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Renewable energy consumption and economic efficiency: Evidence from European countries

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Abstract

This paper examines the relationship between renewable energy consumption and economic efficiency. For this reason conditional Data Envelopment Analysis (DEA) estimators alongside with nonparametric regressions are applied in a sample of 25 European countries for the year 2010. Our results reveal that renewable energy consumption has a positive effect on countries' economic efficiency for lower consumption levels while for higher levels the analysis reveals mixed effects, which are also subject to regional disparities. Finally, it appears that the effect of renewable energy consumption on countries' economic efficiency depends also on countries' specific regional characteristics as well as on the environmental policies adopted.

Keywords: Renewable energy consumption; economic efficiency; data envelopment analysis; nonparametric regression.

JEL classifications: C14; O44; Q20; Q40

1. Introduction

The highly dependence of the global economy on fossil fuels such as oil, gas and coal does not conform to the concept of sustainable development. Fossil fuels are one of the main reasons behind the greenhouse gases (particularly carbon dioxide emissions, CO_2), which in turn result to global warming. Among others, climate change can cause the rising of the sea levels, the intensity of hydrological cycles and winds and the frequency of hurricanes and cyclones (Sadorsky, 2009a). Since energy is an important factor for economic growth, a more environmental-friendly path is needed. This path can be achieved by using sustainable energy sources which will reduce the emissions and therefore the global pollution. Substituting fossil fuels with renewable energy sources (RES) appear to be the solution for this problem.

RES include solar, wind, geothermal, biomass, hydroelectricity, wave and tidal energy sources. According to Apergis and Payne (2010a) the substitution of fossil fuels with RES is taking place because of the volatility in the price of oil, the environmental pollution problem caused by fossil fuels and the independency from foreign countries the RES are offering. In addition, a number of incentives such as tax credits and renewable energy standards further promote RES (Bowden and Payne, 2010).

International agreements have been signed towards the substitution of fossil fuels with RES. The Kyoto Protocol which was initiated by the United Nations Framework Convention on Climate Change (UNFCC) is the most important and widely known agreement for the promotion of RES and reduction of greenhouse gases. Furthermore, the European Commission has issued the Renewable Energy Directive (2009/28/EC) which sets targets for the European Union country-members. European Commission wishes the 20% of total energy and the 10% of transport energy to come from RES by 2020[1]. Additionally, every country member has set individual goals towards 2020.

Based on these lines our paper applies conditional data envelopment analysis (DEA) estimators alongside with bootstrap techniques and in order to investigate for the first time the renewable energy consumption economic efficiency relationship. Specifically, we first develop the economic efficiency indicators and then we use conditional efficiency estimators to investigate the underlined relationship.

2. Literature Review

The promising future of RES and the efficiency of renewable energy technologies are examples of the topics which have been investigated in the literature. Boubaker (2012) employs a data envelopment analysis (DEA) model in order to study the perspectives of RES in North Africa towards 2025. The author finds that optimally the maximum per capita energy savings can be achieved by the time target of 2025. Cristobal (2011) used multiple criteria data envelopment analysis to analyze the efficiency of 13 renewable energy technologies in Spain. The results suggest that wind energy technology is the most efficient energy source. In a similar study, Lins et al. (2012) examine the case of Brazilian power sector and find that biomass from solid wastes should be promoted as the most efficient choice.

Other researchers study the connection between countries' technical efficiency and RES. Chien and Hu (2007) apply a DEA model to investigate the effects of RES on technical efficiency of 45 OECD and non-OECD countries. The authors use labor, capital and energy consumption as inputs and real gross domestic product as the only output. They note that an increase in energy consumption results in a decrease in

[1] http://www.seai.ie/Publications/Statistics_Publications/Statistics_FAQ/Energy_Targets_FAQ/

technical efficiency while an increase in renewable energy consumption results in an increase in technical efficiency. Therefore, the substitution of non-renewable energy with renewable is the desirable outcome for an economy. Moreover, OECD countries are found as more technical efficient than non-OECD countries. Domac et al. (2005) claim that bioenergy can improve the macroeconomic efficiency of a country by creating extra jobs (and thus limiting unemployment), promoting industrial competitiveness and other economic gains. Also, the authors argue that bioenergy does not hurt the environment and only the misuse of bioenergy can potentially damage the environment.

Awerbuch and Sauter (2006) examine the relationship between oil and GDP. Volatility in oil price has a significant effect on economic growth through inflation and unemployment. It is noted that a 10% increase in oil price will result in 0.5% loss of the global GDP. The authors propose that the substitution of oil with RES will countermeasure the adverse effects of volatility in oil price which will results in macroeconomic gains. Halkos and Tzeremes (2011) study the connection between oil consumption and economic efficiency and they find an inverted U-shape relationship which indicates that oil consumption promotes economic growth but at a certain point overconsumption leads to adverse results.

Chien and Hu (2008) apply Structural Equation Modeling at a panel of 116 countries to investigate the connection of RES and GDP. They use the "expenditure approach" to decompose GDP and find that RES promotes growth through capital formation but not through trade balance. Sadorsky (2009a) use panel cointegration approach to study the RES consumption in G7 countries. The results indicate that GDP per capita and CO_2 per capita have significant effects on renewable energy consumption per capita. Similar results found by Sadorsky (2009b) for 18 emerging economies. The author applies panel cointegration and a vector error correction model for the time period 1994-2003 and verifies that per capita GDP has a significant positive influence on per capita renewable energy consumption.

