Energy Policy 132 (2019) 965–977

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

Factors affecting the efficiency of wind power in the European Union countries

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ARTICLE INFO

Keywords:
Wind power efficiency
Renewable energy policy
EU countries
Bias-corrected DEA
Bootstrapped truncated regression model

ABSTRACT

The study uses the two-stage bias-corrected DEA approach of Simar and Wilson (2007) to assess the efficiency of the EU countries in terms of their wind power investment in 2015. The set of input variables includes installed wind power capacity and average wind power density, while output variables include wind-generated electricity and three additional aspects: environmental, economic and energy security. Next, the study examines the effect of renewable energy policy regarding wind energy, the energy mix, and the offshore wind power utilisation on the wind power efficiency of the analysed countries.

The results obtained reveal that the United Kingdom, Sweden, Denmark, and Ireland are the most efficient countries in terms of wind power investment. The inclusion of additional aspects demonstrates the greatest improvement of efficiency in Belgium, Cyprus, the Netherlands, Estonia and Germany.

The results seem to indicate that economic instruments used within renewable energy policy have a positive effect on wind power efficiency, while policy support and regulatory instruments might negatively impact. Moreover, the results show that the energy mix explains the variation of the efficiency of the EU countries when their economic and environmental aspects are considered. The analysis of the geographic location indicates that countries with a high share of offshore wind capacity are the most efficient.

1. Introduction

The rapid development of renewable energy sources in the EU member states results from the common energy policy aimed at improving energy security and reducing greenhouse gas emissions. In accordance with the Directive 2009/28/EC, the share of renewable energy in the overall energy consumption in the EU member states should be increased to - on average - 20% by 2020 as part of its efforts to cut carbon dioxide emissions. This target, connected with reducing CO_2 emissions by 20%, became part of Europe's climate policy (EU 2020 Energy Strategy, 2014). The European climate and energy package specifies a national renewable target for each EU member state ranging from 10% in Malta to 49% in Sweden. To meet this target, each EU country, having the choice of renewable energy sources and means of using them in the most effective way, has created its own national renewable energy action plan (for instance, implementing a climate change mitigation strategy linked with decarbonisation of the power sector).

On the one hand, the viability of investment in renewable energy sources (especially wind farms and solar parks, which are conducive to decarbonisation of the power sector) to a great extent depends on the supply of a given energy source. The EU countries are highly diversified in terms of their wind potential: countries from northern Europe and the ones neighbouring the Atlantic Ocean, the North Sea and the Baltic Sea have much greater wind potential than countries from southern Europe and the centre of the continent.

On the other hand, each country, even the ones with relatively low wind potential, can introduce its own energy policy and support the development of e.g. wind power by offering specific incentives, such as feed-in tariffs, green certificates, promotional loans, investment grants, tax exemptions, etc., which will increase the viability of investments in renewable energy sources. If efficiency is understood as wind power generation, such support can be seen as an obstacle. A broader perspective, however, indicates that the development of renewable energy sources leads to positive changes in the natural environment, increases energy security, and decreases the costs of importing energy sources. The assessment of the viability of investment in wind power should take all these factors into account.

There are numerous studies dedicated to the explanation of the dynamics of the development of renewable energy, and they usually examine the role of different aspects of energy and climate policy. Best and Burke (2018), Newbery (2018) investigate the role of carbon

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https://doi.org/10.1016/j.enpol.2019.06.036
Received 29 October 2018; Received in revised form 31 May 2019; Accepted 20 June 2019
0301-4215/

pricing in the adoption of solar or wind energy. Jenner et al. (2013), Zhoa et al. (2013), Yamamoto (2017) analyse the effect of the feed-in tariff (FIT) efficacy. Ince et al. (2016) and Romano et al. (2017) examine the influence of informal institutions on renewable strategy development, fiscal incentives, and public investments. All these studies focus on the capacity (generation) of renewable energy achieved by countries or the share of renewable electricity generation in total electricity generation. However, only several of them admit that energy policy can result in inefficiency, redundancy or overlapping of renewable energy (see Del Río and Mir-Artigues, 2014). Our study follows this important remark extending the findings of other studies in two directions. First, it concentrates on the efficiency of renewable energy (wind power), not just capacity or electricity generation, which provides a deeper insight into the process, as it takes into account a larger set of input and output variables. The set of outputs covers environmental, economic and energy security aspects and thus constitutes the second extension. It shows that the effects of energy policy applied to promote renewable energy should be analysed in a broader perspective. Especially the environmental effects of energy policy, frequently discussed in the literature (see Dowling, 2013; Totschnig et al., 2017), seem to be an important outcome of energy policy.

The study has two aims. The first one is to assess the efficiency of 27 EU countries regarding their wind power investments. The second one is to identify the impact of external factors on wind power efficiency in these countries. The factors considered in the study are related to renewable energy policy regarding wind energy, the energy mix, and the offshore wind power utilisation.

The assessment of the efficiency in this study takes into account not only the technical efficiency but also environmental, economic and energy security aspects. Such a wide approach has not been adopted in previous studies. The study considers the reduction of greenhouse gas emissions, savings resulting from the replacement of conventional energy with wind power, and an increase in energy security stemming from the reduction of fossil fuel imports. The differences between the EU countries in the above areas are linked to the differences in their energy mixes.

The study analyses the efficiency of wind power with a two-stage procedure. In the first stage, an input-oriented Data Envelopment Analysis (DEA) model is applied to assess the efficiency of the EU countries regarding different aspects of wind power generation. It is assumed that the EU countries are unlikely to change their outputs related to energy mix within a short period of time, although it is possible over a longer timespan (see Papież et al., 2018). Consequently, the efficiency can be increased by lowering input variables in the model.

In the second stage, the analysis utilises the https://www.sciencedirect.com/science/article/pii/S0140988308000637 Simar and Wilson (2007) procedure to bootstrap DEA scores with a truncated regression to identify and explain the role of factors which affect the relative efficiency scores of the EU countries. The results reveal the importance of a given factor to the wind power efficiency in a given area. In particular, it will be possible to gain insight into the relations between renewable energy policy and the development of wind power.

There are two approaches in the literature related to this study. The first one assesses eco-efficiency of European countries (Menagaki, 2013; Robaina-Alves et al., 2015; Gómez-Calvet et al., 2016; Madaleno et al., 2016; Moutinho et al., 2017). The EU countries in these studies are defined as decision-making units. Output and input variables are part of the Cobb–Douglas production function.

The second approach measures the efficiency of wind power plants (Iglesias et al., 2010; Azadeh et al., 2014; Ederer, 2015; Sameie and Arvan, 2015; Wu et al., 2016; Sağlam, 2017a, 2017b; Niu et al., 2018). Wind farms or wind turbines in a given country are treated as decision-making units (DMUs). Installed wind capacity is the input variable, and the output variables can include, for example, electricity generation, production optimisation process, location optimisation of wind plants, or investment performance.

This study implements both approaches used in the literature. First, it assesses the efficiency of the EU countries regarding their wind power investments, like in the first approach, but uses variables from the second approach (e.g. installed capacity, plus average wind power density as the input variable, and wind-generated electricity as the output variable). In contrast to the second approach, this study uses the EU countries (and not wind farms or wind turbines) as the decision-making units. Second, it extends the analysis by including additional output variables covering various economic, environmental and energy security aspects. Consequently, the study comprehensively compares the EU countries in terms of benefits gained by replacing conventional energy with wind power, thus filling the gap in the literature.

The novel aspects of this study can be summarised as follows.

The most important novelty lies in the selection of objects used in the analysis, that is the EU countries, as they have not been compared in this context so far. There are three reasons why these countries are an interesting object of study. First, all of them are obliged to meet the targets set in the climate and energy package. Second, they are highly diversified with reference to their wind potential, which is directly linked with their offshore wind power utilisation, and, as a result, the efficiency of investment aimed at increasing capacity of wind farms may differ in particular countries. Third, their energy mixes differ.

Next, the approach adopted in the study is based on a comprehensive view of the wind power efficiency on the country level. The study assesses not only the technical efficiency, which transforms wind power investment into electricity generation but additionally considers economic, environmental and energy security aspects, which seem to play a crucial role and have motivated the EU legislation in this area.

Finally, the study does not only estimate the efficiency of the EU countries regarding their wind power investment but additionally interprets the results obtained. Thus, three external types of factors which affect renewable energy policy regarding wind energy, the energy mix, and the offshore wind power utilisation are treated as potential variables influencing the efficiency of wind power in the analysed countries. The assessment of their influence could prove beneficial for policymakers, as it points at possible constraints to be taken into consideration while deciding on renewable energy policy.

The paper consists of the following sections. Section 2 presents a brief literature review. Section 3 describes a two-stage DEA. Section 4 describes the data, and section 5 reports and comments on the empirical results. The paper ends with the conclusions, discussion and policy implications.

