-increasing population ratio. Because of the foreseeable potentials of these cities, the improvements of the investments that needed to be made are already completed or are being done.

The results of CCR model indicated that eleven provinces were efficient, but we can't identify which one was the most efficient. Hence, we introduced the super-efficiency DEA model and provided a ranking for all cities, including the efficient ones. And the results of these calculations showed that Yalova was the most efficient province, followed by Kilis, Igdir, Izmir, Gumushane, Kutahya, K. Maras, Batman, Gaziantep, Elazig and lastly Sirnak, while Manisa was the most inefficient province followed by Kirikkale, Aksaray and Bilecik provinces.

5.3. Reasons for technical inefficiencies

Given the fact that there was a relatively high number of inefficient provinces throughout the country, there was an obvious need to investigate further the potential source of technical inefficiencies. To this end, the input excesses and the output deficits were individually derived for each of the inefficient provinces. The results of averaging the input excesses and output deficits for each input and output variables are summarized in Table 8.

As it is clear from Table 8, the following three variables—network length, transformer and total installed capacity—were featured as the top-three with the highest *input excess* for the provinces in the assessment of the energy efficiency of Turkey. However, total renewable energy potential was ranked as having the least input excess according to results. Energy policy makers or managers tend to put too much emphasis on managing network length and transformer capacity as a way of upgrading their efficiency. It can be concluded that the provinces in Turkey are spending more resources and efforts on managing network length, transformer capacity and installed power of renewable energy, all of which are relatively important influencers on the efficiency of their renewable energy management practices. In terms of the overall average of output deficits, energy generation from renewable sources and number of the consumer have significantly high scores and thus, these factors have aroused as the critical reasons of the inefficiency of the provinces.

These findings, in general, suggest that too much effort exerted on these energy infrastructure practices may degrade the relative efficiency of operational performance of the districts. In other

Table 8
The average of input excesses and output deficits.

Input Factors	Average Improvement Potential	Rank
Total Renewable Energy Potential	0.00074	4
Network Length	1082.61616	1
Total Installed Power of Renew. Energy	12.20963	3
Transformer Capacity	75.53578	2
Overall	1170.3623	1
Average	292.5906	1
Output Factors	**Average Improvement Potential**	**Rank**
Energy Generation from Renewable Sources	2787.5071	1
Number of Consumer	285.6490	2
Overall	3073.1560	1
Average	1536.5780	1

words, the government should seek the ways to improve the implementation of these practices. It should be noted that inputs of the energy systems should be transformed into the operational performances, known as output, effectively with avoiding losses. Idle resources should be used efficiently to obtain a real gain from the system for the long term.

From the technical dimensions of DEA case study for Turkey, according to improvable spaces of input and output items of DMUs, Kirklareli had the worst overall technical efficiency (0.0363); for instance, the improvable spaces of this DMU's input item was (0.0001) and the improvable spaces of its output item was (4102.5914). Namely, to enable such DMU to utilize resources as efficiently as other DMUs (with the overall technical efficiency values of 1), its “total renewable energy potential” has to be decreased by 0.0001%, and “energy generation from renewable sources” has to be increased by 4102.5914 MW; after these adjustments, Kirklareli would become a relatively efficient province.

From a wider perspective, efficiency is described as the ratio of outputs to inputs. The following are the three potential ways to improve efficiency: (i) reduce the amount of input while keeping output constant, (ii) increase the amount of output while keeping input constant, and (iii) increase output while at the same time decreasing input. The essence of the matter is that the energy need of Turkey has been in an increasing trend and this rising trend will continue in the future. For this reason, we may expect that the efficiencies of the provinces may increase without any need to reduce the input usage.

Loss and theft, a serious problem in electricity networks, can and should be reduced (or eliminated) during electricity distribution in the network line. More resistant and qualified transmission lines should be installed and supported with new technological equipment and infrastructure attempts. Moreover, capacity expansion efforts should be increased steadily. Renewable energy investments should be encouraged, projects on this subject should be accelerated.