Chang et al. (2009) employ a panel threshold regression model to examine the connection of energy prices and RES under different levels of economic growth in OECD countries for the time period 1997-2006. They conclude that countries which experience higher economic growth have the ability to respond when energy prices rise by increasing RES consumption. On the contrary, countries which experience lower growth rates appear to be unresponsive to higher energy prices since it is found that there is no relationship between energy prices and RES.

Another strand in the literature investigates the causal relationship between energy consumption (and therefore RES consumption) and economic growth. According to Apergis and Payne (2010b), there are four hypotheses concerning this relationship. First, the *growth hypothesis* describes the situation where energy consumption affects directly and indirectly economic growth. This hypothesis implies unidirectional causality from energy consumption to economic growth. Additionally, policies which aim to the conservation of energy might have adverse effects on economic growth. Next, the *conservation hypothesis* concerns the situation where there is a unidirectional causality from economic growth to energy consumption. This hypothesis does not allow conservation policies to have adverse effects on economic growth.

The *feedback hypothesis* supports the bidirectional causality between energy consumption and economic growth. Again, energy conservation policies may have adverse effects on economic growth and these adverse effects could have a further negative effect on energy consumption. Last, *neutrality hypothesis* is about the situation where energy consumption has no effect on economic growth and therefore conservation policies will have insignificant effect on economic growth. For a detailed review about these hypotheses see Ozturk (2010).

The results about the aforementioned hypotheses are rather mixed. Bowden and Payne (2010) analyze the causal relationship between renewable and non-renewable energy and GDP by sectors using a Toda-Yamamoto approach. Specifically, the authors verify the growth hypothesis for residential RES consumption. Also, commercial and industrial consumption is explained by the neutrality hypothesis. Ozturk et al. (2010) study the causal relationship for 51 countries and find that the conservation hypothesis is verified for low income countries while for middle income countries the feedback hypothesis is valid.

The majority of the studies about energy consumption and particularly renewable energy consumption and GDP support either the feedback hypothesis or the neutrality hypothesis. Apergis and Payne (2010b) employ a multivariate panel model to study 13 Eurasian countries for the time period 1992-2007. The results indicate that the feedback hypothesis for RES consumption and GDP exists both in short and long run. Apergis and Payne (2010a) and Apergis and Payne (2012) conduct a similar study for 20 OECD countries and 80 countries respectively, and verify the results about feedback hypothesis.

Tugcu et al. (2012) analyze the causal relationship of RES and non-RES consumption and GDP for G7 countries using ARDL approach and a newly developed test by Hatemi (2012). The estimates reveal that feedback hypothesis is supported by the majority of the results. Ozturk and Acaravci (2010a, 2010b) apply ARDL approach at four Eastern and Southeastern European countries and Turkey respectively. The authors study the causal relationship between energy consumption and GDP and they find significant evidence to support the neutrality hypothesis. The neutrality hypothesis between electricity and GDP is also supported by Ozturk and Acaravci (2010c) for eleven Middle East and North Africa countries.

Halkos and Tzeremes (2009) study the effect of electricity generation on economic efficiency using DEA window analysis and econometric panel data approaches and they find a U-shape relationship. Menegaki (2011) investigates the connection between RES consumption and GDP for 27 European countries by applying a random effects model and finds evidence for the neutrality hypothesis. Yildirim et al. (2012) find additional evidence about the neutrality hypothesis studying the case of RES in the USA.

3. Data and Methodology

3.1 Description of variables

In order to model countries' economic efficiency we follow Halkos and Tzeremes (2009, 2010, 2011, 2012a) by defining countries' production function using as inputs total labor force, capital stock and as output GDP (constant 2000 $ U.S.). The data refer to the year 2010 and have been extracted from the World Bank database[2]. However, since countries' capital stock values are not available, we have calculated them using the perpetual inventory method (Feldstein and Foot, 1971; Epstein and Denny, 1980; Nadiri and Prucha, 1996) as:

$$K_t = I_t + (1-\delta)K_{t-1} \tag{1}$$

where K_t and K_{t-1} are the gross capital stock in current year and in the previous year respectively and δ represents the depreciation rate of capital stock[3]. Moreover in

[2] The data are available from: http://data.worldbank.org/indicator/

[3] Following Zhang et al. (2011) we set δ equal to 6%.

order to capture the effect of renewable energy consumption on countries' economic efficiency we are using as external variable primary energy consumption for renewables measured in million tonnes oil equivalent (mtoe). Renewables consist of solar, wind, geothermal and biofuels and have been extracted from the Statistical Review of World Energy concerning the year 2010[4]. Descriptive statistics of the variables used are presented in Table 1.

Table 1: Descriptive statistics of the variables considered

	Total Labour Force	Capital stock	Real GDP 2000 prices	Primary energy consumption (Renewables)
Mean	13962922.59	1.30135E+12	4.38375E+11	2.780583209
Std	17272528.65	1.60061E+12	5.65105E+11	4.286901541
Min	1628492.198	44526427404	17527068250	0.067215602
Max	75601032.32	5.45526E+12	2.07879E+12	18.86448387

3.2 Performance measurements

Farrell (1957) introduced the first estimator in order to measure technical efficiency. Charnes et al. (1978)[5] assuming constant returns to scale (CRS) operationalized DEA by allowing the estimation of the production set Ψ. The production set Ψ of the physically attainable points (x, y) can be formally defined as:

$$\Psi = \left\{ (x, y) \in \Re_{+}^{N+M} \middle| x \quad can \quad produce \quad y \right\} \tag{2}$$

where $x \in \Re_{+}^{N}$ is the input vector and $y \in \Re_{+}^{M}$ is the output vector. Later, Banker et al. (1984) introduced a DEA estimator allowing for variable returns to scale (BCC estimator). The CCR estimator uses the convex cone of $\hat{\psi}_{FDH}$ (Deprins et al., 1984) to estimate Ψ, whereas the BCC estimator uses the convex hull of $\hat{\psi}_{FDH}$ to estimate Ψ.