2. Literature review

The DEA method was developed by Charnes et al. (1978) and is frequently used in studies devoted to energy and environment. Emrouznejad and Yang (2017) give an overview of articles published between 1978 and 2016 in which DEA is used, listing over 10,000 studies, about 290 of which investigate efficiency or productivity in the electricity generation sector. Mardani et al. (2017) review 144 articles published between 2006 and 2015 in which DEA is used to assess energy efficiency. Also Sueyoshi et al. (2017) summarise the results of 693 studies on energy efficiency in which DEA is employed to measure energy efficiency and environmental protection during the last 40 years.

Despite a large number of studies in which the DEA method is employed to investigate energy efficiency, only several of them address the efficiency of the renewable energy sector. This method is used to compare the efficiency of different renewable energy sources (Cristóbal, 2011; Kim et al., 2015) and to evaluate the efficiency of individual renewable energy sources, e.g. solar (Sueyoshi and Goto, 2017), biogas (Madlener et al., 2009; Lijó et al., 2017), or hydroelectric power (Barros et al., 2017).

Not many papers deal with the wind power efficiency (Iglesias et al., 2010; Azadeh et al., 2014; Ederer, 2015; Sameie and Arvan, 2015; Wu et al., 2016; Sağlam, 2017a, 2017b; Niu et al., 2018), and their authors use the DEA method or the two-stage (DEA and Tobit) analysis to measure the efficiency of wind power farms or wind turbines. They take into consideration various factors including, for example, electricity generation, location optimisation of wind plants, investment performance, financial performance, and operating costs and capital costs of wind farms. In these studies wind farms or wind turbines are defined as the decision-making units (DMUs).

Azadeh et al. (2014) and Sameie and Arvan (2015) investigate optimum location of wind plants in Iran. Niu et al. (2018) assess the efficiency of 32 wind turbines in China. Ederer (2015) studies capital and operating costs of offshore wind farms in Europe. Iglesias et al. (2010), Wu et al. (2016) and Sağlam (2017a) measure the productive efficiency of wind farms in Spain, China and the USA. Iglesias et al. (2010) identify the relevance of the economic impact of wind farms for wind farm development companies, technology suppliers and operators. Wu et al. (2016) demonstrate that most wind farms in China are efficient and installed capacity and wind power density are the most important factors in their efficiency. Sağlam (2017a) reveals that about two-thirds of wind farms in the USA operate wind power efficiently and that the choice of the brand of the wind turbine significantly contributes to the productive efficiency of wind farms.

In the above-mentioned studies, wind farms or wind turbines are treated as the decision-making units (DMUs). However, Sağlam (2017b) uses two-stage DEA to measure the wind power efficiency of 39 states in the US. He treats individual states in the USA as DMUs and uses the following output variables: the production-related output variables, the economic and environmental output variables, and the following input variables: installed wind capacity, the number of wind turbines, total project investment, and the annual land lease payment. The DEA results indicate that more than half of the states operate wind power efficiently. The results of the Tobit regression model reveal that early installed wind plants were more expensive and less productive than more recently installed ones.

The DEA method is also used to measure eco-efficiency of countries or regions (defined as DMUs) and three related efficiencies: economic efficiency, energy efficiency, and environmental efficiency. Menegaki (2013), Robaina-Alves et al. (2015), Gómez-Calvet et al. (2016), Madaleno et al. (2016) and Moutinho et al. (2017) apply the DEA framework to analyse the eco-efficiency of European countries which are treated as the decision making units (DMUs), with GDP as the output variable, the ratio GDP per GHG emissions as the undesirable output variable, and capital, labour, fossil fuels and renewable energy consumption as the input variables.

Menegaki (2013) applies the DEA model to benchmark the efficiency of European countries' growth in the period 1997–2010 with respect to their RES performance, as the main input using variables typically employed in the growth-energy nexus literature, such as energy consumption, carbon emissions, employment and capital, but she also takes into consideration consumption of renewable energy sources. Similarly, Gómez-Calvet et al. (2016), Madaleno et al. (2016) and Moutinho et al. (2017) estimate the efficiency of different European countries using the DEA method to compare their performance. The results reveal that economic and environmental estimates change depending on the models used.

3. Methodology

3.1. First-stage of the Simar and Wilson procedure

The first-stage of the Simar and Wilson (2007) procedure estimates the DEA efficiency scores and next corrects them for bias using the homogeneous bootstrap procedure.

The DEA method originated in microeconomics, in the production theory and the production function, in which a single output was connected to a single input. The authors of this method transferred this relation to multidimensional situations. It is a frontier method, as it allows for setting a so called production-possibility frontier on and below which all possible combinations of inputs and outputs are found. In this method, the frontier is based on the best objects in the group, which become the benchmark for the remaining objects. The frontier is built in a non-parametric manner without a priori assumption on the distribution or production function considered.

The CCR model (Charnes, Cooper and Rhode's model), proposed by Charnes at al. (1978), assumes constant returns to scale, and the modification of the model presented in 1984 by Banker, Charnes and Cooper (Banker et al., 1984) (the BCC model) allows for variable returns to scale (VRS). The latter approach allows for assessing countries not only from the perspective of their pure technical efficiency (the best use of input) but also from the perspective of economies of scale (operating within the area of optimal benefits). Consequently, the BCC model enables us to uncover sources of inefficiency resulting either from imperfect investment or from operating within non-optimal economies of scale.

Basic DEA models consist of two approaches: input-oriented and output-oriented. The first specification maximises the proportional reduction of inputs X while holding outputs constant Y. The second one maximises the proportional increase of outputs Y whilst inputs X are constant. Our study utilises an input-oriented model, as it focuses on assessing optimal investment (and wind density) made to provide output reached by efficient countries. To obtain the efficiency scores θ in the input-oriented BCC model, a quadratic programing of the following form is implemented:

$$\theta^* \rightarrow min,$$

Subject to:

$$\sum_{j=1}^{n} x_{ij}\lambda_j \leq \theta x_{i0}, \quad i = 1,2, \ldots, m$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j \leq y_{i0}, \quad r = 1,2, \ldots s,$$

$$\lambda_j \geq 0, \ \sum_{j=1}^{n} \lambda_j = 1$$

The condition $\sum_{j=1}^{n} \lambda_j = 1$ is included to represent the convexity constraint for λ_j in VRS condition. This way each country (DMU) can be compared only to the group of similarly-sized DMUs with similar returns to scale.[1] The optimisation procedure yields the score ranges between 0 and 1. The larger the score is obtained, the more efficient the given DMU appears. The most efficient countries, whose efficiency score is 1, lie on the constructed frontier.

Statistical properties of the efficiency scores in a finite sample are studied by Simar (1992), Simar and Wilson (1998, 2000, 2002), who propose a statistical model and consistent bootstrap procedures to provide a statistical inference of the technical efficiency measures. In particular, their bootstrap-DEA method corrects the bias of estimators and provides the confidence interval of the efficiency scores.

3.2. Second-stage of the Simar and Wilson procedure

A conventional approach in the DEA literature used to analyse dependency between the efficiency scores and the set of explanatory variables employs Tobit regression. Simar and Wilson (2007), demonstrate, however, that this approach leads to inconsistent and biased estimates of the parameters. As a remedy, Simar and Wilson (2007)

[1] The previously mentioned input or output oriented DEA models can be generalised into both orientations combined in a single model i.e. an additive model proposed by Charnes et al. (1985).

propose a truncated bootstrapped (Tobit) regression, and our study follows their approach. Formally, we assume and infer the following specification:

$$\theta^* = a + Z_j\delta + \varepsilon_j, \quad for\ j = 1, ..n$$

where: a is a constant, Z_j is a vector of variables which are expected to affect DMU's efficiency scores, ε_j is a vector or error term. The distribution of ε_j is restricted by the condition $\varepsilon_j \geq 1 - a - Z_j\delta$, and is assumed to be normally distributed with zero mean and variance σ_ε^2 before truncation ($\varepsilon_j \sim N(0, \sigma_\varepsilon^2)$).

Asymptotic theory finds confidence intervals using normal distribution, however, in a small sample, more efficient estimators can be obtained using a bootstrap approach (Simar and Wilson, 2007). It is even more important when the efficiency scores are correlated with environmental variables. The bootstrap confidence intervals for the regression parameters and variance of the error term distribution are constructed by the parametric bootstrap which incorporates information on both the parametric structure and regardless of the errors distribution.

