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What is the role of ecological footprint on renewable energy deployment? Sustainability perspective for EU region

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Abstract Because of the concerns about global warming, climate change and energy security, issues many countries try to increase the share of renewable energy sources. Renewable energy has become key to ensure sustainable economic development as well. Therefore, the current study aims to analyze the role of environmental degradation, GDP, energy import and urbanization on renewable energy deployment in 26 European Union countries by using panel data over the 1990-2018 period. Against this backdrop, we employed Ecological Footprint to represent environmental degradation in these countries. Our results indicate that while GDP per capita and urbanization are not a significant driver of RE deployment, energy import and EFP negatively affect RE deployment. On the contrary, increasing GDP and urbanization have a deterring impact in some EU countries (Romania, Czechia, and Denmark). Moreover, energy requirement of growing income is mostly met by non-renewable energy and environmental pressure is not a strong driver for renewable energy development in the EU countries. We provided some policy recommendations in the conclusion part.

Keywords: Renewable energy deployment, Ecological Footprint, European Union, sustainable economic development.

JEL: Q01, Q43, Q56

Introduction

Due to the environmental concerns, such as global warming, climate change and energy security issues, many countries try to replace fossil fuels with the renewable energy (hereafter REN) in their energy mix. As it is known, increasing fossil fuel utilization is seen as the major factor that worsens the environmental degradation. Energy fuels e economic activities but increasing production and consumption parallel with the rising income harms the environmental quality. As reported by IEA (2021), more than two thirds of GHG are attributed to the energy sector and fossil fuels constitute more than 80 % of total energy supply all over the world. Although global CO_2 emissions decreased due to Covid-19 pandemic in 2020, total emissions rebounded to pre-Covid 19 levels with a 4.8 % increase (Januta, 2021). As highlighted by the Brundtland Report in 1987, it is necessary to achieve sustainable economic development by setting up balance between economic growth and environment (Salman and Hosny, 2021). Due to the energy security problems, limited proven fossil fuel reserves and increasing environmental deterioration, REN has become a major tool to ensure sustainable economic development. Moreover, since developments of REN technologies ensure mini grid systems and rural electrifications, it contributes to rural development as well. In this context, an increasing number of countries (around 165 countries in 2020) has put into force some incentive mechanisms such as FITs, taxes, quota, tradeable REN certificates, tendering, etc., to promote REN in their energy mix. As result of these efforts, the share of REN in global energy supply increased significantly. However, although IEA (2022) projects that REN will provide more than 32 % of global energy supply by 2024, there are significant differences in the share of REN in the energy mix among the different countries and REN's penetration progress is slow. Therefore, it is vital to explore the factors that determine REN development to ensure sustainable economic development.

Since REN has become a key factor in promoting environmental sustainability, the link between REN deployment and factors that affect the development of REN has been the focus of policy makers and researchers. There are many studies in the literature that empirically analyze REN deployment in different countries and/or country groups by using different econometric methodologies in the recent decades. The explanatory variables incorporated into these models can be grouped as socioeconomic factors, policy, and country specific factors (Acquire and Ibikunle, 2014; Marquez et.al., 2010). For example, one research strand investigates the role of incentive policies on REN development in some countries and/or country groups (see Menz and Vachon, 2006; Carley, 2009; Nicolini and Tavani, 2017, Liu et.al., 2019; Bölük and Kaplan, 2021; among others). These studies also investigated some control variables, such as Gross Domestic Product (GDP), energy import, energy prices, GHGs (proxied by CO_2 emissions) (see Liu et.al., 2019; Bölük and Kaplan, 2021). However, they revealed controversial results about the effectiveness of different kind of incentive policy schemes. Another research strand, however, focused on the impact of macro-economic and environmental variables on REN development by using linear econometric models. These studies generally found stimulating effect of GDP, energy import and energy and/or electricity consumption (see Sadorsky 2009; Gan and Smith, 2011; Omri and Nyugen, 2014; among others). In both research strands, environmental degradation was represented by CO_2 emissions. However, emissions are only a specific part (air pollution) of environmental degradation and CO_2 cannot fully represent the environmental deterioration. Including the CO_2 emissions as the proxy of environmental deterioration is argued, as production-based approach and this method is criticized due to the lack of an aggregate measure of environmental quality (Bagliani et.al., 2008; Caglar et.al., 2021). Following the pioneering studies of Rees (1992) and Wackernagel and Rees (1996), it has been argued that EFP poses more comprehensive and composite environmental indicator than emissions and it is a more convenient tool to ensure environmental sustainability (Hassan et.al., 2019; Caglar et.al., 2021). Apart from the emissions, using more than 6000 units of data for every individual country, EFP presents consumption-based indicator, since it includes the stress of economic activities on cropland, grazing land, forest land, fishing grounds and built-up land on the Earth (Global Footprint Network, 2022).