[4] The data are available from:
http://www.bp.com/extendedsectiongenericarticle.do?categoryId=9041234&contentId=7075077

[5] Known also as the CCR estimator.

In our case we are using the input oriented efficiency score for a unit operating at the level (x, y) which can be defined as:

$$\theta(x,y)=\inf\left\{\theta\,\middle|\,(\theta x,y)\in\Psi\right\} \tag{3}$$

The DEA efficiency score for the CCR estimator for each data point $\left(x_i, y_i\right)$ can be calculated as:

$$\hat{\theta}_{DEA,CRS}\left(x_i,y_i\right)=\inf\left\{\begin{matrix}\theta>0\,\middle|\,\theta x_i\geq\sum_{i=1}^{n}\gamma_i x_i;\ y\leq\sum_{i=1}^{n}\gamma_i y_i\ \text{for}\ \left(\gamma_1,\ldots\gamma_n\right)\\ \text{such that}\ \gamma_i\geq 0, i=1,\ldots n\end{matrix}\right\} \tag{4}$$

Similarly, the DEA efficiency score for the BCC estimator allowing variable returns to scale (VRS) can be calculated as:

$$\hat{\theta}_{DEA,VRS}\left(x_i,y_i\right)=\inf\left\{\begin{matrix}\theta>0\,\middle|\,\theta x_i\geq\sum_{i=1}^{n}\gamma_i x_i;\ \ y\leq\sum_{i=1}^{n}\gamma_i y_i\ \text{for}\ \left(\gamma_1,\ldots\gamma_n\right)\\ \text{such that}\ \sum_{i=1}^{n}\gamma_i=1;\ \gamma_i\geq 0, i=1,\ldots n\end{matrix}\right\} \tag{5}$$

3.3 Bias correction using the bootstrap technique

It has been proven by Simar and Wilson (1998, 2000) that DEA estimators are biased by construction. In order to correct and estimate the bias of the DEA estimators, they have introduced a bootstrap algorithm (Efron, 1979). Then the bootstrap bias estimate for the original DEA estimator $\hat{\theta}_{DEA}(x,y)$ can be calculated as:

$$\widehat{BIAS}_B\left(\hat{\theta}_{DEA}(x,y)\right)=B^{-1}\sum_{b=1}^{B}\hat{\theta}^*{}_{DEA,b}(x,y)-\hat{\theta}_{DEA}(x,y) \tag{6}$$

Given that $\hat{\theta}^*{}_{DEA,b}(x,y)$ are the bootstrap values and B is the number of bootstrap replications, a biased corrected estimator of $\theta(x,y)$ can then be calculated as:

$$\hat{\hat{\theta}}_{DEA}(x,y) = \hat{\theta}_{DEA}(x,y) - \hat{BIAS}_B\left(\hat{\theta}_{DEA}(x,y)\right) = 2\hat{\theta}_{DEA}(x,y) - B^{-1}\sum_{b=1}^{B}\hat{\theta}^*_{DEA,b}(x,y) \tag{7}$$

However, according to Simar and Wilson (2008) this bias correction can create an additional noise and the sample variance of the bootstrap values $\hat{\theta}^*_{DEA,b}(x,y)$ need to be calculated. The calculation of the variance of the bootstrap values is illustrated below:

$$\hat{\sigma}^2 = B^{-1}\sum_{b=1}^{B}\left[\hat{\theta}^*_{DEA,b}(x,y) - B^{-1}\sum_{b=1}^{B}\hat{\theta}^*_{DEA,b}(x,y)\right]^2 \tag{8}$$

In addition we need to avoid the bias correction illustrated in (7) unless:

$$\frac{\left|\hat{BIAS}_B(\hat{\theta}_{DEA}(x,y))\right|}{\hat{\sigma}} > \frac{1}{\sqrt{3}} \tag{9}$$

By expressing the input oriented efficiency in terms of the Shephard (1970) input distance function as $\hat{\delta}_{DEA}(x,y) \equiv \frac{1}{\hat{\theta}_{DEA}(x,y)}$ we can construct bootstrap confidence intervals for $\hat{\delta}_{DEA}(x,y)$ as:

$$\left[\hat{\delta}_{DEA}(x,y) - \hat{\alpha}_{1-a/2}, \hat{\delta}_{DEA}(x,y) - \hat{\alpha}_{a/2}\right] \tag{10}$$

3.4 Modelling the effect of external (environmental) factors on the efficiency scores

We follow the probabilistic formulation introduced by Daraio and Simar (2005, 2007a, 2007b) in order to allow in to the production process external-environmental factors denoted as $Z \in \Re^r$. They suggest that the joint distribution of (X,Y) conditional on the environmental factor Z=z defines the production process if $Z = z$. Then, the production set Ψ^z can be defined in the following way as