5.4. *Models for second-stage analyses: explaining the determinants of efficiency*

The dependent variables employed in the comparative second-stage analysis were the technical efficiency scores from super-efficiency and the CCR-DEA analyses.

5.4.1. *OLS results based on super-efficiency DEA*

By the help of super-efficiency DEA the efficiency scores of the provinces were obtained as dependent variables and then using these measures, we can assess the effects of the environmental variables on the efficiency scores. OLS regression is a proper and applicable method for these depended variables, which are uncensored due to the working principle of the super-efficiency analysis. Depending on the OLS regression model, the second-stage regression model employing super-efficiency scores can be specified as follows:

$$y_i(\mathrm{CCR-DEA}) = \alpha + \beta_1\, ln(Export) + \beta_2\, ln(GDP) + \beta_3(\mathrm{HDI}) + \beta_4\, ln(\mathrm{En\_Prod}) + \beta_5\, ln\,(\mathrm{Pop}) + \beta_6\, ln(\mathrm{Area}) + \varepsilon$$

The OLS model was similar to the Tobit regression expression. The OLS regression results showed five variables as significant at the 1% and 5% levels. As in the Tobit regression, the area factor was negatively and GDP per capita variable was positively correlated with efficiency in the OLS analysis. Total exports and total energy production variables have shown a significant impact on the efficiency, with a negatively correlated efficiency, whereas population positively affected the efficiency of the OLS analysis as one of the significant factors.

In Table 9, the parameter β_{Export} (coefficient) indicates that each unit increase in export reduces energy efficiency by 0.714 units. One unit increase in GDP (β_{GDP}) provides energy efficiency increase by 2.068 units. Each unit increase in energy production (β_{En_Prod}) leads to energy efficiency decreases by 0.306 units. Each unit increase in population (β_{Pop}) causes energy efficiency increase by 2.509 units. The increase in each unit area (β_{Area}) shows that the energy efficiency decreases by 2.611 units.

Export activities are provided based on the technologies, services, and platforms that ensure system-level energy efficiency to sustain uninterrupted manufacturing process. All of these processes require intensive energy usage besides electricity generation, transmission, and distribution. The used energy-intensive infrastructure such as equipment and machinery consume more energy, hence the energy efficiency is slightly decreased [70]. Despite all this, it should be noted that commercial income provided by exports contributes to the economy of the country and increases the level of prosperity.

Total energy production includes other types of energy sources, such as fossil fuel, coal, thermal, natural gas, etc. to create the supply for the electricity demand. In this study, we specifically investigated the energy efficiency of the provinces in Turkey. Thus, other types of energy sources, mostly believed to produce more

Table 9
Results of OLS regression analysis.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ln(*Export*)	−0.713990	0.294543	−2.424061	0.0178***
ln(*GDP*)	2.067609	0.739193	2.797117	0.0066***
HDI	−4.935394	4.125681	−1.196262	0.2354
ln(En_Prod)	−0.306668	0.165391	−1.854198	0.0677*
ln (Pop)	2.509509	0.959343	2.615863	0.0108***
ln(Area)	−2.610619	0.743633	−3.510626	0.0008***
C	−0.348090	8.122985	−0.042852	0.9659
R-squared	0.287155	Mean dependent var		1.042051
Adjusted R-squared	0.229356	S.D. dependent var		3.473514
S.E. of regression	3.049270	Akaike info criterion		5.150137
Sum squared resid	688.0555	Schwarz criterion		5.357065
Log-likelihood	−201.5805	Hannan-Quinn criteria.		5.233159
F-statistic	4.968219	Durbin-Watson stat		1.936467
Prob (F-statistic)	0.000253			

***, **, *denotes the significance at the 1%, 5%, 10% level using two-tailed test, ln denotes the natural logarithm of the related variable.

pollutant emissions, compete with the renewable energy sources. As each type of energy source becomes a part of the restricted capacity of the electricity generation, the renewable energies do not have much of a share. It is known that to maintain energy reliability and sustainability interrupted, energy diversity should be implemented in the energy market because electricity production from renewable energy sources highly depend on changing and uncertain climatic conditions such as sunlight, wind and hydro. Therefore, energy production from other fossils decreases the renewable energy efficiency in the certain districts [71,79].