Unlike the previous studies, this paper discusses the impact of EFP on REN deployment by including some control variables such as GDP and energy import. According to the best of our knowledge, this study is the first attempt that analyzes the role of EFP in REN deployment in energy economics. Our paper contributes to existing energy economics literature as following. First, we employ EFP, which is commonly accepted as more comprehensive indicator of environmental quality of economic activities and/or environmental sustainability. As discussed in detail under the "literature review", existing studies used CO_2 emissions to evaluate the impact of environmental pressure. Second, previous studies provide limited understanding related to determinants of REN development and reveal controversial results. What is more, determinants of REN deployment have not been studied enough empirically yet. Hence our results will provide hints about efficient policy design related to REN deployment. We focus on the EU countries over the 1990-2015 period since the EU desires to be leader in REN in the world. We employ panel data analysis. Since RE production and/or installed capacity can affect the future RE development, we included lag of dependent variable (REN) in our model. Therefore, a dynamic model is defined. It is also thought that it is useful to consider heterogeneity in order to reach country-specific results. Therefore, a dynamic and heterogeneous model was employed.

The rest of the paper is organized as follows. Section 2 summarizes the existing literature on drivers of RE development. Section 3 provides the data and econometric model structure. Section 4 presents the results. Conclusion and some policy recommendations are given in the Section 5.

Theoretical premises

It appears that there are two main research strands in the literature on determinants of REN deployment. The drivers and/or stimulating factors have been studied since the beginning of 2000s. The first strand basically investigates the stimulating effect on implemented policy incentives on REN deployment. The earlier studies in this strand analyzed the role of one and/or few REN incentive tools on REN development in individual countries. In this context, while Verbruggen (2004) investigated the role of tradable certificate mechanism on REN installed capacity for Flenders, Birds et.al. (2005) demonstrated the stimulating effect of renewable portfolio standards (hereafter RPSs) and other financial incentives, such as state tax, on wind capacity in USA. Similarly, Wüstenhagen and Bilharz (2006), and Mitchell et.al. (2006) discussed the role of FITs on REN installed capacity development for Germany. In this strand, however, effectiveness of policy schemes on REN development has been started to be discussed empirically after the pioneering study of Menz and Vachon (2006). In their study, the authors analyzed the role of policy incentives on wind capacity in 39 states in the USA. By using panel data analysis, they found stimulating effects of REN policies (such as RPSs) on REN electricity capacity from wind. Another empirical study for the USA implemented by Carley (2009) found a positive impact of RPSs on REN power generation as well. While Menz and Vachon (2006), and Carley (2009) discuss either FITs or RPS for single country, some studies in this strand analyzed the effectiveness of many REN policy tools on REN development in some country groups. Dong (2012) demonstrated that FITs are a stronger incentive tool than RPS for wind power in 53 countries. Nicolini and Tavani (2017) compared the FIT and tradable green certificates for five largest European countries and found that 1% (Euro cent) increase in FIT rises the REN installed electricity capacity by around 18-26 %. Liu et.al. (2019) analyzed the role of REN incentives in 29 countries from the EU and OECD by using panel data analysis. Authors concluded that fiscal and financial incentives, R&D and policy supports are important mechanisms for REN development. Among the studies discussing the effects incentive policies on REN development, some have also questioned the effects several control variables, such as income, population, energy prices, energy import, nuclear power, etc., in their models. For example, using Tobit regression for 30 countries, Kim and Park (2016) confirmed the positive impact of FITs, financial development, electricity consumption and GDP on REN. Moreover, authors highlighted the stimulating effect of international finance possibilities. Marquez and Fuinhas (2011) focused on the role of incentive policies in fostering REN installed capacity and found that FIT and policy process like strategic planning are effective policy devices for EU countries and Turkey. However, quota obligations, product labelling, R&D, CO_2emissions and tradeable certificates were found to be insignificant schemes for RE in this study. Similarly, using dynamic panel data analysis, Bölük and Kaplan (2021) analyzed the effectiveness of a rich set of incentive policies including the "net metering" on REN development in the EU countries and Turkey. The authors found that among the other grants, tax, R&D, certification, and policy support have encouraging impact on REN deployment. Moreover, authors confirmed that fossil energy use, nuclear power and GDP stimulate the REN installed capacity in these countries.

