The Effectiveness of Environmental Policy Instruments for Promoting Renewable Energy Consumption : Command-and-control policies Versus Market-based policies

Abstract

Understanding the impact of market- and non-market-based environmental policy instruments on renewable energy consumption (REC) is crucial for the design and choice of policy packages. This study aims to empirically investigate the effect of environmental policy stringency index (EPS) and its components on REC in 27 OECD countries over the period from 1990 to 2015, and then use the results to identify what the appropriate environmental policy mix should look like. By relying on the two-step system GMM estimator, we provide evidence that increasing environmental policy stringency as a whole promotes renewable energy consumption in these 27 developed economies. Moreover, policy makers are able, through market- and non-market-based environmental policy instruments, to increase the use of renewable energy. However, not all of these instruments are effective for achieving this goal. The results indicate that R&D subsidies and trading schemes have a positive and significant impact on REC, while taxes, feed-in tariff and emission standards have not a significant effect. Furthermore, R&D subsidies are more effective than trading schemes for stimulating the use of clean energy. These findings proved to be robust across the three alternative panel techniques used.

Keywords: Environmental policy stringency, renewable energy consumption, Two-step system-GMM estimation, linear dynamic panel data model

JEL Classification Codes : Q580, H230

1. Introduction

Today, global warming, climate change and environmental degradation are existential threat to every region on Earth. To overcome these challenges and move towards low-greenhouse gas emitting economies, many environmental policies have been implemented by the majority of the countries around the world over the last three decades. Market-based (MB) and non-market-based (NMB) environmental policy instruments have been used to achieve this target. Recently, many very important international commitments to reach net-zero emissions by 2050 and limit the rise in global temperatures to 1.5 °C have been made. For instance, On 11 December 2019, the European Commission announced the European green deal to transform the EU into the first climate neutral continent by 2050 with a 55%-reduction in emissions by 2030, compared to 1990 levels, as an intermediate goal[1]. In the same context, as part of re-entering the Paris Agreement, President Biden announced on April 2021 a new goal for the United States to achieve a 50-52 % reduction from 2005 levels in economy-wide net greenhouse gas pollution by 2030 and net zero emissions by no later than 2050.

In this regard, promoting the use of renewable energy plays a key role for accelerating the carbon neutrality process in the coming decades[2].The use of renewable energy can achieve multiple benefits, including sustainable economic growth, reducing dependence on importing non-renewable energy, reduction in greenhouse gas emissions, better health and job creation (Akella et al, 2009; Marques and Fuinhas, 2012). According to the statistics of the World Bank, the share of renewables energy in total final energy consumption, in the OECD zone, has increased from 7,22% in 1990 to 12,37% in 2015.

Given the global importance of the use of clean energy, there is an increasing need to identify the most efficient environmental policy instruments for stimulating renewable energy consumption. A new index of environmental policy stringency (EPS) have been constructed by Botta et Koźluk (2014). It is based on 14 environmental policy instruments used in OECD countries, including both Market- Based (MB) and Non-Market-Based (NMB) instruments (see Figure 3). This paper aims to evaluate the effect of environmental policy stringency index and its components on REC in the OECD countries, and then use the results to identify what the appropriate environmental policy mix should be for promoting REC.

The review conducted by Can Şener et al., (2018) and Bourcet (2020) based on a large number of empirical papers puplished before 2018 on the empirical determinants of renewable energy

deployment confirms that the EPS has not been used as a determinant of renewable energy deployment before 2018. In addition, many of the recent studies that examine the determinants of REC did not use the EPS as explanatory variable of of renewable energy use (see e.g Baye et al., 2021; Chen et al., 2021; Li and Leung 2021; Nguyen and Kakinaka 2019). To the best of our knowledge, only two recent empirical works have been examined the effect of EPS on REC. They are Bashir et al., (2021) and Marra and Colantonio (2021). However, they have contradictory results. Bashir et al., (2021) found a negative impact, whereas Marra and Colantonio (2021) reveal a positive one. Thus, there is no consensus on the nature of the impact of EPS on REC. In addition, these studies did not analysis the impact of EPS' components of REC. Therefore, their results do not enable policy makers to know the most effective environmental policy tools for promoting renewable energy consumption. Moreover, these studies did not present direct analyses on the impact of EPS on renewable energy consumption. They used the EPS as a control variable involved in their models. They also used many predictors that could be highly correlated as control variables, such as economics growth and financial development. This may generate multicollinearity problem which can lead in turn to an "incorrect" parameter estimates sign (Greene 2012). This perhabs explain why they got different effects of EPS on REC.

Building on this context, the contribution of this paper to the existing literature is two-fold. First, it re-evaluates the impact of EPS, at aggregated and disaggregated level, on REC, using a larger number of OECD countries[3] and a dynamic analysis instead of the static approach used in the previous studies. Second, it examines the efficiency of the market-and non-market-based environmental policy instruments in accelerating clean energy use in the OECD zone. Thus, this paper help policy makers to design and choose environmental policy packages.

The rest of this paper has the following structure : the second section contains a review of the previous research, while the third section describes the data and the econometric method. In the fourth section, we discuss the results found and in the fifth section conclusions and policy implications of the research are presented.