$H_{X,Y|Z}\left(x,y|z\right)=\text{Prob}\left(X\le x,Y\ge y|Z=z\right)$ when $Z=z$. Then for the input oriented case we can decompose the joint distribution by:

$$H_{X,Y|Z}\left(x,y|z\right)=F_{X|Y,Z}\left(x,y|z\right)S_{Y|Z}\left(y|z\right) \tag{11}$$

for all y such that $S_{Y|Z}\left(y|z\right)=\text{Prob}\left(Y\ge y|Z=z\right)>0$ and $F_{X|Y,Z}\left(x,y|z\right)=\text{Prob}\left(X\le x|Y\ge y,Z=z\right)$. Therefore the input oriented efficiency score with an environment described by the value z can be defined as:

$$\theta(x,y|z)=\inf\left\{\theta|F_{X|Y,Z}\left(\theta x|y,z\right)>0\right\} \tag{12}$$

The production set defined by an environmental factor can be formally expressed as:

$$\Psi^{z}=\left\{\left(x',y\right)\in\Re_{+}^{N+M}\middle|x'\ge x^{\partial,z}\left(y\right)\text{ for }\left(x,y\right)\in\Psi\right\} \tag{13}$$

where $x^{\partial,z}\left(y\right)$ defines the efficient level of input conditioned on the external factor and for an output level $y: x^{\partial,z}\left(y\right)=\theta\left(x,y|z\right)x$ given that $\left(x,y\right)\in\Psi$ so that $\Psi^{z}\subseteq\Psi$. According to Daraio and Simar (2005, 2007a, 2007b) a nonparametric estimator can be obtained by plugging an estimator of $F_{X|Y,Z}\left(.|y,z\right)$ in (12) by applying some smoothing techniques as:

$$\hat{F}_{X|Y,Z,n}\left(x|y,z\right)=\frac{\sum_{i=1}^{n}I\left(x_i\le x,y_i\ge y\right)K\left(\left(z-z_i\right)/h\right)}{\sum_{i=1}^{n}I\left(y_i\ge y\right)K\left(\left(z-z_i\right)/h\right)} \tag{14}$$

where $K(.)$ is a univariate kernel with compact support (Epanechnikov in our case) and h is the appropriate bandwidth calculated following the approach by Bădin et al. (2010).

Hence, we can obtain a conditional DEA efficiency measure as[6]:

$$\hat{\theta}_{DEA}(x, y|z) = \inf\left\{\theta \middle| \hat{F}_{X|Y,Z,n}(\theta x|y, z) > 0\right\} \tag{15}$$

The conditional DEA efficiency score under the constant returns to scale assumption can be calculated as:

$$\hat{\theta}_{DEA,CRS}\left(x_i, y_i \middle| z_i\right) = \inf\left\{\begin{array}{l} \theta > 0 \middle| \theta x_i \geq \sum\limits_{\{i|z-h\leq z_i\leq z+h\}}^{n} \gamma_i x_i;\ y \leq \sum\limits_{\{i|z-h\leq z_i\leq z+h\}}^{n} \gamma_i y_i \text{ for } \left(\gamma_1, \ldots \gamma_n\right) \\ \text{such that } \gamma_i \geq 0, i = 1, \ldots n \end{array}\right\} \tag{16}$$

Assuming variable returns to scale assumption additionally can be calculated as:

$$\hat{\theta}_{DEA,VRS}\left(x_i, y_i \middle| z_i\right) = \inf\left\{\begin{array}{l} \theta > 0 \middle| \theta x_i \geq \sum\limits_{\{i|z-h\leq z_i\leq z+h\}}^{n} \gamma_i x_i;\ y \leq \sum\limits_{\{i|z-h\leq z_i\leq z+h\}}^{n} \gamma_i y_i \text{ for } \left(\gamma_1, \ldots \gamma_n\right) \\ \text{such that } \sum\limits_{\{i|z-h\leq z_i\leq z+h\}}^{n} \gamma_i = 1;\ \gamma_i \geq 0, i = 1, \ldots n \end{array}\right\} \tag{17}$$

Then in order to establish the influence of the environmental variable (in our case the quantity of renewable energy consumption) on countries' economic efficiency scores we obtain a scatter of the ratios $Q = \dfrac{\hat{\theta}_{DEA}\left(x, y|z\right)}{\hat{\theta}_{DEA}\left(x, y\right)}$ against Z and its smoothed nonparametric regression lines. The nonparametric regression smoothing can be presented as:

$$Q = g\left(z_i\right) + \varepsilon_i, i = 1, \ldots, n \tag{18}$$

where ε_i is the error term with $E\left(\varepsilon_i \middle| z_i\right) = 0$, and g is the mean regression function, since $E\left(Q \middle| z_i\right) = g\left(z_i\right)$[7].

[6] For the theoretical background and the asymptotic properties of nonparametric conditional efficiency measures see Jeong et al. (2010). For other applications of DEA conditional estimators see Simar and Vanhems (2012) and Halkos and Tzeremes (2013).

According to Daraio and Simar (2005, 2007a, 2007b) an increasing smoothing nonparametric regression line will indicate a negative effect of the renewable energy consumption on countries' economic efficiency levels. On the other hand, a decreasing nonparametric regression line highlights a positive effect of renewable energy consumption on countries' economic efficiency levels. Finally, a neutral effect of renewable energy consumption is denoted by a straight line.