Another empirical research strand studied the macroeconomic and/or microeconomic drivers of REN development. For example, using ECM and SUR, Sadorsky (2009) focused on the determinants of REN consumption for G7 countries and found that real income per capita, real oil prices and CO_2emissions are important factors for REN. Similarly, Gan and Smith (2011) analyzed the drivers for OECD countries by using panel data analysis. The authors found that while GDP per capita increases the REN capacity, CO_2emissions, energy prices and government policies have no significant impact on REN generation. Focusing on EU countries over the 1990-2004 period, Bengochea and Faet (2012) found positive relationship between high level of CO_2emissions and REN generation. However, they found prices of fossil fuels to be insignificant for REN development. Pfeiffer and Mulder (2013) empirically proved that real GDP per capita, education level, government policies and electricity consumption level are the significant contributors of REN generation in 108 developing countries. By using global panel data covering the 64 countries for the 1990-2011 period, Omri and Nyugen (2014) found CO_2 emissions and trade openness are the major drivers for REN consumption. The authors, however, found smaller but negative impact of oil price increases on REN consumption. Smilarly, Ackah and Kizys (2015) found that while CO_2 emissions and energy prices deter REN generation, GDP per capita, population, capital formation contribute to REN development in oil producing African countries. Li et.al. (2020) empirically proved positive role of eco-innovation and energy efficiency on REN installed capacity. Murshed et.al. (2021) found positive role of regional trade integration on REN development for South Asia. Przychodzen and Przychodzen (2020) attempted the determine the factors stimulating REN production in 27 transition countries in the 1990-2014 period and revealed that while GDP increase, government debt, unemployment and Kyoto Protocol contribute to REN production, CO_2 emissions and anti-competitive market conditions in energy markets limit REN development in these countries. Apart from the macro-economic factors, Chen et.al. (2021) highlighted the importance of democratic institutions. Using threshold panel data of 97 countries over the 1995-2015 period, authors demonstrated that while democratic institutions play vital role in REN investments, trade openness slows down REN development. Using panel ARDL for Sub-Saharan countries, de Silva et.al. (2018) found that while real income, energy use stimulates REN deployment, CO_2 emissions, energy prices, energy import and Kyoto agreement decreases REN consumption. Although many studies confirmed the stimulating effect of GDP, Akar (2016) found negative impact of economic growth for REN share for Balkan countries. Bourcet (2020) provides a detailed review of empirical literature that focusses on determinants of REN since 2000s.

As discussed above, previous studies provide little consensus on both the effectiveness of policy incentives and the role of other socio-economic and environmental determinants of REN development. Moreover, although many drivers have been discussed for REN consumption and/or REN installed capacity, the role of EFP has not been discussed by any empirical studies. This is a gap that our research paper aims to fill in the energy economic literature.

Methodology

In this study, a panel data model structure is proposed to understand how socio-economic factors and ecological pressure affect REN development in EU countries. The time interval has been determined on the basis of data availability. As a dependent variable, REN is used to represent REN development in energy mix. REN is represented by renewable energy consumption (measured as % of total final energy consumption).

EFP is defined as explanatory variable and per capita EFP data are obtained from Global Footprint Network (GFN, 2020). Moreover, socio-economic drivers as explanatory variables are arranged as GDP per capita (real GDP in terms of PPP based on 2017 USD, hereafter GDP), energy imports (net, % of energy use, hereafter EIMP) and urbanization (% of total population, hereafter URB). All data incorporated into our model have been compiled from the World Bank (2022). Data covers the 1990-2018 period from 26 countries. Summary statistics for data are given in Table 1.

Table 1. Summary Statistics

	ren_{it}	efp_{it}	gdp_{it}	$eimp_{it}$	urb_{it}
Obs.	754	712	726	670	754
Mean	14.872	5.523	35430.34	53.400	70.247
Std. Dev.	11.439	2.218	18475.5	27.673	11.814
Min.	0.335	1.74	9600.9	-65.694	47.915
Max.	52.892	17.78	120647.8	99.675	98.001

The data set is an unbalanced panel according to number of observations. The share of ren in total energy consumption is 14.87% on average. The minimum ren value is 0.34% (Cyprus), and the maximum value is 53% (Sweden). The average value of efp is 5.5, with a minimum value of 1.74 (Slovakia), and a maximum value of 17.78 (Luxembourg). The mean of gdp value of the overall panel is approximately $35,430. The minimum gdp value is approximately $9,601 (Latvia), while the maximum value is approximately $120,648 (Luxembourg). The average of eimp is 53.4%. The minimum value of this variable is approximately -65.7% (Denmark), while its maximum value is approximately 99.7% (Cyprus). Finally, for the summary statistics of the urb variable, the share in the total population is approximately 70%. The minimum urb value was approximately 48% (Portugal), and the maximum value was 98% (Belgium).