1. Literature review

Two points of view can be distinguished by the existing literature on the relationship between environmental regulations and renewable energy consumption. First, as the environmental regulations incite people and firms to invest in renewable energy and adopt it as an energy source, more strict environmental policy can stimulate renewable energy use (Grossman et Krueger, 1995; Bae and Yu 2018; Hille et al., 2020a). In this line, Marra and Colantonio (2021) explored the role of socio-technical aspects on renwable energy consumption for 12 EU-net-energy-importing countries for the period from 1990 to 2015. They used a panel vector autoregressive model in first differences and demonstrated that environmental policy stringency index has a positive impact on renewable energy consumption. In the same context, Shahzad et al., (2021) analyzed the relationship between environmental regulation instruments and renewable energy production for 29 OECD economies during the period from 1994 to 2018. They used the fully modified ordinary least square (FMOLS), fixed effects OLS and quantile estimators. They found that environmental policy stringency index and environmental taxes display a positive influence on renewable energy generation. Marques and Fuinhas (2012) evaluted the impact of public policy measures on renewable energy use for 23 European countries over the period 1990-2007. Using a panel corrected standard errors estimator, their resultd illustretad that quota obligations, product labeling, R&D programs and tradable certificates have no impact on REC, while "Incentive/subsidy" policies, like feed-in tariffs, and "policy processes", like strategic planning can promote renewable energy use. Polzin et al., (2015) also investigated the effect of many public policy instruments on renewable energy investments in electricity-generating capacity in OECD countries for the period from 2003 to 2011. They found that feed-in tariffs, grants and subsidies, codes and standards, GHG emissions allowances, and strategic planning have a positive impact on the installed capacity additions of renewable energy sources, while the taxes and funds to sub-national governments have a negative effect, and loans, green certificates and obligation schemes did not show an influence. Kilinc-Ata (2016) examined the effectiveness of four instruments of green power policies in promoting renewable energy deployment in 27 EU countries and 50 US states over the period 1990-2008. Using the fixed effect estimator. he found that tenders, tax incentives and feed-in tariffs are effective instruments for increasing deployment capacity of renewable energy sources for electricity, while quota is not. In a similar study, Menz and Vachon (2006) explored the effectiveness of five renewable energy policy instruments (renewable portfolio standards, mandatory green power options, fuel generation disclosure rules, public benefits funds and retail choice) to promote wind power for 39 US states during the years 1998 to 2003. Using the

ordinary least squares method, their results suggest a positive correlation between renewable portfolio standards and wind energy development, while there is a negative association between retail choice and wind energy development. The other policy intruments did not show a significant impact. In more recent studies, Wang and Pisarenko (2020) studied the impact of oil price, energy intensity, R&D, air pollution (PM 2.5) and policy on renewable energy consumption for the countries of Groupe of Twinty over the period 1990 to 2017 by using FMOLS and DOLS methods. Thier results show that research and development are main drivers to enhance renewable energy consumption in 60% of the countries, while the policy and energy intensity rank as second and third drivers respectively. Hille et al., (2020b) explored the effect of renewable energ support policies on innovation in solar and wind power technologies by using a sample of 194 countries over the period from 1990 to 2016. Their results indicat that public research, development and deployment programs are major drivers of patenting activity in solar and wind power technologies. In addition, their results suggest that the targets, fiscal incentives and feed-in tariffs are positive determinants of solar- and wind power-related technologies. In the same context, Schleich, et al., (2017) by using 12 OECD countries for the period from 1991 to 2011, found that only public R&D spending fostered patenting activity in wind-power technologies.

On the other hand, environmental regulations may reduce the renewable energy use (Hájek et al. 2019). This can be explained by the fact that the restriction of technological transmission and the high intellectual property rights costs may impede the use of renewable energy (Cheng et al. 2019). In line with this assumption, Bashir et al. (2021) used the fully modified ordinary least squares, OLS with fixed effects, and panel quantile regressions to investigate the effect of environmental regulations on renewable energy consumption, they found that environmental policy stringency index carries a negative effect on the renewable energy consumption in the OECD economies. In a similar study but on environmental related technologies, Bigerna et al., (2020) investigated the the effects of environmental regulation on environmental and technical efficiency between 2006 and 2014 by using the Bayesian shrinkage estimator. They found that the EPS and its components have a negative impact on environmental and technical efficiency growth.

2. Methodology and data

3.1. Model Construction

This study aims to explore the effect of EPS and its composites on renewable energy consumption, using the panel data method over the period 1990–2015. Therefore, a standard panel data model will be:

$$REC_{it} = \mathrm{a}_0 + \mathrm{a}_1\mathrm{EPS}_{it} + \gamma\mathrm{Z}_{it} + \mu_i + \varepsilon_{it} \quad (1)$$

With $t = \{1990, \ldots 2015\}$ the period on which EPS data have been obtained, *i* corresponds to each of the 27 OECD countries. *EPS* is the main independent variable; and *Z* includes control variables that affect the renewable energy consumption. In an attempt to avoid the multicollinearity problem, *Z* only contains environmental innovation (EINNOV) and CO2 emissions (CO2). The heterogeneity is measured by the constants μ_i which account for those fixed and inherent factors in country that may be observed or unobserved; all of which are considered constant over time t. Finally, ε_{it} includes effects of variables that are not considered in the model. Unlike previous studies that used static analysis to study the effect of environmental policy stringency on REC, this work uses dynamic analysis where the dependent variable is considered to be partially dependent on its value during previous periods. As the level of renewable energy consumed in previous periods are believed to be carried on to the current period, we assume that the level of REC in the last year (REC_{it-1}) is a determinant of REC in the current year. In other words, if a country has consumed a high level of renewable energy in last year, it would probably remain at a high level of renewable energy consumption also the current year. Thus, the specification of the model becomes:

$$REC_{it} = \mathrm{a}_0 + \mathrm{a}_1\mathrm{REC}_{it-1} + \mathrm{a}_2\mathrm{EPS}_{it} + \gamma\mathrm{Z}_{it} + \mu_i + \varepsilon_{it} \quad (2)$$