4. Empirical results

Table 2 presents the results obtained from the DEA estimators. Under the assumption of constant returns to scales (CRS) Norway, Sweden and Turkey appear to be economic efficient. At the same time, in the case of variable returns to scale (VRS) ten countries are reported to have economic efficiency score equal to one. However, after correcting for the bias and under the assumption of CRS (CRSbc) the three countries with the highest performance are Sweden, Norway and Poland, whereas the three countries with the lowest performance are Hungary, Greece and Portugal. Similarly in the VRS case the biased corrected results (VRSbc) reveal Switzerland, Poland and Ireland as the three highest performers whereas Hungary, Greece and Portugal are still the lowest performers[8].

After applying the conditional DEA estimators (in order to account for the effect of countries' renewable energy consumption levels), the results report changes both for the conditional CRS (CRS|z) and conditional VRS (VRS|z) cases. More analytically, Poland and Norway are efficient under the CRS assumption, whereas

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[7] In our case we use the Nadaraya (1964) and Watson (1964) nonparametric regression estimator and the least square cross-validation data driven method (Hall et al., 2004) for the bandwidth selection.

[8] Halkos and Tzeremes (2012b) used financial ratios in a bootstrapped DEA formulation to construct efficiency ratios and evaluated the financial performance of the firms operating in the Greek renewable energy sector.

Poland, Norway, Sweden, Switzerland, Ireland, Bulgaria, Lithuania and Germany are economic efficient under the assumption of VRS. Again as before, the biased corrected results of the conditional estimators both for CRS (CRSbc|z) and for the VRS (VRSbc|z) cases report different results compared to the original estimates. These variations can also be observed from the descriptive statistics presented in Table 2.

Table 2: Bias corrected efficiency scores of the conditional and unconditional DEA estimators

Regions	Countries	CRS	CRSbc	CRS|z	CRSbc|z	VRS	VRSbc	VRS|z	VRSbc|z
3	Austria	0.690	0.627	0.670	0.593	0.716	0.667	0.737	0.650
3	Belgium	0.802	0.742	0.765	0.697	0.827	0.773	0.887	0.800
2	Bulgaria	0.776	0.667	0.676	0.606	1.000	0.879	1.000	0.815
2	Czech Republic	0.613	0.567	0.615	0.565	0.665	0.630	0.672	0.623
4	Denmark	0.775	0.686	0.752	0.668	0.839	0.785	0.831	0.747
4	Finland	0.798	0.713	0.803	0.735	0.865	0.811	0.857	0.777
3	France	0.778	0.697	0.083	0.077	0.915	0.848	0.084	0.078
3	Germany	0.793	0.633	0.570	0.529	1.000	0.848	1.000	0.745
1	Greece	0.432	0.390	0.449	0.411	0.455	0.425	0.456	0.412
2	Hungary	0.453	0.411	0.435	0.401	0.516	0.480	0.507	0.455
4	Ireland	0.777	0.654	0.759	0.681	1.000	0.923	1.000	0.900
1	Italy	0.611	0.522	0.059	0.051	0.810	0.760	0.085	0.077
4	Lithuania	0.662	0.527	0.581	0.521	1.000	0.845	1.000	0.785
3	Netherlands	0.720	0.663	0.418	0.378	0.808	0.767	0.490	0.442
4	Norway	1.000	0.893	1.000	0.870	1.000	0.904	1.000	0.853
2	Poland	0.993	0.888	1.000	0.883	1.000	0.923	1.000	0.845
1	Portugal	0.412	0.375	0.424	0.394	0.446	0.421	0.440	0.409
2	Romania	0.846	0.771	0.808	0.727	0.921	0.859	0.910	0.805
2	Russian Federation	0.959	0.851	0.645	0.581	0.989	0.912	0.724	0.639
2	Slovak Republic	0.787	0.712	0.742	0.677	0.927	0.872	0.908	0.816
1	Spain	0.456	0.417	0.137	0.125	0.526	0.495	0.139	0.124
4	Sweden	1.000	0.920	0.913	0.847	1.000	0.904	1.000	0.862
3	Switzerland	0.904	0.817	0.790	0.699	1.000	0.938	1.000	0.849
2	Turkey	1.000	0.878	0.743	0.659	1.000	0.890	0.845	0.722
4	United Kingdom	0.852	0.735	0.087	0.080	1.000	0.892	0.088	0.080
1 = Southern EU countries	Mean	0.756	0.670	0.597	0.538	0.849	0.778	0.706	0.612
2 = Eastern EU countries	Std	0.181	0.162	0.276	0.245	0.188	0.163	0.327	0.274
3 = Western EU countries	Min	0.412	0.375	0.059	0.051	0.446	0.421	0.084	0.077
4 = Northern EU countries	Max	1.000	0.920	1.000	0.883	1.000	0.938	1.000	0.900

Figure 1 illustrates the global effect of countries' renewable energy consumption (z) on their obtained economic efficiency levels. Subfigure 1a presents the results under the assumption of CRS[9]. The results reveal a positive effect (a decreasing nonparametric regression line) up to a certain renewable energy consumption level (5 mtoe). After that point the effect is negative (indicated by an increasing nonparametric regression line) up to 11 mtoe and then it becomes gradually positive. Similar results are obtained also under the assumption of variable returns to scale (subfigure 1c). Subfigure 1e presents the effect of renewable energy consumption on countries scale efficiency levels[10]. It appears that the effect is negative up to 6 mtoe and then the effect is slightly positive up to 11 mtoe; after this point a neutral effect is observed.