The main purpose of the current study is to reveal the effects of ecological pressure (represented by efp) and different socio-economic variables on ren development in the EU region. Our results will provide important implications for the sustainability aspect of the EU countries. For this purpose, we constructed a dynamic panel data model to examine ren development and some control variables. The variables in the model context are defined as follows:

(1) $$ren = f(efp, gdp, eimp, urb)$$

We also added the lag of ren in the model to make the econometric model dynamic. The model discussed in the study is defined as follows:

(2) $$ren = f(efp, gdp, eimp, urb)$$

In Eq.2, α is the constant, θ is the coefficient for dynamic variable, and the coefficients of the β are slope coefficients of independent variables. All coefficients are used as cross-sectional specific, assuming only unit effects in the model.

Some preliminary tests should be performed before estimating the model in equation (2). These statistical pre-tests are cross-sectional dependency, unit root, cointegration and slope homogeneity tests. The appropriate econometric method is determined based on the results of the pre-tests. The test results will be presented in the next section. In this section, the dynamic common correlated effects (DCCE) technique used in the study is mentioned.

In economic studies, dynamic models are widely used, because variables have significant persistence over time and react slowly to changes. A typical way to include the dynamic process in an analysis is to add the lagged dependent variable to the model (Vos and Everaert, 2019). However, due to the dynamic factors used, the problem of endogeneity may arise. The GMM method, which is frequently used in dynamic panel data analysis, is based on the homogeneity assumption. However, in practice, heterogeneity is a fairly common feature. MG and PMG estimators that take heterogeneity into account can be considered, but these estimators are not consistent due to their disregard for cross-sectional dependence (Turkay, 2017).

Therefore, another consideration in panel data is cross-sectional dependency. Since traditional methods ignore cross-sectional dependence, panel data analysis techniques developed in recent years take this problem into account. Because today, with the globalized economy, unobserved factors and shocks have important effects on the economies. ofcountries (Ali et al., 2020). DCCE, which is preferred in this study, is a technique that performs the estimation of dynamic heterogeneous panel data models that also take into account cross-sectional dependency. DCCE, developed by Chudik and Pesaran (2015), is based on MG by Pesaran ve Smith (1995), PMG by Pesaran et al. (1999) and CCE by Pesaran (2006) approaches (Arain et al., 2019). Chudik and Pesaran (2015) describe a dynamic structure by expanding CCE (Turkay, 2017). CCE estimator is robust to nonstationarity, cointegration, structural breaks and serial correlation. However, it is not suitable for a dynamic specification (Chaudhry et al., 2022). Since the lagged dependent variable in CCE is not strictly exogeneity, CCE estimator is not consistent in dynamic panel models (Liddle and Huntington, 2020). Chudik and Pesaran (2015) added cross-sectional averages, in addition to making the estimator consistent. In this context, DCCE can be presented as follows:

$$ren_{it} = \theta_i ren_{it-1} + \beta_{ki} X_{it}^{(k)} + \sum_{p=0}^{p_T} \delta_{kpi} \bar{X}_{t-p}^{(k)} + \sum_{p=0}^{p_T} \gamma_{pi} \bar{Y}_{t-p} + u_{it} \quad (3)$$

where X represents each independent variable in the model shown in equation (2) (k=1, 2, 3, 4). It also shows the cross-sectional averages $\bar{X}$ and $\bar{Y}$, while p_T is the lag of the cross-sectional averages. Finally, it should be noted that the DCCE method is suitable for unbalanced panels (Ditzen, 2016).

Results

First of all, the question whether there is cross-sectional dependence in variables is examined using LM and CD tests. The obtained results are important for determining the unit root test and estimation method to use. According to the results in Table 2, all variables have a cross-sectional dependence. Based on this result, second-generation unit root tests that take cross-sectional dependence into account should be implemented to examine the stationarity of the series.

Table 2. Cross-Sectional Dependence Tests

H_0: No CSD	ren_{it}	efp_{it}	gdp_{it}	$eimp_{it}$	urb_{it}
Breusch-Pagan LM	6301.5***	1874.6***	6902.9***	2719.5***	6471.3***
Pesaran CD	77.131***	27.051***	81.606***	6.866***	15.693***

Note: (*), (**) and (***) show the significance level at 10%, 5% and 1% respectively.