Energy consumption may vary depending on population size, and affect the energy efficiency directly. In this study, we have examined the population and the area of the provinces separately, but some studies have considered population density as an exogenous variable that is measured by the number of people per square kilometre [80]. We have analyzed both population variable and population density variable to understand the effects of the renewable energy, and have reached almost the same results, which indicate positively significant coefficient in Tobit and OLS regressions. According to energy planning studies, firstly electric service is provided to the most populated and industrialized regions and communities. In particular, the generated energy in crowded and developed provinces such as Istanbul and Ankara is consumed instantaneously. Unless energy demand is still not met, energy support is provided from nearby regions. Therefore, it can be considered that the population is positively associated with energy efficiency. Çelen and Yalçın (2012) state that electricity companies operate primarily in crowded regions due to the efficiency advantage. In addition, the government should take some actions to increase energy efficiency through energy infrastructure works such as increasing the transformer capacities, extending the network lengths, reducing the electricity loss and theft ratios. In some points, the analysis results may differ in both OLS and Tobit regressions. The HDI variable is insignificant according to OLS regression at 5% level, but it shows a significantly negative coefficient in the Tobit regression results.

Although the total energy production variable was not significant in Tobit regression, it was very close to becoming a significant variable (p-value = 0.167). It was a significant variable in the OLS regression and the sign occurred as a negative impact on the efficiency, on the contrary of the Tobit regression results. The standardized coefficients given in Tables 9 and 10 allow us to realize the relative impact of each independent factor on the efficiency in each regression set. For instance, on the Tobit regression, the two variables that indicate the most impact on efficiency were HDI and the GDP per capita; in the OLS regression, the related variables were area and the population.

5.4.2. Tobit results based on CCR scores

The other analytical approach was employed when the CCR score was utilized as the dependent variable. Tobit regression model was constructed to measure other instruments behind energy efficiency of the districts and the obtained scores. Tobit regression take values between 0 and 1, making the depended variable in the second stage limited. EViews 9 Software is utilized to implement this econometric model. The calculated efficiency score in the first stage (y_i) was corrected by the environmental variables in this second stage (z_i). The relationship between energy efficiency and influencing factors can be expressed as follows:

$$y_i(\mathrm{CCR-DEA}) = \alpha + \beta_1\, ln(Export) + \beta_2\, ln(GDP) + \beta_3(\mathrm{HDI}) + \beta_4\, ln(\mathrm{En\_Prod}) + \beta_5\, ln\,(\mathrm{Pop}) + \beta_6\, ln(\mathrm{Area}) + \varepsilon$$

Table 10
Results of Tobit regression analysis.

Variable	Coefficient	Std. Error	z-Statistic	Prob.
ln(*Export*)	0.000204	0.013621	0.015012	0.9880
ln(*GDP*)	0.080522	0.034184	2.355562	0.0185***
HDI	−0.553683	0.190792	−2.902024	0.0037***
ln(En_Prod)	0.010563	0.007649	1.381066	0.1673
ln (Pop)	0.033279	0.044365	0.750127	0.4532
ln(Area)	−0.056401	0.034389	−1.640082	0.1010*
C	0.778287	0.375647	2.071858	0.0383
Error Distribution				
SCALE:C(8)	0.141013	0.011079	12.72792	0.0000
Mean dependent var	0.894372	S.D. dependent var		0.158291
S.E. of regression	0.148539	Akaike info criterion		−0.882394
Sum squared resid	1.610665	Schwarz criterion		−0.645905
Log-likelihood	43.73696	Hannan-Quinn criteria.		−0.787512
Avg. the log likelihood	0.539962			
Left-censored obs	0	Right-censored obs		0
Uncensored obs	81	Total obs		81

***, **, *denotes the significance at the 1%, 5%, 10% level using two-tailed test, ln denotes the natural logarithm of the related variable.