4. Data

The empirical part of the study incorporates two stages based on different datasets. The first one, used in the bias-corrected DEA method, contains two input variables and a subset of four output variables. The selection of input and output variables is based on literature. Wu et al. (2016), Sağlam (2017a, 2017b), and Niu et al. (2018) measure the productive efficiency of wind farms as the input using wind power density and installed wind capacity, which is a common metric for the capital input. Wu et al. (2016), Sağlam (2017a, 2017b), and Niu et al. (2018) [2] consider CO_2 emissions avoided and electricity generation as a set of output variables. The second dataset used in the truncated bootstrapped regression is directed at assessing factors affecting the efficiency of 27 EU countries regarding their wind power investment and, next, at explaining their influence. The bias-corrected efficiency scores of the analysed countries obtained from the bias-corrected DEA method are used as the dependent variable. Factors linked with the following three areas: renewable energy policy regarding wind energy, the energy mix, and the offshore wind power utilisation, are considered as independent variables. All data describe 27 European Union countries (excluding Malta, which did not generate any wind power in the analysed period) in 2015[3] and are obtained from the European Commission webpage.[4]

4.1. Input variable

Cumulative installed wind capacity (MW) per capita in 2015 (**CAP**) serves as the input variable in the DEA models. The variable is a proxy for total wind power investment in particular countries which cannot be measured directly. The data describing investment in renewable energy (including wind power) are available for the EU countries since 2010 and do not include previous investment (*EurObserv'ER*). This approach follows the one adopted in numerous other articles (e.g. Iglesias et al., 2010) and assumes that the costs of building a wind farm with given capacity are similar in all EU countries (at least, in the last decade), thus, can be expressed by total cumulative installed wind capacity.

The average wind power density (**DEN**) is the second input variable in DEA, and it is calculated using wind speed, which is a crucial parameter in describing wind resources. The average wind power density allows for evaluating the potential of wind resources for a specific area (Wu et al., 2016; Saglam, 2017a; Niu et al., 2018). Following the suggestions offered by Niu et al. (2018), wind farms should be built in places where the annual average wind speed at 50 m above the ground is higher than 7.5 m/s, and wind power density at 50 m above the ground is higher than 200 W/m2 (Zhao et al., 2009). Therefore, this study uses the wind power density at 50 m height. The data for 10% of the windiest areas are obtained from the Global Wind Atlas.[5]

4.2. Output variables

The first variable used as the output in the DEA models is wind-generated electricity (TWh per capita) in 2015 (**GEN**), which is a basic output variable used in other studies analysing the efficiency of wind power (Saglam, 2017b).

The economic aspect of wind power (**ECON**) is the second output variable. This variable measures avoided costs of generating electricity from fossil fuels after replacing conventional energy with wind power (per capita). The prices of fossil fuels and their contribution to GEN in the analysed countries are needed to calculate **ECON**. The following formula is used:

$$ECON = \frac{CFF}{\sum_{i=1}^{3} GEN_i} \cdot GEN$$

where: $CFF = \sum_{i=1}^{3} GEN_i \cdot price_i; i$ = coal, crude oil, natural gas, $price_i$ – average price of *i-th* fossil fuel, GEN_i – generated electricity from *i-th* fossil fuel, GEN – wind-generated electricity (TWh per capita). The more expensive energy sources are used in a given country, the more efficient wind power in terms of economy appears to be.

The environmental aspect of wind power (**ENV**) is the third output variable in the DEA models, and it measures carbon dioxide (CO_2) emissions avoided by replacing conventional energy with wind power (per capita). To calculate the CO_2 emissions avoided, the following formula is used:

$$ENV = \frac{CO_2}{TGEN} \cdot GEN$$

where: CO_2 – total CO_2 emission from power industry,[6] $TGEN$ – total electricity generation. The environmental benefits should be the most significant in countries with the highest CO_2 emissions.

The energy security aspect of wind power (**DEP**) is the fourth output variable. This variable measures to what extent energy security of a given country would improve if conventional energy were replaced by wind power (per capita). This variable is calculated as:

$$DEP = \frac{IMPORT}{TGEN} \cdot GEN$$

where: *IMPORT* – total fossil fuel imports. The more energy sources a country imports, the more beneficial - in terms of energy security - wind power generation is in it. On the other hand, if a country does not

[2] To measure the efficiency of wind power, Wu et al. (2016), Sağlam (2017a, 2017b) and Niu et al. (2018) also use the following input variables: wake interaction, wind direction and tower height, wind speed, the number of wind turbines, wind turbines location, operation cost, total project(s) investment, and the annual land lease payment, and the following output variables: the value of production, the percentage of in-state energy production, the number of homes powered, the economic output variables (wind industry employment), and the environmental output variables (annual water savings). However, we do not take them into account in our analysis as we were unable to gain access to these data.

[3] The study investigates 27 EU countries, and, formally, is conducted using a cross-sectional data set from 2015. However, since one of the input variables in the model is installed wind power capacity, its timespan covers the period beginning with the introduction of wind power in each country.

[4] Energy datasheets: EU-28 countries (https://ec.europa.eu/energy/en/data-analysis/country) accessed on 10.01.2018.

[5] https://globalwindatlas.info/accessed on 31.01.2019. A free tool provided by the Technical University of Denmark (DTU) in partnership with the World Bank Group.

[6] Fossil CO2 emissions of all world countries, 2018 report: http://edgar.jrc.ec.europa.eu/overview.php?v=booklet2018 accessed on 05.04.2019.

Table 1
Descriptive statistics of independent variables in the DEA model.

	Description	Unit	Mean	Min	Max	SD	Median
Input							
CAP	Installed wind capacity	MW per capita	23.650	0.055	89.669	21.230	18.367
DEN	Wind power density (at 50 m above the ground)	W/m^2	428.778	170.000	1243.000	250.697	331.000
Output							
GEN	Wind-generated electricity	TWh per capita	54.750	0.111	249.712	56.830	35.545
ECON	Economic aspect	USD per capita	8.392	0.016	31.806	8.214	5.965
ENV	Environmental aspect	Mt CO_2 per capita	20.471	0.028	90.917	21.873	11.861
DEP	Energy security aspect	Mtoe per capita	29.696	0.063	160.152	35.345	14.252

import any energy (i.e. it is energy self-sufficient), it does not benefit from wind power in this aspect.

Table 1 presents descriptive statistics of the input and output variables in the analysed EU countries. The values of variables for each country are reported in Table A.1 in Appendix.

The comparison of installed wind capacity in the EU countries per capita in 2015 reveals that Denmark is the country with the highest installed wind capacity (MW) per capita (CAP). Countries with installed wind capacity above average include: Sweden, Germany, Ireland, Spain, Portugal and Austria. Countries with the lowest installed wind capacity (i.e. below the first quartile) include Slovakia, which is the country with the lowest capacity, Slovenia, the Czech Republic, Hungary, Lithuania, Bulgaria and Croatia. Austria has the highest average wind power density in the EU countries (W/m^2). Countries with the wind power density above average include: United Kingdom, Croatia, Greece, Sweden, Ireland, France, Slovenia, Spain, and Italy. Countries with the lowest installed wind capacity (i.e. below the first quartile), include Hungary, which is the country with the lowest capacity, Luxembourg, Lithuania, Latvia, Poland, Cyprus and Belgium. When wind-generated electricity (TWh per capita) (GEN) is considered, Denmark again is the leader. Countries with wind-generated electricity above the third quartile (which is almost the same as the average) include Sweden, Ireland, Portugal, Spain, Germany and the United Kingdom. The greatest reduction of costs of electricity generated from fossil fuels replaced with wind power (ECON) is noted in Sweden, Denmark, Ireland, Spain. The highest values of the environmental aspect (ENV) per capita are noted in Denmark, Estonia, Ireland, Germany, and Portugal. Denmark, the Netherlands, Lithuania, and Ireland are countries with the highest energy security per capita (DEP). Energy security indicates to what extent a country relies on import to meet its energy requirements. The lowest values of this variable are found in Slovakia and Slovenia.

4.3. Factors in the truncated bootstrapped regression models

The second dataset includes three factors related to: renewable energy policy regarding wind energy, the energy mix, and the offshore wind power utilisation.

The first factor affecting the efficiency of the EU countries in terms of their wind power embraces decisions regarding wind energy policy, which are vital for all aspects of the energy market. Moreover, these decisions and the environmental issues (the EU countries are obliged to reduce their CO_2 emissions) seem the leading ones (see Johnstone et al., 2010). Marques and Fuinhas (2012), Aguirre and Ibikunle (2014), Polzin et al. (2015) and Liu et al. (2019) attempt to measure policy design using different aggregate and specific policy instruments. They use different types of policy instrument to examine the effects of renewable energy policies on renewables development and investment. Aguirre and Ibikunle (2014) formulate thirteen policy-related variables: direct investment, feed-in tariff, fiscal and financial support, grants and subsidies, green certificates, information and education, loans, market-based instruments, negotiated agreements, R&D, policy support and planning and voluntary agreements to discuss policies and other factors affecting renewable energy deployment. Similar, Polzin et al. (2015) examine the impact of different renewable energy policy instruments on subsequent investments in renewable energy by private institutional investors in OECD countries. They use five categories of aggregated policy instruments: economic instruments—fiscal/financial incentives, economic instruments — market-based instruments, economic instruments—direct investment, policy support and regulatory instruments. Liu et al. (2019) expand Polzin et al. (2015) by applying a fixed effect model to evaluate the effect of renewable energy policy using a panel dataset covering 29 countries during the period of 2000–2015. They consider seven aggregate (e.g. fiscal and financial incentives, market-based instruments, direct investments, policy support, regulatory instruments, information and education, and research, development and deployment) and fourteen specific policy instruments to examine the effect of particular policies on renewables to discover the effects of different policies on renewables development and to detail the function of specific instruments in aggregate policies.