Pesaran's (2007) CIPS test is applied as a second-generation panel unit root test. Table 3 shows panel unit root test results at level and 1st difference of the series. The null hypothesis that there is no unit root at the level for ren and efp is rejected. However, gdp, eimp, and urb are stationary in the 1st differences. Therefore, all variables are stationary at the level and at the 1st difference and none of them is stationary at the 2nd difference.

Table 3. Pesaran (2007) CIPS Panel Unit Root Test

H_0: Unit Root	ren_{it}	efp_{it}	gdp_{it}	$eimp_{it}$	urb_{it}
Level	-1.784**	-3.307***	2.162	0.733	5.907
1st difference	-16.560***	-19.403***	-8.511***	-15.098***	-3.052***

Note: (*), (**) and (***) show the significance level at 10%, 5% and 1% respectively.

Second-generation panel cointegration tests should be preferred if there is a cross-sectional dependence to determine the cointegration relationships between the series. Error correction-based panel cointegration test based on Westerlund (2007) is conducted to determine whether there is a cointegration relationship between series. The null hypothesis that there is no cointegration could not be rejected for all test statistics (G_t, G_a, P_t and P_a), as seen Table 4. This result shows that there is no cointegration relationship between the series. Therefore, in order to estimate the equation (2), it is necessary to work with stationary series. Otherwise, the obtained estimation results would constitute a spurious regression. For this purpose, model estimation should be realized by taking into account the *gdp*, *eimp* and *urb* variables in the 1st difference according to the results in Table 3.

Table 4. Westerlund Error Correction-Based Panel Cointegration Test

H_0: No cointegration	Statistics	p-value	Robust p-value
G_t	-1.899	0.998	0.503
G_a	-4.055	1.000	0.913
P_t	-8.368	0.992	0.400
P_a	-3.535	1.000	0.633

An important point to consider in order to determine the estimation method is the cross-sectional dependence. The other important test is the slope homogeneity. For this purpose, Swamy (1970) $\tilde{\Delta}$ and $\tilde{\Delta}_{adj}$ tests of Pesaran and Yamagata (2008) are employed. According to the test results in Table 5, the null hypothesis of slope homogeneity is rejected. Therefore, heterogeneous panel data methods should be used instead of methods that assume the slope homogeneity.

Table 5. Slope Homogeneity Test

H_0: Slope Homogeneity	Statistics	p-value
Swamy	63237.05***	0,000
$\tilde{\Delta}$	7.342***	0,000
$\tilde{\Delta}_{adj}$	8.892***	0,000

Note: (***) shows the significance level at 1%.

In order to estimate equation (2), DCCE approach, which allows dynamic specification, as well as taking into account cross-sectional dependence and slope heterogeneity, is preferred. Panel mean group (MG) and country-specific DCCE estimation results are given in Table 6. According to MG estimation results, *efp* and *eimp* have statistically significant and negative effect on *ren*. However, the effect of *gdp* and *urb* variables on *ren* has not been determined. In addition, *ren* are highly permanent, highly affected by the past period. This result is also supported by country-specific estimation results. According to country-specific estimation results, the coefficient of the lagged *ren* is a statistically significant and positive sign, except for 7 of the 26 countries. In addition, *efp* in 6 countries (Croatia, Denmark, Greece, Ireland, Lithuania, and Spain) has a significant negative effect on *ren* in accordance with expectations. When looking at *gdp* results, it is only significant for 3 countries, but the coefficient signs are not in line with economic expectations. Because when there is an increase in *gdp*, *ren* is expected to increase. A similar incompatible result applies to the *urb* coefficients. Although the *urb* coefficients are significant for only 2 countries, it seems that the coefficients of urb are negatively marked. Finally, when the results of the *eimp* variable are examined, it is seen that the coefficient is significant in 12 countries. However, in 2 of these, *eimp*'s estimation results are positively marked in the opposite direction. In the results of the other 10 countries, it is determined that *eimp* had a negative effect on *ren* as expected.