Tobit results showed three variables that affect energy efficiency at the 1% and 10% significance levels: Human development index and area, both variables showed negative coefficients. This means that these factors reduce the efficiency. That is, the one-unit increase in HDI causes 0.55% increase and one-unit increase in the area brings about 0.06% increase in the efficiency scores according to Tobit regression.

HDI is a sign of the development to live in well conditions, which include a combination of the healthcare system, education system and industrial progress of the related district because the high technologic developments facilitate life to get comfortable environment. It leads to more energy consumption depending on the utilized machines and other services received. The United Nations Development Programme (UNDP) establishes the relationship among energy use, economic growth, and social development. There is a high correlation between lower energy and lower HDI.

Smaller area with less development consumes less energy. This means larger areas tend to be more inefficient, which seems to be a reasonable result. Energy need will increase depend on a regions' size since the power of lightning around the service area, networks lines and other infrastructure parameters will be consumed more energy to be serviced. Unless focusing on the technical level of operations and the design of transmission-distribution system to get better performance, energy efficiency will reduce automatically [48].

GDP per capita significantly contribute to efficiency and positively correlated with efficiency. The magnitude of the coefficiency was 0.081, which indicates that every 1% increase in the efficiency scores leads to 8.1% increase in the overall efficiency score. Districts with higher GDP per capita are in a more advantageous stage in economic expansion, which provides for the augmentation of industrial structure and the move to a service-oriented society. The awareness of the energy efficiency has emerged as a subject that needs to be paid more attention to the public in developed countries or regions. Different studies in the literature show that developed regions have higher energy efficiency than less developed regions [69; 65; 67]. Performance indicators (R^2, Akaike criterion etc.) are shown in Tables 9 and 10 for the relevant analysis.

As seen from OLS and Tobit regression analyses, OLS regression provided a more comprehensive analysis while Tobit regression narrowed the boundaries of the analysis because of censoring nature of the method. The common significant variables have emerged as GDP per capita and the area in both approaches. The other influential variable was HDI, and total energy production can be considered as a significant factor in Tobit regression whereas export, total energy production factors are obtained as significant variables in OLS regression. The study was mainly based on the OLS methodology, and then checked/confirmed the obtained OLS results with the Tobit regression. The only variable that is not significant in OLS method was HDI. However, according to the Tobit regression, HDI was obtained as a significant variable and the sign of the variable was negative. According to the focus group meetings and expert opinions, it is understood that HDI was an influential factor in energy efficiency. Therefore, the Tobit regression acted as a complementary method in the overall methodology.

6. Conclusions

This study evaluated the energy efficiency of Turkey, in both provincial and regional levels, based on the super-efficiency DEA and CCR-DEA models. The influencing environmental factors of energy efficiency were investigated by OLS and Tobit regression models. In the literature, the studies generally employ two-stage DEA applications, which consist of DEA application in the first stage and Tobit regression model in the second stage. However, the procedure has a disadvantage. Because DEA assigns “1” score to the efficient units, no information is available about the relative order of the efficient units or the influence of the managerial/environmental variables on their relative position on the efficiency process. The analyses were primarily based on the OLS method, after implementing the super-efficiency DEA analysis. In this study, we first perform the analysis with using the super-efficiency DEA and OLS methods together to reveal influences of environmental variables on energy efficiency and then we present a confirmation using the CCR-DEA and Tobit regression approaches. Using the proposed two-stage approach, the energy efficiency and influential environmental/managerial factors at the provincial and regional level of Turkey were discovered and presented. With Tobit regression approach (used in Stage 2), we are trying to make a confirmation of the OLS method. For this reason, the Tobit method is considered as a useful tool for the complementary or confirmatory approach.

As shown in this study, it can be said that Tobit regression leads to information loss due to the censored nature. On the contrary, it is evident that super-efficiency analysis provides more comprehensive results as it employs all relevant knowledge in data by relaxing the limits. However, both methods provide more meaningful and helpful results when used together rather than used separately. Particularly for multi-dimensional, complex and strategic decision-making problems can be assessed according to this structure. Because principally in this kind of problems it may provide a clue that which factors should be examined in more detail if the efficient variables rarely change in both analyses owing to the specific structure of problem/subject.