Following Marques and Fuinhas (2012), Aguirre and Ibikunle (2014), Polzin et al. (2015), Marques et al., 2018 and Liu et al. (2019), the three aggregated categories of policy instruments regarding wind energy policy are analysed in the study and the policy-related variables are measured by the number of active policies in a country per year; in these previous studies they were called “accumulated number of renewable energy policies and measures (ANPM)”. These policy-related variables are obtained from the IEA's Global Renewable Energy Policies and Measures.

This approach to policy measurement is also similar to the one used by Schmidt and Fleig (2018), as it measures only the existence of a policy in a given category in a country (density related to its presence or absence) and is not able to take into account the quality of the policy.[7] A purely quantitative approach to policy instruments which does not take into account the quality of these policies or the policies of the Member States regarding their wind policy support (e.g. the development of wind energy may be adversely affected by the lack of consistent state policy, delays in the issuance of implementing regulations, the lack of a stable and friendly legal environment ensuring the safety and predictability of investments in the electricity sector, or the introduction of regulations that are unfavourable for the development of the industry) could have an impact on the methodological limitations of this study regarding renewable energy policy.

Due to a limited number of active policies in a country regarding the wind energy policy target, we analyse three bundles of formulated policies regarding economic instruments, policy support and regulatory

[7] Literature offers a second stream of research on quantitative measurements of the policy output that has been initiated by Schaffrin et al. (2014) and Schaffrin et al. (2015). Schaffrin et al. (2014, 2015) propose the Index of Climate Policy Activity which provides a way of measuring the policy output and is a function of policy density (e.g. the number of policies relating to a particular goal) and policy intensity (e.g. the content of policy instruments in relation to meeting specific goals). This approach to quantitative measurement of policy outcomes is continued by Schmidt and Sewerin (2018). This approach is more difficult to apply for a larger set of countries, which is the case of our study, as it requires studying the content of policy instruments.

instruments instead of each type of policy instruments. As a consequence, the results, conclusions and policy recommendations are related to bundles of policies instead of each type of policy instruments.

a) Economic Instruments (**EI**), which include the following types of policy instruments: direct investment (funds to sub-national governments, infrastructure investments, procurement rules, RD&D funding), fiscal and financial incentives (support) (feed-in tariffs, grants and subsidies, loans, tax relief, taxes, user charges) and market-based instruments (GHG emissions allowances, green certificates, white certificates). These policy instrument types are designed to reduce investors' risk by providing a premium on top of regular market prices for the sale of RE electricity and offering a long-term agreement and regulation remunerating the sale of RE electricity at a fixed price. They also offer capital subsidies, consumer grants or discounts, and guarantees for private RE investors that all generated electricity will be bought. They promote direct investment aimed at reducing the capital cost of investment in renewable energy.
b) Policy Support (**PS**), which includes two types of policy instruments to define strategies and to outline specific programs to promote renewable capacity inside a country, such as institutional creation and strategic planning.
c) Regulatory Instruments (**RI**), which include the following types of policy instruments: auditing, codes and standards, monitoring, obligation schemes and other mandatory requirements. These policy instruments impose requirements on the minimum amount of electricity supplied mainly from renewable sources and set standards for entities that require them to undertake specific measures and/or report on specific information.

The second factor related to the energy policy of each country is its energy mix. The energy mix is used to assess the efficiency of the EU countries regarding environmental, economic, and energy security aspects. The truncated bootstrapped regression models use either the share of fossil fuels in the total electricity generation i.e. the coal share (COAL), the petroleum products share (OIL), the natural gas share (GAS), or the remaining shares of non-fossil fuels i.e. the nuclear power share (NUCL) and renewable energy sources share (RES).

The third factor is related to the country's offshore wind power utilisation. The share of installed offshore wind capacity (OFF) is used to approximate it. Many authors (e.g. Wu et al., 2016) find that offshore wind farms are more efficient than the onshore ones. This variable is included in the study to discover to what extent the offshore wind power capacity influences the wind power efficiency of the EU countries.

A detailed description of these variables is provided in Table 2.

5. Results

5.1. Bias-corrected DEA

To analyse the efficiency of the EU countries regarding their wind power investments, the study considers five models with cumulative installed wind capacity and average wind power density as the input variables, and selected combinations of variables described in Section 4.2 as the output variables. The models are presented in Table 3.

Table 3
Input-output variables of five models.

	M1	*M2*	*M3*	*M4*	*M5*
	GEN	*GEN_ECON*	*GEN_ENV*	*GEN_DEP*	*ALL*
CAP + DEN	X	X	X	X	X
GEN	X	X	X	X	X
ECON		X			X
ENV			X		X
DEP				X	X

Note: in bold: the variable, in italics: the model.

The results of the bias-corrected DEA analysis, i.e. the bias-corrected efficiency scores (θ) of the EU countries in 2015 in all five models, are reported in Table 4, Fig. 1, and Fig. 2 a-d. The position of a given country in the rank is given in Table 4 in the parentheses.

Fig. 1 presents the efficiency scores obtained by baseline model M1-GEN. The countries are ranked in a descending order according to the value of the bias-corrected efficiency scores in the first (baseline) model with electricity generation (M1-GEN) as the output variable. Fig. 2a–c illustrate the efficiency scores obtained by models M2-GEN_ECON, M3-GEN_ENV, and M4-GEN_DEP. These figures allow for comparing the results of the baseline model (M1-GEN) with the remaining models which include additional aspects. Fig. 2d demonstrates the efficiency scores obtained by the most comprehensive model (M5-ALL). As the model covers all the output variables, the efficiency scores obtained in it are the highest in comparison with the remaining five models.

Table 4 demonstrates that the efficiency scores of the EU countries in the baseline model (M1-GEN) are relatively high. The overall bias-corrected DEA efficiency scores range from 0.478 to 0.978, and the average efficiency score is 0.809. It is worth noting that no country reaches the maximum value equal 1. This means that no country is efficient in terms of investment in wind power at 100 per cent. This is due to the bootstrap procedure used.

In the next four models, only one additional aspect (except for wind-generated electricity) is taken into consideration as the output variable, and their relative bias-corrected efficiency scores are similar to the ones obtained in the first model. In all these models (M2-GEN_ECON, M3-GEN_ENV, M4-GEN_DEP, and M5-ALL) the average efficiency scores are about 0.8. The lowest average efficiency score (0.783) is obtained in the second model (M2-GEN_ECON) including the economic output. The highest average efficiency score (0.826) is obtained in the model including the environmental output M3-GEN_ENV).

Table 4 and Fig. 1 reveal that in the baseline model, with installed wind capacity (CAP) and average wind power density at 50 m height (DEN) used as input variables and wind-generated electricity (GEN) used as the output variable, (model M1-GEN), the United Kingdom, Sweden, Denmark, and Ireland are the most efficient countries in terms

Table 2
Descriptive statistics of factors used in the truncated bootstrapped regression models.