Table 6. DCCE Results

Country	$\mathrm{ren_{it-1}}$	$\mathrm{efp_{it}}$	$\Delta\mathrm{gdp_{it}}$	$\Delta\mathrm{eimp_{it}}$	$\Delta\mathrm{urb_{it}}$	C
Panel (MG)	0.603***	-0.721***	3.10e-05	-0.226***	-1.401	0.775
Austria	0.883***	0.993	-5.3E-06	-0.616***	-2.338	7.772
Belgium	0.826**	-0.209	2.1E-04	0.004	-1.567	-0.952
Bulgaria	0.286	-1.835	3.5E-04	-0.000	6.906	-9.102
Czechia	0.926***	0.485**	-3.7E-04*	0.072*	-2.905	-3.815
Croatia	0.596**	-5.252**	2.9E-04	-0.289*	-1.733	-0.502
Cyprus	0.498	-0.625	9.0E-05	-1.193***	-0.708	-4.077
Denmark	0.751***	-1.872***	-9.6E-04**	-0.069***	1.299	12.115
Estonia	0.140	0.430	-7.1E-04	-0.129	-15.039	28.078
Finland	0.324	-1.567	4.7E-04	-0.122	-3.078	7.786
France	0.653***	1.405	-4.1E-04	0.023	-5.781	5.135
Germany	0.899***	-0.726	2.8E-04	-0.216***	1.803	3.783
Greece	0.335***	-1.174***	1.7E-04	0.028	-0.674	13.451***
Hungary	0.584***	-0.338	-3.1E-04	-0.274	2.345	13.536
Ireland	0.860***	-0.521*	3.7E-05	-0.009	-4.322	-1.547
Italy	0.619***	-1.123	2.1E-04	-0.409***	0.855	-4.283

Latvia	0.896**	-0.727	1.3E-03	-0.361**	-5.970	-0.197
Lithuania	0.579**	-1.921***	-8.9E-05	-0.055	-7.139*	-12.004
Luxembourg	0.798**	-0.274	-4.3E-05	-0.637	-0.765	9.129
Netherlands	0.868***	-0.052	3.0E-04	0.022**	0.419	-3.326*
Poland	0.518*	-0.459	7.4E-04	-0.041	-4.722	10.604
Portugal	0.868***	-1.843	-3.1E-05	-0.778***	15.381	-4.898
Romania	0.277*	1.491	-1.5E-03**	-0.286	-10.122**	-58.168***
Slovakia	0.200	-1.156	9.3E-04	0.229	-0.063	-6.647
Slovenia	0.679*	0.273	-1.2E-03	-0.375**	-6.286	3.694
Spain	0.254	-2.502***	5.6E-06	-0.316***	7.651	13.966**
Sweden	0.563	0.361	-4.6E-04	-0.089	0.137	0.603

Note: (*), (**) and (***) show the significance level at 10%, 5% and 1% respectively.

Summary, recommendations

The purpose of this paper is to examine the effects of EFP, GDP, energy import, and urbanization on REN deployment in 26 EU countries. For this purpose, we constructed a panel data that covers the 1990-2018 period. Against backdrop of the available literature, our study analyzes the impact of EFP on REN deployment for the first time. Moreover, we provide country specific situation related to REN among the EU countries.

Based on the analysis, dynamic panel estimation indicates that REN deployment in previous years has positive and significant stimulating effect on the present REN level in the analyzed countries. Interestingly, our results indicate that while GDP per capita and urbanization are not significant drivers of REN deployment, and that energy import and EFP negatively affect REN deployment. These results show that increasing EFP (increasing environmental pressure) cannot create a strong incentive to the deployment of REN in the EU countries. This result implies that economic targets are more dominant than the environmental concerns, and that the energy requirement of growing income is met by non-renewable energy sources. Hence, growing fossil fuel consumption creates environmental degradation and/or pollution. Moreover, it seems that energy dependency is considerably high, and it leads a strong lobby effect in the EU countries. This situation may be the result of low cost of fossil fuels.

Like growing income, urbanization has no significant effect on RE development. Increasing urbanization, however, has a deterring impact on RE deployment in Romania and Lithuania. This means that higher rate of urbanization leads to fossil fuel use in energy mix. Like urbanization, increasing GDP has a negative and significant impact on REN deployment in Czechia, Denmark, and Romania. Our results show that increasing GDP stimulates much more non-renewable energy consumption in output creation process in these countries.

Against expectations, GDP increase is not an important driver for RE deployment. We cannot say that richer countries will be in a better position for RE development. Hence, apart from the growing income, the EU should more widely implement a stronger and more efficient support mechanism, such as subsidies, FITs, R&D, green certificates, etc. Furthermore, the EU countries should increase the environmental awareness and financially support the R&D policies to eliminate the cost disadvantages of REN in energy mix towards sustainable economic growth.

References

ACKAH, I., KIZYS, R. (2015). Green growth in oil producing African countries: A panel data analysis of renewable energy demand, Renewable and Sustainable Energy Reviews, 50, 1157-1166.

ALI, S., YUSOP, Z., KALIAPPAN, S.R., CHIN, L. (2020). Dynamic common correlated effects of trade openness, FDI, and institutional performance on environmental quality: evidence from OIC countries, Environmental Science and Pollution Research, 27(11), 11671-11682.