As $\mathrm{REC}_{it-1}$is not a strictly exogenous variable but a weakly exogenous regressor, the standard panel-data estimation approaches, such as the *Random Effects* or the *Fixed Effects* estimators, could lead to inconsistent estimates. That is due to the problems of autocorrelation of the residuals and endogeneity of some regressors. To overcome these problems, Generalized Method of Moments GMM-based approaches have been developed. In general, the GMM-based approaches have important advantages over other panel data methods for estimating a dynamic panel data model. For instance, the use of instrumental variables in the *GMM* procedure allows consistent estimation even in the presence of measurement errors (Bond et al. 2001), endogenous right-hand-side variables (Arellano and Bond 1991; Blundell and Bond 1998) and omitted variables (Holtz-Eakin et al., 1988).

There are two kinds of GMM estimators : the difference-GMM estimator and the system-GMM estimator. They could both be one-step and two-step versions. Arellano and Bond (1991) suggested the one-step difference-GMM. The main idea is to use all the available lags of the strictly exogenous regressors and the endogenous variables as instruments to overcome the endogeneity problem. However, the difference-GMM approach eliminates the time-invariant variables and the non-observed cross-section individual effect, and when the series used in the regression exhibit significant persistence, the difference-GMM estimator poses serious bias problems (Blundell and Bond 1998; Bond et al. 2001). This persistence generates weak instruments, meaning that the association between the variable to be instrumentalized and the instrument is small. In addition, as the Sargan test in the one-step GMM does not take into account the heteroscedasticity problem, the estimated coefficients may be biased (Bond et al. 2001). To overcome these problems, the two-step system GMM estimator for dynamic linear panel data model developed by Arellano et Bover (1995) and Blundell and Bond (1998) is used in this study. This estimator includes the lagged values of the dependent variable as instruments in addition to the previous instruments of the difference-GMM. This solves the bias because they assume in the first stage that the error terms are independent and homoscedastic, then the first-stage residuals are used to construct consistent variance and covariance matrices in the second step. Following the methodology proposed by Windmeijer (2005), we also compute robust two-step standard errors[5]. Therefore, the system GMM regression becomes:

$$REC_{it} = \mathrm{a}_0 + \mathrm{a}_1\mathrm{REC}_{it-1} + \mathrm{a}_2\mathrm{EPS}_{it} + \gamma\mathrm{Z}_{it} + \varepsilon_{it} \quad (3)$$

To verify the validaty of the assumptions involved in the *GMM*, the first and second-order serial correlation tests of the estimated residuals, *sc1* and *sc2* respectively, and the *Hansen test*[6] *are* used. If the error term ε_{it} is serially correlated, this means that some of the instruments will not be valid and thus GMM estimators will be inconsistent. In the contrary, the instruments will be valid, if the error term $\varepsilon_{it}$is not serially correlated. This implies that the statistics of the first-order serial correlation *sc1* should be negative and statisticaly significant, while the statistics of the second-order serial correlation tests sc2 should be statisticly insignificant (P-value higher than 10%). *Hansen* test is used to verify the validity of the over-identifying restrictions. In other words, *Hansen statistic* determines whether the moment conditions selected are valid. The null hypothesis of this test is *'instruments used are not correlated with the residuals*', which means that over-identifying restrictions are valid. Therefore, the null hypothesis of *Hansen* test should not be rejected. meaning that the *Hansen statistic* should not be statistically significant *(P-value* should be greater than 10%).

In order to control heteroscedasticity and outliers effect, the natural logarithms for the variables that are measured in their original units are used. The use of log-transformation help to minimize variability and to smooth the data. In addition, it makes the coefficients easier to interpret because the resulting coefficient directly shows the score of elasticity. Thus, the model becomes:

$$REC_{it} = \mathrm{a}_0 + \mathrm{a}_1\mathrm{REC}_{it-1} + \mathrm{a}_2\mathrm{LogEPS}_{it} + \mathrm{a}_3\mathrm{EINNOV}_{it} + \mathrm{a}_3\mathrm{LogCO2}_{it} + \varepsilon_{it} \quad (4)$$

To explore the correlation between Market-Based (MB) instruments, Non-Market-Based (NMB) instruments of environmental policy and REC, we replace $LogEPS_{it}$ by $LogMB_{it}$ and $LogNMB_{it}$ in the Eq. (4). We thus have the following equation:

$$REC_{it} = \mathrm{a}_0 + \mathrm{a}_1\mathrm{REC}_{it-1} + \mathrm{a}_2\mathrm{LogMB}_{it} + \mathrm{a}_3\mathrm{LogNMB}_{it} + \mathrm{a}_4\mathrm{EINNOV}_{it} + \mathrm{a}_5\mathrm{LogCO2}_{it} + \varepsilon_{it} \quad (5)$$