	Description	Unit	Mean	Min	Max	SD	Median
EI	Economic Instruments	ANPM	2.481	0.000	8.000	2.173	2.000
PS	Policy Support	ANPM	0.815	0.000	3.000	0.962	1.000
RI	Regulatory Instruments	ANPM	0.926	0.000	5.000	1.274	0.000
COAL	The coal share in the total electricity generation	%	0.235	0.000	0.791	0.215	0.203
OIL	The petroleum products share in the total electricity generation	%	0.051	0.000	0.912	0.171	0.011
GAS	The natural gas share in the total electricity generation	%	0.181	0.000	0.498	0.150	0.143
NUCL	The nuclear power share in the total electricity generation	%	0.173	0.000	0.770	0.212	0.037
RES	The renewable share in the total electricity generation	%	0.350	0.088	0.778	0.198	0.299
OFF	The share of installed offshore wind capacity	%	0.044	0.000	0.357	0.099	0.000

Table 4
The bias-corrected efficiency scores of the EU countries in 2015 for five models.

country	M1	M2	M3	M4	M5
	GEN	GEN_ECON	GEN_ENV	GEN_DEP	ALL
AT - Austria	0.674 (24)	0.664 (24)	0.676 (24)	0.677 (24)	0.663 (24)
BE - Belgium	0.927 (5)	0.929 (3)	0.924 (6)	0.926 (5)	0.827 (13)
BG - Bulgaria	0.772 (18)	0.745 (21)	0.794 (21)	0.759 (20)	0.784 (19)
CY - Cyprus	0.761 (21)	0.841 (7)	0.806 (19)	0.733 (22)	0.875 (5)
CZ - Czech Republic	0.842 (11)	0.789 (13)	0.880 (10)	0.800 (14)	0.885 (4)
DE - Germany	0.770 (19)	0.753 (18)	0.856 (13)	0.769 (18)	0.847 (10)
DK - Denmark	0.956 (3)	0.940 (2)	0.964 (3)	0.967 (3)	0.911 (3)
EE - Estonia	0.859 (10)	0.832 (8)	0.933 (5)	0.861 (8)	0.942 (1)
ES – Spain	0.749 (22)	0.713 (22)	0.751 (22)	0.751 (21)	0.722 (21)
FI – Finland	0.815 (15)	0.805 (10)	0.814 (18)	0.814 (13)	0.791 (18)
FR – France	0.725 (23)	0.690 (23)	0.725 (23)	0.725 (23)	0.691 (23)
GR – Greece	0.770 (20)	0.757 (17)	0.802 (20)	0.777 (16)	0.802 (15)
HR – Croatia	0.661 (25)	0.650 (25)	0.661 (25)	0.666 (25)	0.646 (25)
HU – Hungary	0.840 (12)	0.759 (16)	0.848 (14)	0.775 (17)	0.841 (12)
IE – Ireland	0.939 (4)	0.879 (5)	0.950 (4)	0.939 (4)	0.862 (7)
IT - Italy	0.569 (26)	0.553 (26)	0.568 (26)	0.564 (26)	0.590 (26)
LT - Lithuania	0.911 (6)	0.880 (4)	0.910 (7)	0.822 (11)	0.797 (17)
LU - Luxembourg	0.881 (8)	0.843 (6)	0.885 (9)	0.836 (9)	0.845 (11)
LV - Latvia	0.877 (9)	0.762 (15)	0.878 (11)	0.836 (10)	0.716 (22)
NL – Netherlands	0.793 (16)	0.782 (14)	0.816 (17)	0.893 (6)	0.817 (14)
PL – Poland	0.779 (17)	0.747 (20)	0.863 (12)	0.764 (19)	0.866 (6)
PT – Portugal	0.888 (7)	0.809 (9)	0.892 (8)	0.883 (7)	0.781 (20)
RO - Romania	0.824 (14)	0.796 (12)	0.825 (16)	0.820 (12)	0.801 (16)
SE - Sweden	0.969 (2)	0.803 (11)	0.974 (2)	0.973 (2)	0.852 (8)
SI – Slovenia	0.478 (27)	0.445 (27)	0.486 (27)	0.460 (27)	0.488 (27)
SK - Slovakia	0.833 (13)	0.749 (19)	0.843 (15)	0.787 (15)	0.848 (9)
UK – United Kingdom	0.977 (1)	0.958 (1)	0.977 (1)	0.980 (1)	0.916 (2)
Min	0.478	0.467	0.486	0.461	0.489
Max	0.978	0.967	0.977	0.980	0.943
Mean	0.809	0.783	0.826	0.799	0.793

Note: The numbers in parentheses are country ranking. The DEA is performed using the Stata "simarwilson "command and 1000 bootstrap replication.

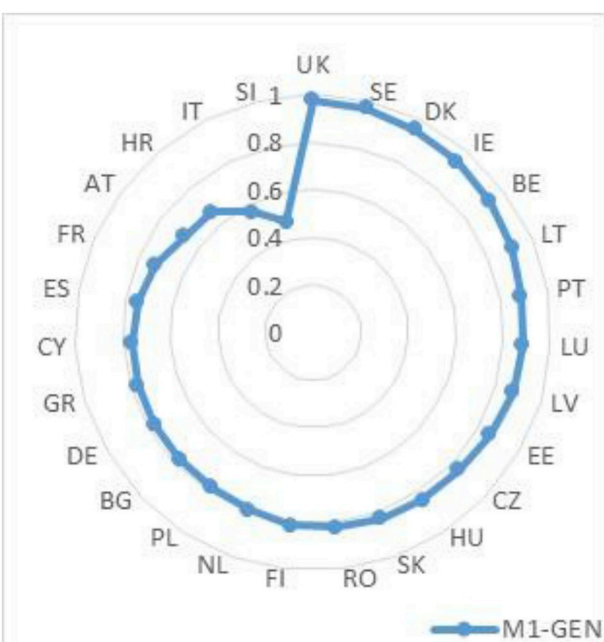

Fig. 1. The bias-corrected efficiency scores of the EU countries in 2015 obtained by baseline model M1-GEN.

of wind power investment. Although their efficiency scores are lower than 1, they are the highest in all analysed countries and range between 0.940 and 0.978, which means that these countries are the most effective, i.e. their wind power productivity is relatively high. The decisions regarding investments in wind power taken by their authorities proved successful and adequate, taking into account the conditions of offshore wind power utilisation, especially wind conditions. These countries made the relatively smallest investment in comparison with other countries and benefited the most from their investment by generating more wind power than other countries. The results obtained in the study indicate these countries as the benchmark ones, whose example should be followed by other countries in order to reduce their capital expenditure and become effective. The least effective countries are Slovenia and Italy. The efficiency scores obtained for these two countries are 0.478 and 0.569 respectively. This means that their decisions regarding investing in wind power were misguided because about 50% (47.8% and 56.9%) of the capital investment incurred for installed wind power was used to generate electricity from wind.

Table 4 and Fig. 2a–d illustrate the models which account for wind-generated electricity and one other aspect (connected with economy, environment or energy security).

When wind-generated electricity and the economic output (M2-GEN_ECON) (Table 4 and Fig. 2a) are taken into account, the group of the most efficient countries is joined by Belgium and Lithuania. Cyprus gain the most, and its relative efficiency scores increase by 10%. When the economic aspect, i.e. the costs of generating energy from fossil fuels, is analysed, an increase in the relative efficiency scores and a higher position in the rank is observed in countries using oil as the main energy source (i.e. Cyprus, in which in 2015 as much as 91% of total electricity generation comes from heating oil power plants or natural gas power plant (i.e. in Belgium 35% of electricity comes from natural gas power plants). Their position in the rank improves, and the value of parameter θ increases.

When wind-generated electricity and the environmental output are investigated (model M3-GEN_ENV) (Table 4 and Fig. 2b), Estonia, Belgium, and Lithuania join the group of countries with the highest relative efficiency scores. Moreover, Germany, Poland, Estonia, Cyprus, the Czech Republic, Greece, the Netherland, and Bulgaria gain the most in terms of environmental benefits. These countries rely on coal as the