More specifically, according to CCR or BCC results, we can only obtain which DMU is efficient or not, based on the efficiency scores. Additionally, these models do not explicitly provide the actual ranking of the efficient DMUs among themselves. The main point behind the developing super-efficiency DEA was to show sorting/ranking of 10% relative efficiency of these DMUs. In order to eliminate the insufficiencies of the mentioned models and to assess DMUs' efficiencies realistically and comprehensively, the super-efficiency model was developed by Ref. [57]. The Tobit method is limited and its use with CCR-DEA is more appropriate in this context. In addition, the reason for using both methods can be explained as follows: Firstly, to identify meaningful and significant variables. Then, should be concentrated on the governmental politics on these issues. Energy policymakers and investors can constitute an action plan to increase renewable energy utilization rate at a high level according to analysis results. With this study, all authorities in the energy sector can take into account the current conditions of the regions/provinces, which have renewable energy potential at what level.

In the analysis, scale efficiency values were obtained by CCR and BCC models. According to the super-efficiency ranks, Yalova, Kilis, Igdir, Izmir, Gumushane, Kutahya, K. Maras, Batman, Gaziantep, Elazig and lastly Sirnak demonstrated the best performance among all provinces in the model. The Aegean Region and The South Eastern Anatolia Region were more efficient among the regions. The main reason for the efficiency of these regions was having high renewable energy potential and utilization of the potential efficiently depend on regional technological progress. In recent years, renewable energy investments, capacity expansion decisions, and system integration activities have been expanded particularly in these regions. All these factors raise energy efficiencies, stage by stage.

Effective renewable energy management is a core issue of the most of the governments, particularly for the developing countries in order to maintain sustainable development and to manage economic growth. In the view of environmental variables, GDP per capita is very important to determine energy efficiency. Economic growth provides an opportunity to invest in energy resources to generate electricity. Utilizing highly qualified equipment and advanced technology investments decrease the inefficiencies of the energy system with isolated network line. All these are provided by the financial sources. According to researchers, the developed societies (high GDP per capita) are more aware of the energy efficiency issues than poor communities due to the high technological advancement and education level.

The second most important environmental variable is population or population density, which positively affects the energy efficiency due to the potential advantage of the crowded regions. From the standpoint of efficiency, the policy of the state should primarily be centered on providing services to crowded places. And the electricity companies prefer to operate primarily in crowded regions due to the efficiency advantages compared to isolated places.

The third most important environmental variable is total energy production, which considers another kind of energy sources such as fossil fuel. Because all energy sources are part of the limited capacity of the electricity generation, renewable energies do not have much of a share. Therefore, energy production from other fossil-based sources tends to decrease the renewable energy efficiency in the related regions.

Some suggestions for the policy of increasing energy efficiency based on renewable energy sources can be presented as follows: The renewable energy resources should be properly planned and utilized in an optimal way. Renewable energy investments should be encouraged with incentives and feed-in tariffs. Energy investment activities should be carried out starting from low-efficient provinces. Technological investments and capacity expansion activities should be accelerated by the government to meet growing energy need. The loss and theft rate should be reduced and the network lines should be extended by providing energy service to each point of the country.

The results of energy efficiency assessment can be helpful for managers to decide on effective management and investment strategies. Energy policymakers and investors can constitute an action plan to increase renewable energy utilization rate at a high level according to analysis results. With this study, all authorities in the energy sector can take into account the current conditions of the regions/provinces, which have renewable energy potential at what level. All these works provide our country to reduce dependence on foreign energy sources and to maintain sustainable development. This study demonstrates that researchers and policymakers will find DEA, Tobit and OLS useful methods for efficiency analyzing of provinces in the context of developing countries when data can be challenging to obtain. For future directions, this study can be analyzed by adding new inputs/outputs and the results can be compared with, is known as a parametric method Stochastic frontier analysis, and Malmquist productivity index.

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