AQUIRRE, M., IBIKUNLE, G. (2014). Determinants of renewable energy growth: A global sample analysis, Energy Policy, 69, 374-384.

ARAIN, H., HAN, L., MEO, M.S. (2019). Nexus of FDI, population, energy production, and water resources in South Asia: a fresh insight from dynamic common correlated effects (DCCE), Environmental Science and Pollution Research, 26(26), 27128-27137.

AKAR, B.G. (2016). The Determinants of Renewable Energy Consumption: An Empirical Analysis for the Balkans, European Scientific Journal, 12(11), 594-607.

BAGLIANI, M., BRAVO, G., DALMAZZONE, S. (2008). A consumption-based approach to environmental Kuznets curves using the ecological footprint indicator, Ecological Economics, 65(3), 650-661.

BENGOCHEA, A., FAET, O. (2012). Renewable energies and CO_2 emissions in the European Union, Energy Sources, Part B: Economics, Planning, and Policy, 7(2), 121-130.

BIRD, L., BOLINGER, M., GAGLIANO, T., WISER, R., BROWN, M., PARSONS B. (2005). Policies and market factors driving wind power development in the United States, Energy Policy,

33(11), 1397-1407.

BOURCET, C. (2020). Empirical determinants of renewable energy deployment: A systematic literature review, Energy Economics, 85, 104563.

BOLUK, G., KAPLAN, R. (2021). Effectiveness of renewable energy incentives on sustainability: evidence from dynamic panel data analysis for the EU countries and Turkey, Environmental Science and Pollution Research, 29, 26613–26630.

BREUSH, T.S., PAGAN, A.R. (1980). The Lagrange Multiplier Test and İts Applications to Model Specification in Econometrics, The Review of Economic Studies, Vol:47, No:1, pp:239- 253.

CAGLAR, A.E., MERT, M., BOLUK, G. (2021). Testing the role of information and communication technologies and renewable energy consumption in ecological footprint quality: Evidence from world top 10 pollutant footprint countries, Journal of Cleaner Production, 298, 126784.

CARLEY, S. (2009). State renewable energy electricity policies: An empirical evaluation of effectiveness, Energy Policy, 37(8), 3071-3081.

CHADHRY, I.S., NAZAR, R., ALI, S., MEO, M.S., FAHEEM, M. (2021). Impact of environmental quality, real exchange rate and institutional performance on tourism receipts in East-Asia and Pacific region, Current Issues in Tourism, 1-21.

CHEN, C., PINAR, M., STENGOS, T. (2021). Determinants of renewable energy consumption: Importance of democratic institutions, Renewable Energy, 179, 75-83.

CHUDIK, A., PESEARAN, M.H. (2015). Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors, Journal of econometrics, 188(2), 393-420.

da SILVA, P. P., CERQUEIRA, P. A., OGBE, W. (2018). Determinants of renewable energy growth in Sub-Saharan Africa: Evidence from panel ARDL, Energy, 156, 45-54.

De VOS, L., EVERAERT, G. (2021). Bias-corrected common correlated effects pooled estimation in dynamic panels, Journal of Business & Economic Statistics, 39(1), 294-306.

DITZEN, J. (2016). xtdcce: Estimating dynamic common correlated effects in Stata, The Spatial Economics and Econometrics Centre (SEEC), 1601.

GAN, J.B., SMITH, C.T. (2011). Drivers for renewable energy: A comparison among OECD countries, Biomass & Bioenergy, 35(11), 4497-4503.

GFN (2022). Global Footprint Network, 2022.

HASSAN, S.T., XIA, E. KHAN, N.H., SHAH, SMA. (2019). Economic growth, natural resources, and ecological footprints: evidence from Pakistan, Environmental Science and Pollution Research, 26, 2929–2938.

IEA (2020). World energy investment 2020, Flagship Report, https://www.iea.org/reports/world-energyinvestment-2020 (Access date 10.05.2021).

IEA (2021). Greenhouse Gas Emissions from Energy Data Explorer, 10 November 2021, https://www.iea.org/articles/greenhouse-gas-emissions-from-energy-data-explorer (accessed 31 March 2022).

IEA (2022). Electricity market report, https://iea.blob.core.windows.net/assets/d75d928b-9448-4c9b-b13d-6a92145af5a3/ElectricityMarketReport_January2022.pdf.

JANUTA, A. (2021), COP21, Global carbon emissions rebound to near pre-pandemic levels, November 4, 2021, reuters.com/business/cop/global-carbon-emissions-rebound-near-pre-pandemic-levels-2021-11-04/#:~:text=The%20study%20projected%20total%20global, Global%20Carbon%20Project%20research%20group.