To investigate the association between the components of Market-Based instruments, Non-Market-Based instruments of environmental policy and REC, we replace, in Eq. (5), $LogMB_{it}$ and $LogNMB_{it}$ by their components. This means $Log\mathrm{TAXES}_{it}$, $Log\mathrm{TRADSCH}_{it}$, $Log\mathrm{FIT}_{it}$, $Log\mathrm{STAND}_{it}$ and $Log\mathrm{RD}_{it}$. We obtain the following equation:

$$REC_{it} = \mathrm{a}_0 + \mathrm{a}_1\mathrm{REC}_{it-1} + \mathrm{a}_2\, Log\mathrm{TAXES}_{it} + \mathrm{a}_3\, Log\mathrm{TRADSCH}_{it} + \mathrm{a}_4\, Log\mathrm{FIT}_{it} + \mathrm{a}_5\, Log\mathrm{STAND}_{it} + \mathrm{a}_6\, Log\mathrm{RD}_{it} + \mathrm{a}_7\, \mathrm{EINNOV}_{it} + \mathrm{a}_8\mathrm{LogCO2}_{it} + \varepsilon_{it} \quad (6)$$

In order to check the robustness of our results, we compared them with three other classes of estimators (panel-corrected standard errors, multilevel mixed-effects and random effects). Results are presented in the appendix C as a supplementary material in order to save space.

2.2. Statistical Sources

In this study, we used annual data from the OECD, International Energy Agency (IEA) and the World Development Indicators (WDI), which is available online, for 27 countries for the period from 1990 to 2015. The countries and time period were selected for the availability of data for the EPS. As missing data represents only 8.7% of the total, the average method has been used to impute incomplete cases. Therefore, our panel dataset is balanced. The countries are Austria, Australia, Belgium, Canada, Finland, Denmark, France, Greece, Germany, Hungary, Italy,

Ireland, Japan, Korea, Mexico, The Czech Republic, The Netherlands, Poland, Portugal, Norway, The Slovak Republic, Sweden, Spain, Turkey, Switzerland, United Kingdom and The United States. The dependent variable, renewable energy consumption, is measured in percent of total final energy consumption. Figure 1 shows the evolution of the average of renewable energy consumption in the OECD countries over the analysis period. On average, there is an increasing trend of renewable energy use in the OECD zone from the year 2003. However, the level of REC varies a lot among countries, as it has been showed in the figure 2 which displays the level of REC as a percent of total final energy consumption in 27 OECD countries for the years 1990 and 2015. Norway, Finland, Austria, Denmark have the highest level which exceed 30% in 2015. In this work, the main explanatory variable is the environmental policy stringency index (EPS), which is a composite index based on both Market Based (MB) and Non-Market Based (NMB) environmental policy instruments. The detailed instruments used to build this indicator are presented in figure 3. Its values are real numbers between 0 and 6, where 6 is the highest stringency level and 0 is the lowest (Hassan and Rousselière 2021). Figure 4 shows the EPS index scores for the years 1990 and 2015 for OECD countries. An increasing of environmental policy stringency can be noticed in all OECD countries, especially in France; The United Kingdom; Canada; Italy; Australia; Japan; Germany and Korea.

In this study, environmental innovation is used as an explanatory variable of REC. According to Su et al., (2021), environmental innovation is one of the major drivers of renewable energy use. In addition, the expansions in carbon dioxide emissions is also considered as a positive determinant of REC (Sadorsky 2009a; Apergis et al. 2010; Omri and Nguyen 2014). However, some recent empirical works reveal a negative association between CO2 emissions and renewable energy consumption (Marques and Fuinhas 2012; Nguyen and Kakinaka 2019; Zhang et al. 2021). Therefore, the effect of CO2 emissions on renewable energy consumption is ambiguous. This motivated us to include it in the model as an explanatory variable in order to provide new evidence about its impact on green energy consumption. The variables definitions and sources are provided in the appendix A as a supplementary material.

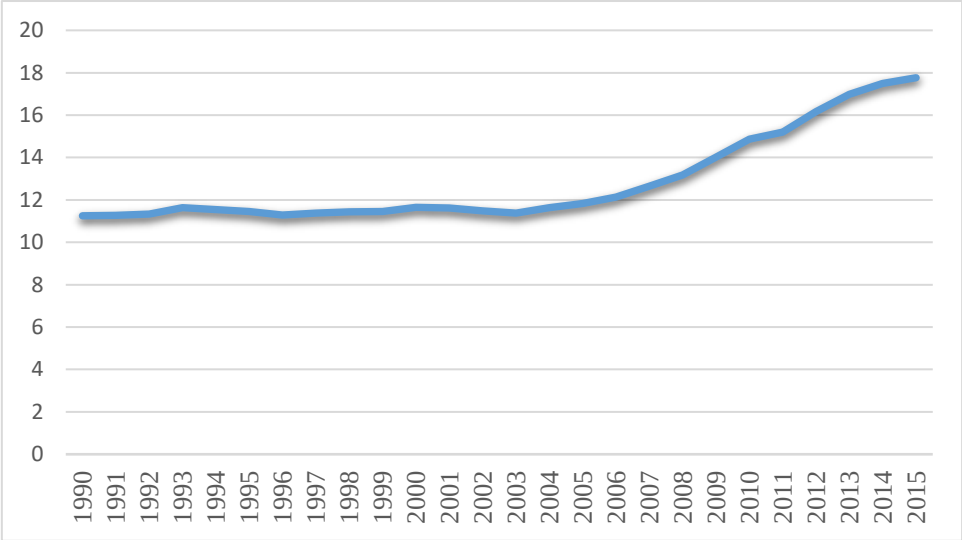

Figure 1. The evolution of renewable energy consumption (% of total final energy consumption) in 27 OECD countries, on average