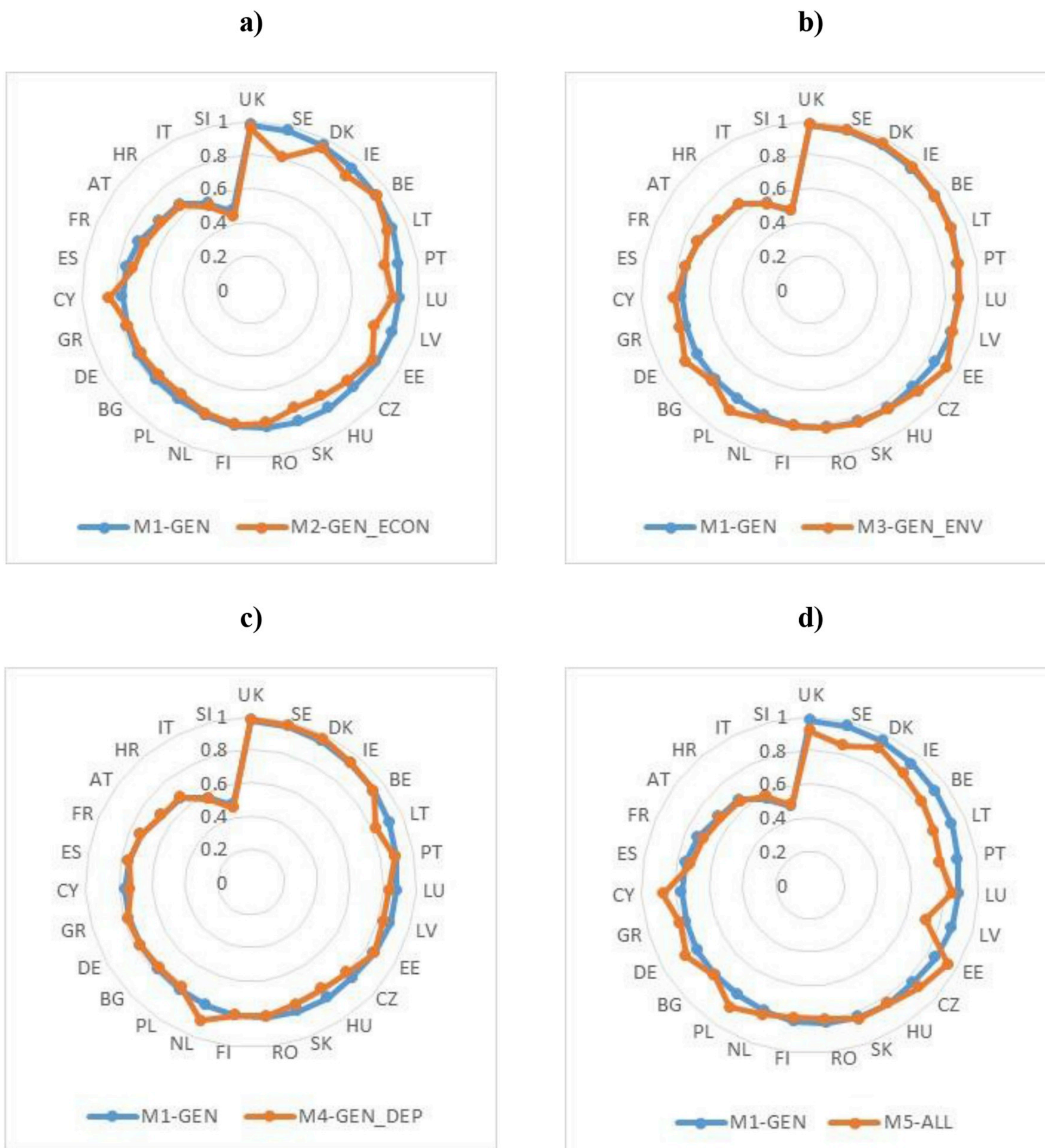

Fig. 2. The bias-corrected efficiency scores of the EU countries in 2015 obtained by M2-GEN_ECON, M3-GEN_ENV, M4-GEN_DEP, and M5-ALL models.

main source in electricity generation: e.g. in 2015 77% of the total electricity generation in Estonia comes from coal power stations, in Poland −79%, in the Czech Republic - 49%, in Bulgaria - 46%, in Greece - 43%, in Germany - 44%, while in Cyprus 91% of electricity is generated by oil power plants. The relative efficiency score of Germany increases by 11%, of Poland by 11%, of Estonia by 9%, of Cyprus by 6%, of the Czech Republic by 5%, of Greece by 4%, of the Netherlands 3%, and of Bulgaria by 3%.

When wind-generated electricity and the energy security output (model M4-GEN_DEP) (Table 4 and Fig. 2c) are taken into consideration, the Netherlands and Belgium join the list of the most efficient countries. The Netherlands efficiency score increases by 13% in comparison with the basic model. An improvement is also noted in Denmark, Greece, and Croatia (their efficiency scores grow by 1%). These countries gain the most in terms of energy security benefits.

When all variables are considered, Estonia, the United Kingdom, Denmark, the Czech Republic, Cyprus, Poland, and Ireland are the most efficient countries (model M5-ALL, Table 4 and Fig. 2d). In other words, Cyprus (where the efficiency score increases by 15%), Poland (11%), Germany (10%), Estonia (10%), the Czech Republic (5%), Greece (4%), Italy (3%) and the Netherlands (3%) gain the most. In this model Slovenia turns out to be the least efficient country. Moreover, the relative efficiency score of Latvia decreases by 18%, while these of Lithuania, Sweden, and Portugal by 12%.

The efficiency of the EU countries obtained in the bias-corrected DEA model are compared, as a robustness check, with two other DEA approaches. The first one is the standard input oriented BCC DEA model[8] (the results of the relative efficiency scores obtained by five models are presented in Table A2 in Appendix). The second one is the additive model proposed by Charnes et al. (1985). The sums of input and output slacks obtained in the additive DEA model are presented in Table A3 in Appendix. The Spearman rank correlation coefficient is calculated for pairs of these three models. The results are presented in

[8] These efficiency scores are bias-corrected by the bootstrap application in the main model in our study, Table 4.

Table A4 in Appendix. As can be noticed, the correlations between equivalent models are quite high. The highest correlation is observed comparing the BCC and additive approaches (the Spearman rank correlation coefficient in M3-GEN_ENV model is 0.944). A high correlation is also obtained between the BCC and bias-corrected approaches (in M1-GEN model the correlation coefficient is 0.893). The bias-corrected and additive approaches are the least similar (for M5-ALL model the coefficient equals 0.384).

5.2. The truncated bootstrapped regression models

The next stage of the study analyses the role of external factors in explaining the bias-corrected DEA efficiency scores obtained by the EU countries. Three factors – renewable energy policy regarding wind energy, the energy mix, and the offshore wind power utilisation - are considered in order to investigate their impact on the wind power efficiency of the analysed countries. Two kinds of truncated bootstrapped regression models are estimated for each efficiency score yielded by models M1-M5. The first set of the truncated bootstrapped regression models includes the following independent variables: Economic Instruments (EI), Policy Support (PS) and Regulatory Instruments (RI) (which describe wind energy policy of a country), the share of installed offshore wind capacity (OFF) (which describes the impact of the offshore wind power utilisation), and the shares of fossil fuels in electricity generation, like the coal share (COAL), the petroleum product share (OIL), and the natural gas share (GAS) (which represent the energy mix[9]). The second set of models includes the same independent variables as the models from the first set, but instead of the shares of fossil fuels in electricity generation, they use the shares of non-fossil fuels in electricity generation, such as nuclear share (NUCL) and renewable energy sources share (RES), due to multicollinearity with the shares of fossil fuels.

Table 5 reports the results of the truncated bootstrapped regression models.

The results (Table 5) reveal that the effect of renewable energy policy regarding wind energy on the wind power efficiency of the EU countries is significant, yet ambiguous. In all five models bundles of policies regarding economics instruments (EI) (i.e. direct investment, fiscal and financial instruments, feed-in tariffs, etc.,) seem to have a significant and positive effect on the efficiency of the EU countries in terms of their wind power investments. Similar results are reported by Polzin et al. (2015), García-Álvarez et al. (2017), and Li et al. (2017). Whereas, bundles of policy support (PS), which covers institutional creation and strategic planning, might negatively influence wind power efficiency. Similarly, bundles of regulatory instrument policies (RI), which include auditing, codes and standards, monitoring, obligation schemes and other mandatory requirements, seem to have a negative and significant (except for M3-GEN_ENV model) impact on the wind power efficiency of the EU countries. This result is surprising, yet frequently observed in previous studies (see Zhao et al., 2013). A negative example of regulatory instruments and policy support is the an act on wind farm investments (Journal of Laws 2016, item 961) which was introduced in Poland in July 2016. The most important changes concerned the location of new wind power plants. According to the regulations, the distance to the nearest buildings must not be shorter than ten times the height of the windmill and shovels. The introduction of this regulatory instrument has resulted in a significant reduction of the areas where new wind power plants can be built. Consequently, the investments in wind farms in Poland were inhibited.

To sum up, it seems that a positive effect on the wind power efficiency of each country is exerted only by bundles of economic instruments (EI), mainly fiscal and financial incentives, such as feed-in tariffs (FIT). These feed-in tariffs are likely to spur deployment and technological diversity and lower risks associated with renewable energy technologies faced by private sectors.

The results presented in Table 5 indicate that the wind power efficiency of the EU countries in terms of environmental, economic and energy security benefits is related to their energy mix. The results are not surprising, as the positive and significant coefficient of COAL is obtained in models M3-GEN_ENV (environmental output) and M5-ALL. Benefits resulting from replacing coal with wind are significant for the environment because coal power plants are responsible for high emissions of CO2. Similarly, the natural gas share (GAS) significantly and positively affects the wind power efficiency (M1-GEN and M2-GEN_ECON) when economic aspect is also taken into account. It means that both the wind power efficiency and energy security benefits would increase if natural gas were replaced with wind power. The results confirm that the energy mix substantially affects the wind power efficiency when the shares of non-fossil fuels are taken into account. When all beneficial aspects are considered (M5-ALL), the results demonstrate that the nuclear share and the renewable energy source share in electricity generation have a negative and significant effect on the wind power efficiency. It means that the lower renewable energy source share in electricity generation, the lower wind power efficiency and the lower the benefits regarding all aspects.

As can be seen in Table 5, almost all coefficients of OFF are statistically significant and positive. The coefficient is positive, which means that the larger the share of the offshore wind farm a country has, the more wind power efficient it is. Similar results are obtained by Wu et al. (2016), Sağlam (2017a), and Sağlam (2017b). Since access to the sea is directly connected with the location of the country, it can be concluded that the wind power efficiency is significantly related to the offshore wind power utilisation.