Subfigures 1b, 1d and 1f represent in a three dimensional manner the effect of regional disparities among the examined countries[11]. As can be observed the effect of renewable energy consumption on countries' economic efficiency varies depending on countries' regional disparities. It appears that the effect on northern European countries differs compared to the southern European countries. Similarly, the same phenomenon appears between the eastern and western European countries.

[9] For all the cases we are using the biased corrected efficiency results following Simar and Wilson (1998, 2000, 2008).

[10] The scale efficiency ratio analogous to Q in equation (18) is calculated as:

$$Q_{scabc} = \frac{\hat{\theta}_{CRSbc}\left(x, y \middle| z\right) / \hat{\theta}_{CRSbc}\left(x, y\right)}{\hat{\theta}_{VRSbc}\left(x, y \middle| z\right) / \hat{\theta}_{VRSbc}\left(x, y\right)}$$

[11] The regional classifications of the examined countries are reported in Table 1. The regional classifications are based on United Nations statistics division and can be found at: http://unstats.un.org/unsd/methods/m49/m49regin.htm#europe

Figure 1: The effect of renewable energy consumption on E.U. countries' economic efficiency

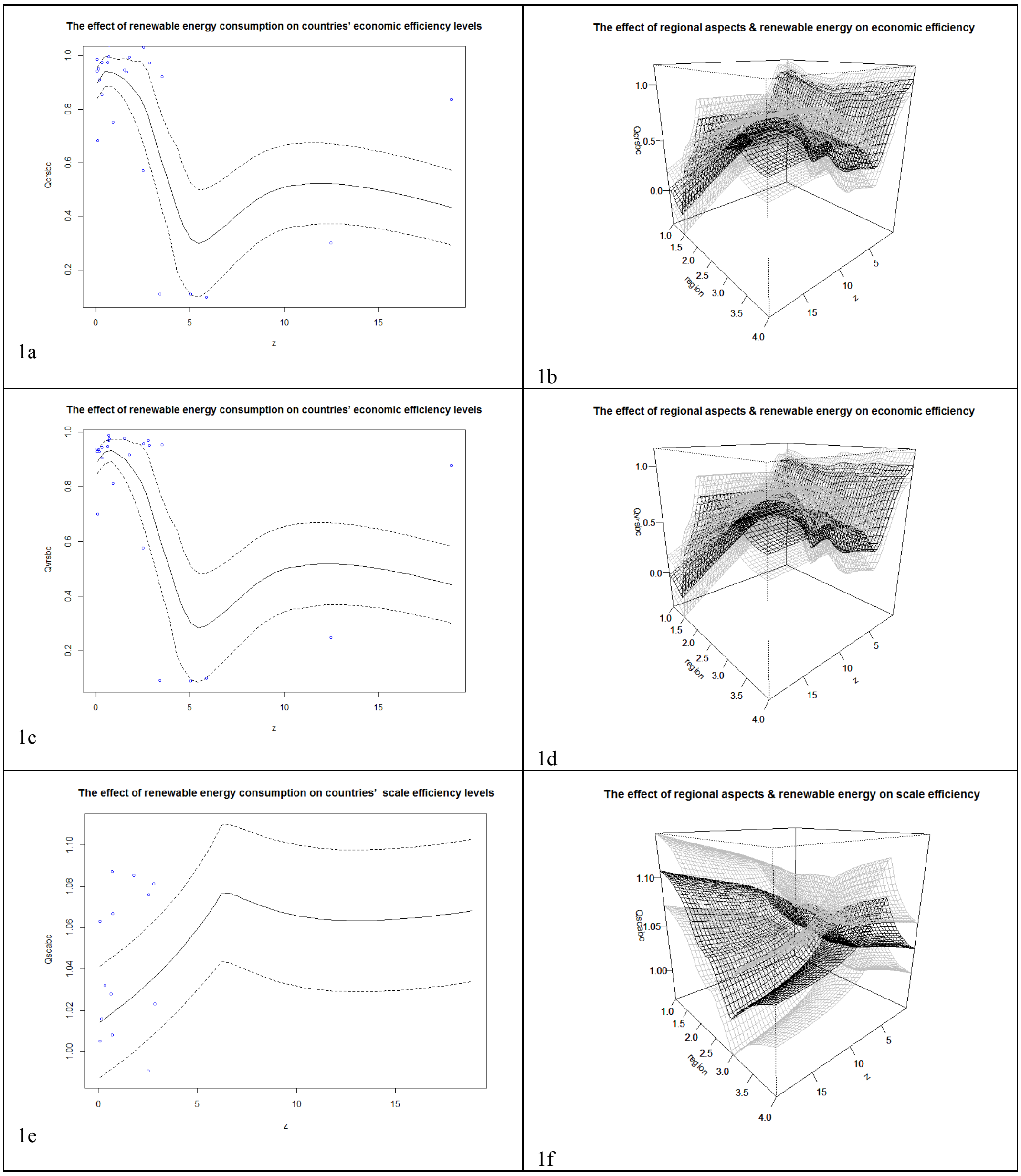
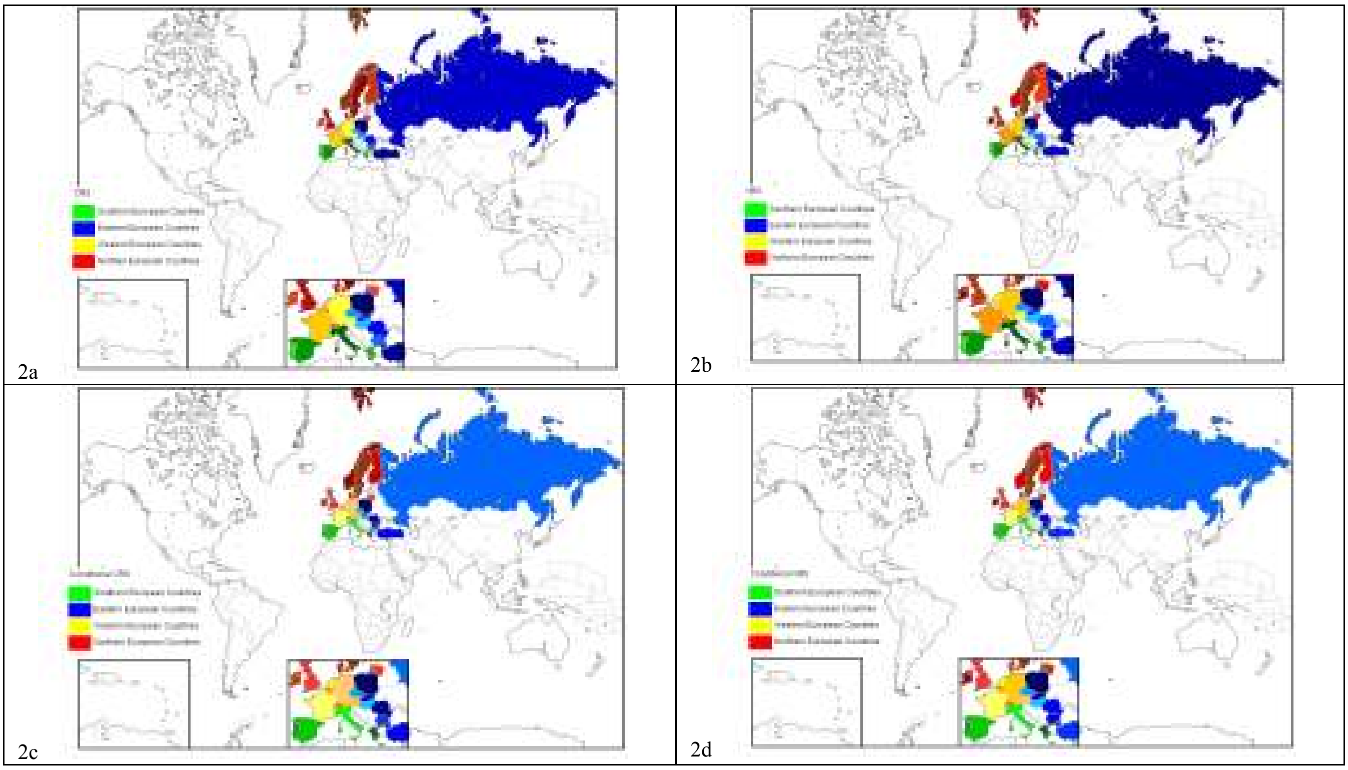