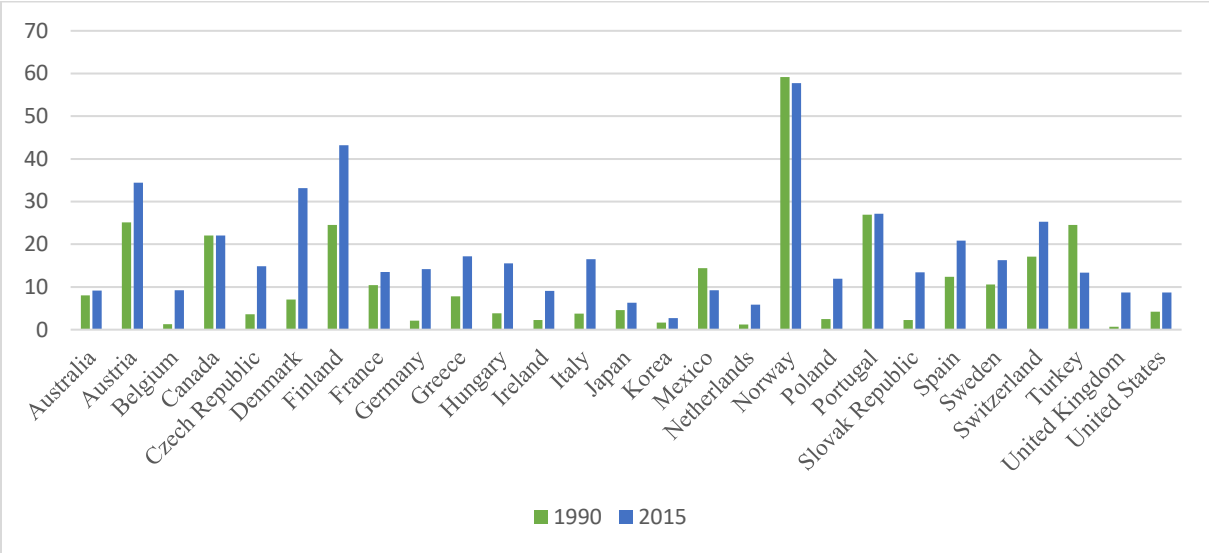

Figure 2. Renewable energy consumption (% of total final energy consumption) in 27 OECD countries

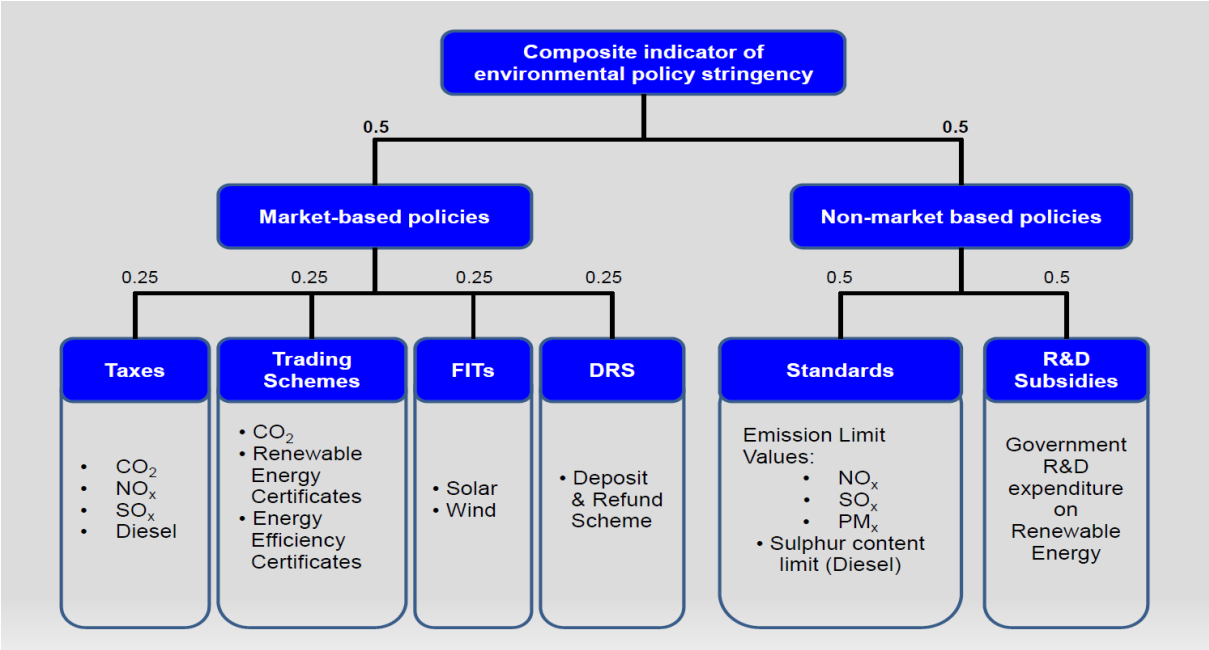

Figure 3. EPS index. Source: (Botta et Koźluk 2014)