6. Conclusions and policy implication

6.1. Conclusions

The empirical strategy applied in the study allows for assessing the efficiency of the EU countries in terms of their wind power investments. Three different aspects (economic, environmental and energy security) measuring the benefits of wind power investment in these countries are considered. Next, the truncated bootstrapped regression model is employed to identify and explain the role of various factors which affect the relative efficiency of the EU countries. These factors are related to: renewable energy policy regarding wind energy, the energy mix, and the offshore wind power utilisation.

The bias-corrected DEA implementation yields the following conclusions.

Four countries - the United Kingdom, Sweden, Denmark, and Ireland - are the most efficient ones when the relationships between both the investment in wind power and the average wind power density and the wind-generated electricity are considered. Moreover, Belgium, Lithuania, and Portugal obtain high relative efficiency scores. The group of the least efficient countries includes Slovenia and Italy.

What is interesting, when additional aspects are included in the models, other countries join the group of the most efficient countries or gain the most, and the assessment of the efficiency of the EU countries regarding their wind power investment offers a broader perspective on these benefits.

When the assessment of the wind power efficiency of the EU countries accounts for economic, energy security, and environmental aspects resulting from replacing conventional energy with wind power, Estonia, the United Kingdom, Denmark, the Czech Republic, Cyprus, Poland, Ireland, and Sweden turn out the most efficient countries. Countries which gain the most are Cyprus, Poland, Germany, Estonia, the Czech Republic, Greece, Italy and the Netherlands.

[9] Different sources of energy are included in the models, as they have different impact on the aspects considered. For example, COAL is crucial for environmental aspects and GAS for economy.

Table 5
The results of the truncated bootstrapped regression models.

	M1		M2		M3		M4		M5	
	GEN		GEN_ECON		GEN_ENV		GEN_DEP		ALL	
EI	0.056***	0.048**	0.038**	0.040***	0.071***	0.058**	0.049***	0.038**	0.041**	0.046***
SP	−0.089**	−0.067*	−0.061**	−0.058**	−0.102**	−0.079*	−0.079**	−0.059*	−0.047	−0.053**
RI	−0.047**	−0.038*	−0.029*	−0.032*	−0.052**	−0.041	−0.039**	−0.033	−0.028*	−0.027*
OFF	0.996**	1.124**	0.829***	0.786***	1.096*	1,090*	1.291**	1.415**	0.422**	2.300
COAL	0.806		0.106		0.250*		0.115		0.290***	
OIL	−0.067		0.120		−0.006		−0.056		0.161	
GAS	0.277*		0.234*		0.298		0.266		0.109	
NUCL		−0.069		−0.114		−0.143		−0.079		−0.144*
RES		−0.048		−0.115		−0.213		−0.069		−0.332***
Const	0.707***	0.786***	0.657***	0.804***	0.671***	0.879***	0.682***	0.797***	0.649***	0.881***

Note: Calculations obtained using STATA program; ***, **, * indicate statistical significance at 1, 5 and 10 per cent level of significance, respectively. Bootstrapped regression models are performed using the Stata "simarwilson" command.

When the environmental output is included, Estonia, Belgium, and Lithuania join the group of the most efficient countries, while Germany, Poland, Estonia, Cyprus, the Czech Republic, Greece, the Netherland, and Bulgaria gain the most. Energy mixes in these countries contain high coal shares, so they benefit the most from investing in wind power as the volume of CO2 emissions avoided is very high. Conversely, the economic output is important in countries with the limited coal share in their energy mixes. When this aspect is included in the models, Belgium and Lithuania become efficient countries, while Cyprus and Belgium gain the most. When the energy security aspect is analysed, the Netherlands and Belgium join the group of the most efficient countries. Moreover, Denmark, Greece, and Croatia benefit the most. Since wind is a local energy source, it allows for reducing fossil fuel imports.

To explain the above results, the efficiency of the EU countries is next interpreted using factors from three areas: renewable energy policy regarding wind energy, the energy mix and the offshore wind power utilisation.

The role of political factors seem to be significant, albeit rather ambiguous.

The wind power efficiency might be positively related to bundles of economic instruments of wind energy policy. These packages of instruments are meant to reduce investors' risk and to offer economic support mainly by the implementation of fiscal and financial incentives and capital subsidies, consumer grants or discounts and guarantees for private RE investors that all generated electricity will be bought. This result is in line with other studies. Polzin et al. (2015) suggest that this type of support instruments proves especially beneficial in the early stages of technological development. Similar results are observed by García-Álvarez et al. (2017) and Li et al. (2017), and they confirm that the feed-in tariff policies promote wind power development in the European Union.

The two remaining wind energy policy areas (bundles of policy support and bundles of regulatory instruments) might play a negative role in the wind power efficiency context. Policy support packages including institutional creation (such as the implementation of an energy agency), strategic planning and regulatory instruments seem to have a negative impact on the efficiency of the EU countries regarding investment in wind power. On the one hand, this result is rather unexpected, as it might be reasonably assumed that a clear long-term energy strategy is conducive to investment, as investors appreciate a long-term framework with a clear vision. This surprising outcome could result from using a purely quantitative approach adopted in the study, which ignores the quality of policies and the design features of policy instruments.

On the other hand, Zhao et al. (2013) and Polzin et al. (2015) report a negative impact of policy support and regulatory instruments on renewable energy sources development.

The energy mix explains the variation of the efficiency of the EU countries when economic, environmental and energy security aspects are considered. The larger the share of coal in the energy mix, the more a country benefits environmentally. Similarly, the wind power efficiency would increase and energy security benefits would grow if natural gas were replaced with wind power. The results confirm that the energy mix significantly affects wind power efficiency when the shares of non-fossil fuels in electricity generation are taken into account. It seems that the energy mix is important not only to the development of renewable energy sources (see Papież et al., 2018) but also to their efficiency.

Finally, the results obtained for the offshore wind power utilisation indicate that the countries with high shares of offshore wind capacity are the most efficient. This result remains positive for each group of benefits considered. Our findings confirm the results obtained by, for example, Wu et al. (2016), Sağlam (2017a), and Sağlam (2017b).

6.2. Policy implications

Knowledge of the factors which contribute to increasing wind power efficiency should prove helpful to policymakers. The results regarding the impact of factors related to national energy policy, including national renewable energy action plans, seem crucial.

The results of the study allow for formulating two policy recommendations. First, policymakers considering wind energy development should take into account its different aspects, as countries differ in their wind potential. However, environmental, economic and energy security aspects influence the energy mix and lead to differences in the wind power efficiency of particular countries. Decisions regarding the wind energy development should be made on the basis of all these aspects. Even countries with relatively poor wind potential could benefit considerably when they use wind power to replace coal power (the environmental benefit), oil power (the economic benefit) or fossil fuel imports (energy security improves).

Second, three renewable policy areas regarding wind energy (i.e. bundles of economic instruments, policy support, and regulatory instruments) seem to have a different impact on wind power efficiency. A positive impact of economic instruments regarding renewable energy policy, including economic and fiscal incentives, on wind power efficiency, offers a relevant recommendation of these tools.

It seems that economic instruments are introduced (so far, at least) reasonably and are likely to contribute to the rational wind power development. On the other hand, policy support covering institutional creation (such as the implementation of an energy agency) and strategic planning might have a negative impact on wind power efficiency. Consequently, these two policy tools should be limited or reconsidered by policymakers who would like to improve the efficiency of different aspects of wind power.

The results related to the impact of different areas of renewable energy policy on the wind power development should be crucial for two groups of countries: the ones which have only recently started using and supporting the wind power development, and the ones which, due to their economic situation, have to be very careful with their expenditure. Promoting renewable energy sources with the use of adequate support methods can significantly improve the efficiency of investment.

Acknowledgments

This study was supported by funds from the National Science Centre (NCN), Poland, through grant No 2015/17/B/HS4/02685. The authors thank two reviewers whose constructive comments have improved the quality of this study.

Appendix

Table A.1The values of variables in DEA.