KIM, J., PARK, K. (2016). Financial development and deployment of renewable energy technologies, Energy Economics, 59, 238-250.

LIDDLE, B., HUNTINGTON, H. (2020). On the Road Again: A 118 country panel analysis of gasoline and diesel demand. Transportation Research Part A: Policy and Practice, 142, 151-167.

LIU, W., ZHANG, X., FENG, S. (2019). Does renewable energy policy work? Evidence from a panel data analysis, Renewable Energy 135:635–642.

MARQUEZ, A.C., FUINHAS, J.A. (2011). Drivers promoting renewable energy: A dynamic panel approach, Renewable & Sustainable Energy Reviews, 15(3), 1601-1608.

MARQUEZ, A.C., FUINHAS, J.A, PIRES, MANSO, J.R. (2010). Motivations driving renewable energy in European countries: A panel data approach, Energy Policy, 38(11), 6877-6885.

MENZ, F.C., VACHON, S. (2006). The effectiveness of different policy regimes for promoting wind power: experiences from the states, Energy Policy 34(14):1786–1796.

MITCHELL, C., BAUKNECHT, D., CONNOR, P.M. (2006). Effectiveness through risk reduction: a comparison of the renewable obligation in England and Wales and the feed-in system in Germany, Energy Policy 34(3):297–305.

MURSHED, M., AHMED, R., KUMPAMOOL, C., BASSIM, M., ELHEDDAD, M. (2021). The effects of regional trade integration and renewable energy transition on environmental quality: evidence from South Asian neighbours. Business Strategy and Environment, 1-17.

NICOLINI, M., TAVONI, M. (2017). Are renewable energy subsidies effective? Evidence from Europe. Renewable and Sustainable Energy Review, 74:412–423

OMRI, A., NYUGEN, D.K. (2014). On the determinants of renewable energy consumption: International evidence, Energy, 72, 554-560.

PESERAN, M.H. (2004). General Diagnostic Tests for Cross Section Dependence in Panels, IZA Discussion Paper, No:1240.

PESERAN, M.H. (2006). Estimation and inference in large heterogeneous panels with a multifactor error structure, Econometrica, 74(4), 967-1012.

PESERAN, M.H. (2007). A Simple Panel Unit Root Test in The Presence of Cross- Section Dependence, Journal of Applied Econometrics, 22(2), 265-312.

PESERAN, M.H. SHIN, Y., SMITH, R.P., (1999). Pooled mean group estimation of dynamic heterogeneous panels, Journal of the American statistical Association, 94(446), 621-634.

PESERAN, M.H. YAMAGATA, T., (2008). Testing Slope Homogeneity in Large Panels, Journal of

Econometrics, 142 (1):50-93.

PFEIFFER, B., MULDER, P. (2013). Explaining the diffusion of renewable energy technology in developing countries. Energy Economics, 40, 285-296.

PRZYCHODZEN, W., PRZYCHODZEN, J. (2020). Determinants of renewable energy production in transition economies: A panel data approach, Energy, 191, 116583.

SADORSKY, P. (2009). Renewable energy consumption, CO2 emissions and oil prices in the G7 countries, Energy Economics, 31(3), 456-462.

SALMAN, D., HOSNY, N.A. (2021). The nexus between Egyptian renewable energy resources and economic growth for achieving sustainable development goals. Future Business Journal 7, 47.

SWAMY, P.A.V.B. (1970). Efficient inference in a random coefficient regression model, Econometrica 38, 311-323.

REES, W.E. (1992). Ecological Footprints and Appropriated Carrying Capacity: What Urban Economics Leaves Out, Environment and Urbanization, 4(2), 121-130.

REES, W., WACKERNAGEL, M. (1996). Urban ecological footprints: Why cities cannot be sustainable—And why they are a key to sustainability, Environmental Impact Assessment Review, 16(4-6), 223-248.

TURKAY, M. (2017). Heterogeneity across emerging market central bank reaction functions, Central Bank Review, 17(3), 111-116.

VERBRUGGEN, A. (2004). Tradable green certificates in Flanders (Belgium), Energy Policy 32(2):165–176.

WESTERLUND, J. (2007). Testing for error correction in panel data, Oxford Bulletin of Economics and Statistics 69: 709–748.

WÜSTENHAGEN, R., BILHARZ, M. (2006). Green energy market development in Germany: effective public policy and emerging customer demand, Energy Policy 34(13):1681–1696