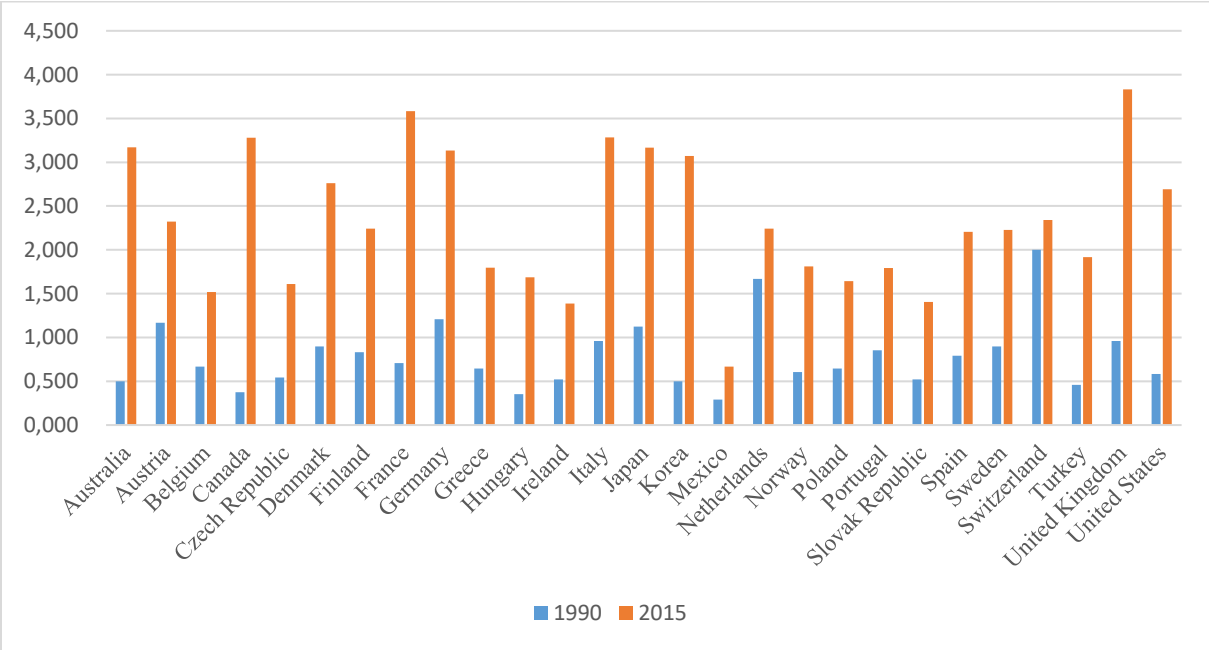

Figure 4. Environmental policy stringency in 27 OECD countries. Source: (Hassan and Rousselière 2021)

The descriptive statistics of our variables are also presented as a supplementary material in the appendix A[7]. The statistics show that the values of EPS, MB and NMB rang from a minimum of 0.2, 0.001 and 0.001 to a maximum of 4.13, 3.9 and 5.5 respectively. This means that the stringency of environmental policies vary a lot among OECD countries. We note also that the mean of NMB is twice as great as the mean of MB, indicating that non-market instruments are more stringent than market-based ones. It looks that, on average, the taxes is the most stringent

tool in the market-based instruments, followed by the feed-in-tariffs, then the trading schemes. Concerning the non-market-based instruments, the emissions standards appears more stringer than R&D subsidies in OECD countries. However, there is no great difference in the level of stringency between them. On average, the difference is 0,414. The statistics of REC, indicate a great variation in the level of renewable energy consumption among OECD countries, ranging from a minimum of 0.441% to a maximum of 61.378%.

A correlation matrix is presented in Table B1 for the variables used in the econometric estimations. In addition, the results of the Variance Inflation Factor (VIF) test are reported in the tables B 2-4 for the equations 4, 5 and 6, respectively. The tables B 1-4 are presented in the appendix B as a supplementary material. The VIF test detects whether multicollinearity problem is present in the regression. Harmful collinearity exists when the value of VIF is higher than 10 (Kennedy 1992). The correlation matrix shows no high correlation between the pair of explanatory variables. Moreover, all the values of VIF test are low, indicating the absence of multicollinearity problem in the regressions.

2.3.Cross-sectional Dependence (CD) analysis

Exploring the presence of cross-sectional dependence is one of the most important diagnostics required before the estimation of panel data models, because its occurrence changes the appropriate econometric techniques that should be used (Le and Sarkodie 2020). The presence of cross-sectional dependence means that shocks of unobserved common factors (strongly or weakly) can affect all panel units and easily spreads across panel units (Chudik, et al, 2011). This can be explained by the increase in financial globalization and economic integration in the world economy (Destek and Aslan 2017). Breusch and Pagan LM (Lagrange Multiplier) test (Breusch and Pagan 1980), Pesaran CD test (Pesaran 2004) and Pesaran, Ullah, and Yamagata bias-adjusted LM test (Pesaran et al., 2008) are the approaches used in this study to investigate the presence of CD. The null hypothesis of these tests is that "no cross sectional dependence exists in the panel" (Tugcu 2018). When the time-period (T) is large and the cross-sections (N) is small, the Breusch and Pagan LM test is suitable, but it is inappropriate when there are a small time-period and a large number of cross-section units (Tugcu 2018). To fix this drawback, the Lagrange multiplier statistic has been developed by Pesaran (2004) for detecting cross-sectional dependence of panels having a large time period $T \rightarrow \infty$ and cross sections $N \rightarrow \infty$. However, in the case of large cross sections and a small time-period, the Pesaran CD test is inappropriate (Li et Leung 2021). Finally, the Pesaran, Ullah, and Yamagata bias-adjusted LM

test suits the case when $N > T$. Consequently, the last test is the fitting test of our data ($N = 27 > T = 26$). However, all the other tests were run as robust tests.