	CAP	DEN	PROD	ECON	ENV	DEP
	MW per capita	W/m^2	TWh per capita	USD per capita	Mt CO_2 per capita	Mtoe per capita
AT	29.022	1243	56.435	11.109	11.861	29.022
BE	19.364	234	49.603	10.59	12.252	19.364
BG	9.719	276	20.161	1.677	11.586	9.719
CY	18.654	226	26.092	8.045	16.943	18.654
CZ	2.666	250	5.437	0.472	3.506	2.666
DE	55.014	272	97.547	10.408	48.643	55.014
DK	89.669	396	249.712	27.052	90.917	89.669
EE	22.816	257	54.378	4.568	61.395	22.816
ES	49.393	584	106.19	18.237	30.754	49.393
FI	18.367	388	42.528	5.806	10.4	18.367
FR	15.367	645	31.959	5.965	1.834	15.367
GR	19.258	694	42.558	6.159	24.998	19.258
HR	9.893	705	18.839	2.521	5.449	9.893
HU	3.338	170	7.032	1.017	2.742	3.338
IE	52.712	646	141.998	24.142	58.695	52.712
IT	15.029	562	24.416	4.696	9.395	15.029
LT	14.925	190	27.728	6.533	9.316	14.925
LU	11.369	185	18.119	4.086	3.16	11.369
LV	3.474	190	7.401	1.669	2.483	3.474
NL	20.064	363	44.673	7.133	25.427	20.064
PL	12.856	222	28.569	2.368	25.958	12.856
PT	47.586	243	111.886	16.029	40.546	47.586
RO	15.752	264	35.545	4.488	15.454	15.752
SE	59.914	693	166.897	31.806	6.362	59.914
SI	0.242	598	0.291	0.024	0.089	0.242
SK	0.055	331	0.111	0.016	0.028	0.055
UK	22.028	750	62.135	9.977	22.525	22.028

Table A.2The results of relative efficiency scores obtained by standard input oriented BCC DEA model

country	*M1*	*M2*	*M3*	*M4*	*M5*
	GEN	*GEN_ECON*	*GEN_ENV*	*GEN_DEP*	*ALL*
AT - Austria	0.689 (24)	0.689 (24)	0.690 (25)	0.689 (24)	0.690 (25)
BE - Belgium	0.951 (11)	0.951 (13)	0.951 (14)	0.951 (12)	0.951 (16)
BG - Bulgaria	0.803 (20)	0.829 (20)	0.806 (21)	0.803 (20)	0.829 (22)
CY - Cyprus	0.810 (19)	0.853 (17)	1 (5.5)	0.811 (19)	1 (6.5)
CZ - Czech Republic	0.924 (12)	0.966 (11)	0.928 (15)	0.924 (13)	0.966 (15)
DE - Germany	0.856 (14)	0.926 (15)	0.856 (16)	0.856 (15)	0.926 (18)
DK - Denmark	1 (3)	1 (3.5)	1 (5.5)	1 (4.5)	1 (6.5)
EE - Estonia	0.881 (13)	1 (3.5)	1 (5.5)	0.881 (14)	1 (6.5)
ES – Spain	0.770 (22)	0.770 (22)	0.770 (23)	0.770 (22)	0.770 (23)
FI – Finland	0.836 (17)	0.836 (19)	0.836 (19)	0.836 (18)	0.836 (21)
FR – France	0.741 (23)	0.741 (23)	0.741 (24)	0.741 (23)	0.741 (24)
GR – Greece	0.786 (21)	0.825 (21)	0.789 (22)	0.799 (21)	0.850 (20)
HR – Croatia	0.676 (25)	0.676 (25)	0.683 (26)	0.684 (25)	0.687 (26)
HU – Hungary	1 (3)	1 (3.5)	1 (5.5)	1 (4.5)	1 (6.5)
IE – Ireland	0.964 (9)	0.975 (9)	0.967 (13)	0.964 (11)	0.975 (14)
IT - Italy	0.586 (26)	0.588 (26)	0.586 (27)	0.586 (26)	0.588 (27)
LT - Lithuania	0.970 (8)	0.970 (10)	0.981 (12)	1 (4.5)	1 (6.5)
LU - Luxembourg	0.960 (10)	0.960 (12)	1 (5.5)	0.968 (10)	1 (6.5)
LV - Latvia	0.977 (7)	0.977 (8)	1 (5.5)	1 (4.5)	1 (6.5)
NL – Netherlands	0.811 (18)	0.840 (18)	0.811 (20)	1 (4.5)	1 (6.5)
PL – Poland	0.856 (15)	0.931 (14)	0.856 (17)	0.856 (16)	0.931 (17)
PT – Portugal	1 (3)	1 (3.5)	1 (5.5)	1 (4.5)	1 (6.5)

RO - Romania	0.847 (16)	0.857 (16)	0.847 (18)	0.847 (17)	0.857 (19)
SE - Sweden	0.998 (6)	0.998 (7)	0.998 (11)	0.998 (9)	0.998 (13)
SI – Slovenia	0.549 (27)	0.549 (27)	1 (5.5)	0.549 (27)	1 (6.5)
SK - Slovakia	1 (3)	1 (3.5)	1 (5.5)	1 (4.5)	1 (6.5)
UK – United Kingdom	1 (3)	1 (3.5)	1 (5.5)	1 (4.5)	1 (6.5)

Note: The numbers in parentheses are country ranking.

Table A.3The sum of input and output slacks resulted from additive DEA model

country	*M1*	*M2*	*M3*	*M4*	*M5*
	GEN	*GEN_ECON*	*GEN_ENV*	*GEN_DEP*	*ALL*
AT - Austria	1043, (27)	1054. (27)	1815. (27)	1112. (27)	1870. (27)
BE - Belgium	27,48 (9)	33.40 (12)	359.7 (14)	45.19 (10)	380.9 (14)
BG - Bulgaria	97,70 (16)	93.13 (16)	385.8 (15)	126.5 (17)	395.2 (15)
CY - Cyprus	50,00 (12)	46.54 (14)	0 (5)	108.9 (15)	0 (6)
CZ - Czech Republic	47,23 (11)	15.11 (8)	105.6 (11)	49.11 (11)	65.38 (13)
DE - Germany	52,46 (14)	41.56 (13)	524.1 (17)	102.6 (13)	541.9 (18)
DK - Denmark	0 (3)	0 (3.5)	0 (5)	0 (4.5)	0.000 (12)
EE - Estonia	52,25 (13)	0 (3.5)	0 (5)	103.0 (14)	0 (6)
ES – Spain	349,1 (21)	358.2 (22)	940.7 (23)	393.2 (22)	984.5 (24)
FI – Finland	193,3 (18)	198.5 (18)	805.9 (20)	233.1 (18)	825.3 (21)
FR – France	459,1 (24)	469.9 (24)	1023. (25)	510.3 (24)	1055. (26)
GR – Greece	500,1 (25)	488.8 (25)	1139. (26)	537.5 (25)	1049. (25)
HR – Croatia	528,3 (26)	530.8 (26)	838.8 (21)	558.7 (26)	829.3 (22)
HU – Hungary	0 (3)	0 (3.5)	0 (5)	0 (4.5)	0 (6)
IE – Ireland	355,1 (22)	346.3 (21)	715.8 (19)	388.4 (21)	737.4 (20)
IT - Italy	384,2 (23)	386.3 (23)	950.9 (24)	443.1 (23)	952.4 (23)
LT - Lithuania	8,444 (6)	10.97 (7)	131.7 (12)	0 (4.5)	0 (6)
LU - Luxembourg	10,63 (7)	16.13 (9)	0.000 (10)	34.10 (9)	0 (6)
LV - Latvia	19,67 (8)	20.06 (11)	0 (5)	0 (4.5)	0 (6)
NL – Netherlands	167,6 (17)	156.6 (17)	854.5 (22)	0 (4.5)	0 (6)
PL – Poland	37,43 (10)	18.04 (10)	485.5 (16)	68.95 (12)	489.2 (17)
PT – Portugal	0 (3)	0 (3.5)	0 (5)	0 (4.5)	0 (6)
RO - Romania	74,53 (15)	71.73 (15)	623.0 (18)	117.3 (16)	649.3 (19)
SE - Sweden	288,3 (20)	342.7 (20)	339.3 (13)	360.8 (20)	466.2 (16)
SI – Slovenia	276,3 (19)	276.4 (19)	0 (5)	276.5 (19)	0 (6)
SK - Slovakia	0 (3)	0 (3.5)	0 (5)	0 (4.5)	0 (6)
UK – United Kingdom	0 (3)	0 (3.5)	0 (5)	0 (4.5)	0 (6)

Note: The numbers in parentheses are country ranking.

Table A.4The Spearman rank correlation coefficient

		bias-corrected DEA	ADD	BCC
M1 GEN	bias-corrected DEA	1	0.646	0.893
	ADD	0.646	1	0.822
	BCC	0.893	0.822	1
M2 GEN_ECON	bias-corrected DEA	1	0.582	0.697
	ADD	0.582	1	0.846
	BCC	0.697	0.846	1
M3 GEN_ENV	bias-corrected DEA	1	0.523	0.620
	ADD	0.523	1	0.944
	BCC	0.620	0.944	1
M4 GEN_DEP	bias-corrected DEA	1	0.572	0.799
	ADD	0.572	1	0.882
	BCC	0.799	0.882	1
M5 ALL	bias-corrected DEA	1	0.384	0.496
	ADD	0.384	1	0.934
	BCC	0.496	0.934	1

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