Figure 2 presents a more detail illustration of the phenomenon between the countries considered. The green colour represents the efficiency levels of southern European countries and the blue represents eastern European countries. Moreover, the yellow colour represents western European countries and finally, the red colour represents northern European countries. The darker the scale of the colour is on the map the higher countries' efficiency levels will be. The top panels (subfigures 2a and

2b) represent the economic efficiency scores under the CRS and VRS assumption, whereas the other two panels (subfigures 2c and 2d) correspond to the conditional equivalent measures. It is clear from the two maps that regional disparities among the examined countries do matter and reflect their environmental policies in terms of the use of renewable energy consumption. As a result we observe a regional dependent effect on their obtained economic efficiency levels.

Figure 2: Map visualization of the regional disparities on countries' economic efficiency levels (Green =Southern European Countries; Blue = Eastern European countries; Yellow = Western European countries; Red = Northern European countries; Darker colors indicate higher efficiency).

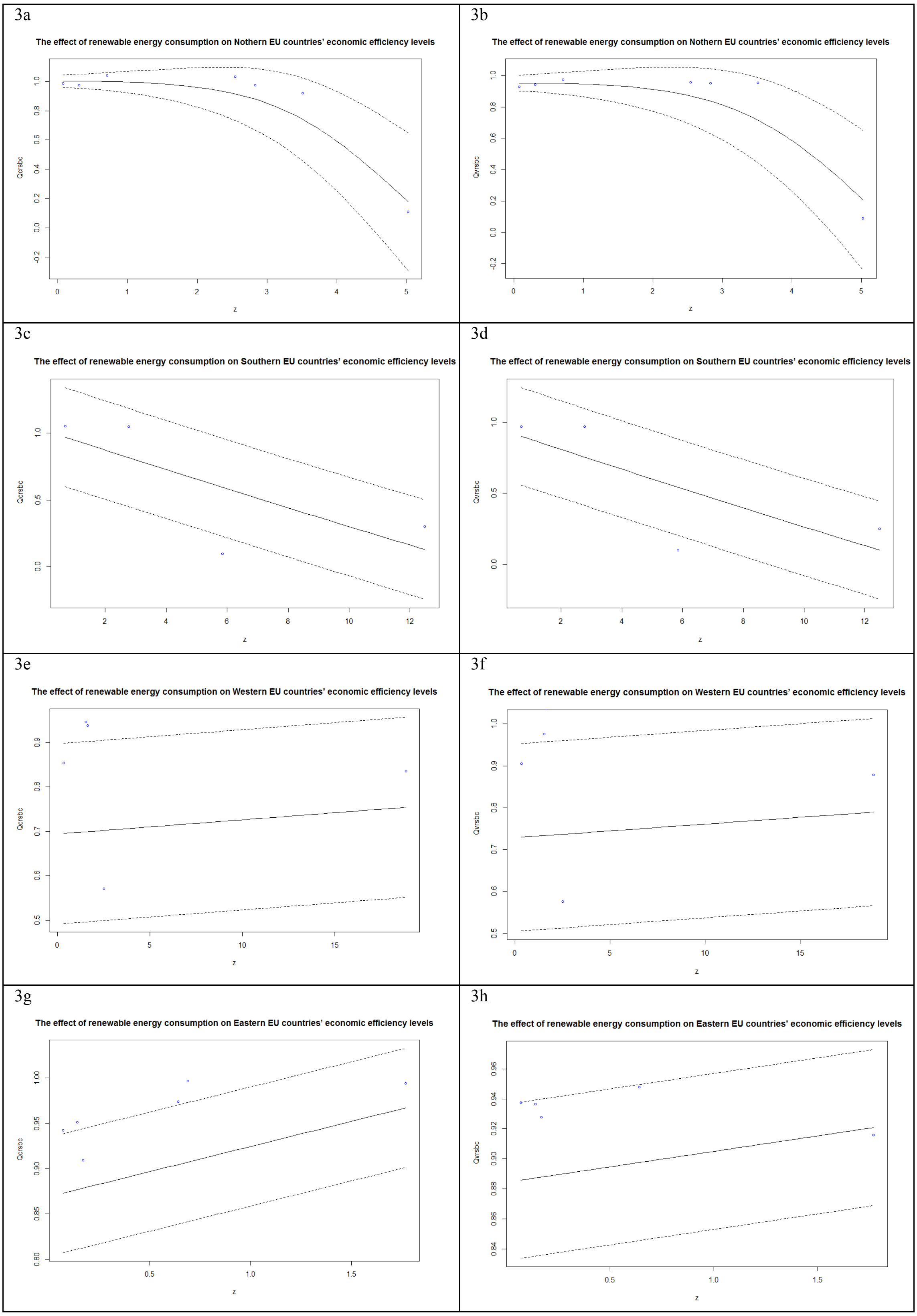


A more detailed analysis of the phenomenon is presented in Figure 3. The graphs on the left column of Figure 3 present the effect under the CRS assumption whereas the graphs on the right the effects under the VRS. As can be observed the global effect of the renewable energy consumption on countries' economic efficiency is similar between the two scale assumptions with no significant differences. If we observe the effect separately for the four regional classifications we verify the observations drawn from Figures 1 and 2. More analytically, for the northern countries (Subfigures 3a, 3b) it is reported that the effect of renewable energy consumption on their economic efficiency levels is neutral for low consumption values and gradually becomes positive as the amount of renewable primary energy consumption increases.

However, when observing the case of southern European countries (3c, 3d) the effect of renewable energy consumption is direct and positive indicated by a steeper decreasing nonparametric regression line. The detailed examination for the western European countries (3e, 3f) reveals a slight increasing nonparametric regression line indicating a neutral effect at lower consumption levels and a minor negative effect at higher consumption levels. Finally, for eastern European countries (3g, 3h) we observe a monotonic increasing nonparametric regression line indicating a negative effect on countries' economic efficiency levels when the usage levels are higher.

Our results support clearly the *growth hypothesis* in terms of renewable energy consumption and countries' economic efficiency levels. However, it must be mentioned that we found evidence that regional disparities and countries' unique characteristics can also in some extent support *feedback* and *neutrality* hypothesis. In spite of this, a further investigation is needed incorporating the dynamic effects in a DEA analysis.

Figure 3: The effect of renewable energy consumption on Northern (3a, 3b), Southern (3c, 3d), Western (3e, 3f) and Eastern (3g, 3h) E.U. countries' economic efficiency



5. Conclusions

Our paper examines for the first time the effect of renewable energy consumption on countries' economic efficiency levels and contributes to the existing literature investigating the renewable energy consumption–economic growth relationship. In our DEA setting we compute conditional DEA estimators incorporating directly the effect of renewable energy consumption into countries production function. The nonparametric analysis reveals economic efficiency variations among the examined countries, which are subject to the different influence of countries' renewable energy consumption levels.

Moreover, it appears that regional disparities among the examined countries are also making an impact on the direction of which the renewable energy consumption affects their economic efficiency levels. We have found evidence supporting the *growth* hypothesis. Especially for lower consumption levels the effect is positive, whereas for medium consumption levels the effect becomes negative.

Finally, for higher renewable energy consumption levels the effect on countries' economic efficiency gradually turns from neutral to positive. However, in some cases and especially for eastern and western European countries we have found evidences for the *feedback* and *neutrality* hypothesis indicating a negative and a neutral effect of renewable energy consumption on their economic efficiency levels. Therefore, it appears that there are different renewable energy policies among the examined countries which are subject to geographical variations and reflect their long term environmental policies.

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