2.4.Panel Unit Root Tests

For verifying the stationarity of the variables, two generations of panel unit root tests can be employed. The first-generation is used when there is no cross-sectional dependence of panel units, while the second-generation is employed when the cross-sectional dependence of panel units occurs (Le and Sarkodie 2020). Since the presence of cross-sectional dependence has been confirmed in our study, the first generation tests are not appropriate. Therefore, we use the CIPS second-generation unit root test developed by Pesaran (2007). The existence of nonstationary is the null hypothesis of the CIPS test. Thus, to confirm the existence of stationarity in the variable, the null hypothesis should be rejected.

3. Results

Table 5 shows the results of cross-sectional dependence tests for Eq.4, Eq.5 and Eq.6. The null hypothesis can be rejected at 1% significance level in the Breusch and Pagan LM test and Pesaran LM adj test ($p < 0.01$), and at 10% significance level for Pesaran CD test ($p < 0.1$). This indicates the presence of panel cross-sectional dependence, which is taken into account by our GMM estimator (Conley 1999). Thus, the first-generation of panel unit root tests, such as, IPS, PP and LLC are not appropriate in this research. Consequently, we utilized the the new panel unit root tests developed by Pesaran (2007), namely CIPS. The results of this approach are presented in the table 6, and provide evidence that the variables are stationary, as the null hypothesis is rejected for all the variables. The results of the two-styp system-GMM method are summarized in Table 7. The columns (1), (2) and (3) show the estimations of Eq. (4), Eq. (5), Eq. (6) respectively. Before the interpretation of the empirical results, the validity of the system-GMM estimator needs to be assessed. This estimator is valid if the instruments are exogen (Hansen test of overidentifying restrictions) and there is no autocorrelation of errors of order 2 (Arellano - Bond test sc2). As the statistics of *sc1* are negative and statisticaly significant (P-value < 5%), and the statistics of sc2 are insignificant (P-value > 10%), the instruments are exogen. In addition, the p-value of *Hansen* test is greater than 10%, there is therefore no autocorrelation of errors of order 2. Consequently, the two-styp system-GMM estimator is valid.

CD Tests	Equation 4		Equation 5		Equation 6	
	Statistics	P-value	Statistics	P-value	Statistics	P-value
Breusch and Pagan LM test	485.4***	0.000	464.9***	0.000	469.7***	0.000
Pesaran LM adj	8.124***	0.000	5.619***	0.000	2.707***	0.000
Pesaran CD	1.701*	0.089	1.68*	0.092	1.665*	0.095
Significance level: ***(1%), **(5%), * (10%)						

Table 5. Results of CD tests.

Variable		Intercept & trend [at level]
REC		-2.878***
Lag1REC		-2.630*
LogEPS		-3.063***
LogMB		-2.606*
LogNMB		-3.146***
LogTAXES		-3.075***
LogTRADSCH		-2.583*
LogFIT		-2.605*
LogSTAND		-2.856***
LogRD		-2.730**
EINNOV		-4.539***
LogCO2		-3.147***
Critical values	1%	-2.81
	5%	-2.66
	10%	-2.58

Significance level: 1% (***), 5% (**), 10% (*)

Table 6. CIPS unit root test.

The coefficient of Lag1REC is significant and positive, meaning that the level of renewable energy consumed in previous year is a positive determinant of renewable energy consumption in the current year. This finding indicates, that when we study the effect of EPS on REC, the dynamic approach should be used instead of the static. The results reported in column (1) of the two-step system GMM estimator show that the coefficient of logEPS is positive and statistically significant, which means that a more strict environmental policy is correlated with an increase in renewable energy consumption. A 1% increase in the EPS generates a 0.611% increase in the share of renewable energy consumption in the total final energy consumption. This result is in line with the finding of Marra and Colantonio (2021). The coefficients of logMB and logNMB, in column (2) of the two-step system-GMM, are positive and statistically significant. However, the magnitude of the coefficient of LogNMB is a little higher than that of LogMB. A

1% increase in the MB is correlated with a 0.209 % increase in the REC, while a 1% increase in the NMB is associated with a 0.296 % increase in the REC over the year. This means that non-market-based instruments could be more effective than market-based environmental policy instruments.

	Two-step system GMM		
	(1)	(2)	(3)
Lag1REC	**0.919*** **	**0.930*** **	**0.885*** **
	(0.055)	(0.049)	(0.095)
LogEPS	**0.611** **		
	(0.300)		
LogMB		**0.209* **	
		(0.129)	
LogNMB		**0.296* **	
		(0.170)	
LogTAXES			0.189
			(0.237)
LogTRADSCH			**0.099** **
			(0.044)
LogFIT			0.017
			(0.026)
LogSTAND			0.041
			(0.105)
LogRD			**0.235* **
			(0.125)
EINNOV	**0.051*** **	**0.050** **	0.025
	(0.018)	(0.021)	(0.016)
LogCO2	**-3.343** **	**-2.824** **	-3.403
	(1.568)	(1.402)	(2.609)
Constant	**17.978** **	**15.088** **	19.313
	(8.321)	(7.727)	(14.813)
sc1 (P-value)	-3.241 (0.001)	-3.275 (0.001)	-3.207 (0.001)
sc2 (P-value)	-1.012 (0.311)	-0.996 (0.319)	-1.055 (0.291)
Hansen p-value	1.000	1.000	1.000
Observations	675	675	675
Number of countries	27	27	27

Table 7. Regressions results of equations (4), (5) and (6); REC is the dependent variable

Note: *, **, and *** indicates the significance level at 10, 5, and 1% respectively based on the two-tailed test. Standard error estimates are in parentheses.

The results in column (3) reveal that not all the market and non-market environmental policy instruments are significant. R&D subsidies and trading schemes have a positive and signifiant impact on REC, while taxes, feed-in tariff and emission standards have not a significant influence on REC in the period analyzed. Furthermore, we notice that the magnitude of the coefficient of LogRD is greater than that of LogTRADSCH. A 1% increase in the trading schemes index is associated with a 0.099 % increase in the REC, while a 1% increase in the R&D subsidies index is correlated with a 0.235 % increase in the REC over the year. This indicates that the R&D subsidies are more effective than trading schemes in promoting green energy use. This finding is consistent with the results of Wang and Pisarenko (2020) who found that research and development are main drivers to enhance renewable energy use in the majority of G20 countries. Interestingly, the same results almost are have been obtained by the alternative estimators (panel-corrected standard errors, multilevel mixed-effects and random effects), indicating the robustness of our findings. The results of alternative estimators are presented in the appendix C as a supplementary material in order to save space. Concerning the control variables, the parameter of environmental innovation, in column (1) and (2), show a positive effect on the use of green power. This finding is similar to that reported by Su et al., (2021). Finally, the expansion of CO2 emissions has a negative association with REC. This result is consistent with the findings of Marques and Fuinhas (2012); Nguyen and Kakinaka (2019); Wang and Wang (2020) and Zhang et al. (2021). According to Wang and Wang (2020), this negative association between CO2 emissions and renewable energy can be explained as follows: the expansion of economic development and industrial scale is one of the main reason of air pollution in a region. In this context, the fossil fuel is considered as one of the main drivers of the economic scale increase. This increase in economic scale will lead to the expansion in the use of local fossil power, which indirectly promote the development of renewable energy. On the other side, Zhang et al. (2021) argues that as the deployment of renewable energy with green technology, especialy in developed countries, can reduce environmental problems of carbon emissions, this can justify the negative correlation of renewable energy use and CO2 emissions.

4. Discussion

Some researchers, by using the environmental policy stringency index (EPS) provided by the OECD statistics, have recommended that imposing strict environmental policy may be a successful policy in promoting renewable energy consumption in developed economies (Marra and Colantonio 2021). However, another recent study has found an opposite view by using the

same index, at aggregate level, for the OECD countries (Bashir et al. 2021). This conflicting results make the vision blurry for policy makers. Consequently, our findings help clarify the nature of the impact of environmental policy stringency as a whole on green energy use. On the other side, Marra and Colantonio (2021) and Bashir et al. (2021) did not analyse the effect of EPS's components on REC. In other words, they did not evaluate the effectiveness of environmental policy instruments on REC. In addition, the existing researches that evaluate the effect of renewable energ support policies on the use and the production of green power provide contradictory results (see Marques and Fuinhas, 2012; Polzin et al. 2015; Kilinc-Ata 2016; Schleich et al., 2017; Hille et al., 2020b; Wang et al., 2020). Therefore, our results provide new evidence on the effectivness of environmental policy instruments in promoting renewable energy consumption, and identify the most efficient tool for achieving this purpose. Overall, the present results support the hypothesis that more strict environmental regulations will stimulate renewable energy consumption. Both market and non-market environmental policy can achieve this objective. However, the non-market environmental policy appears relatively more effective than market-based policy. Furthermore, the analysis shows that not all the environmental policy instruments are effective in stimulating green energy use. According to the results, R&D subsidies and trading schemes have a positive and signifiant impact on REC, while taxes, feed-in tariff and emission standards have not yet produced the desired effect of increasing REC in the period analyzed. In addition, R&D subsidies are more effective than trading schemes for stimulating the use of clean energy.

From the above discussion, the main policy implications for the OECD governments are the follows: in general, the expansion of the use of market- and non-market-based environmental policy instruments is efficient for promoting green energy use in the OECD countries. However, the concentration of the policy makers should be, in particular, on the use of R&D subsidies and trading schemes. Raising the gouvernment R&D expenditure on renewable energy combined with increasing in the emissions trading scheme for CO2 emissions, renewable energy certificates and energy efficiency certificate are the most efficient environmental policy instruments for promoting renewable energy consumption in the OECD area. Green research and development subsidies help lower the costs of adjusting to higher carbon prices and accelerate environmental innovation which increases the production and the use of renewable energy. On the other side, the insignificant impact of taxes, feed-in-tariffs and emissions standards could be a critical insight to be gained here for policymakers. This may mean that

these three instruments were not strict enough during the period of analyse to be effective in promoting renwable energy use. Therefore, they should be more strict in the future.

5. Conclusions

In the face of accelerating climate change, the orientation toward renewable energy use has become a popular goal worldwide to decarbonize economies. Thus, the world is expected to witness an increase in the strictness of environmental regulations in the near future. However, the existing studies that examined the effect of environomental policy strigency on REC provide contradictory results (Marra and Colantonio 2021 and Bashir et al. 2021). In this light, designing a supportive policy mix for increasing green energy use will be a priority for policymakers around the world in the coming decates. In this regard, this study aims first to investigate the effect of the environmental regulation stringency, as a whole, on promoting REC. Second, it evaluates the effectiveness of the environmental policy instruments in stimulating green energy use in order to identify the suitable policy tools mix to achieve this purpose. To this end, the environmental policy stringency index (EPS) provided by the OECD statistics was used as a proxy to measure environmental regulation stringency. The EPS index consists of Market-Based (MB) and Non-Market-Based (NMB) instruments. The market-based instruments are regrouped into 4 categories: taxes, trading schemes, feed-in-tariffs and deposit & refund scheme; while the non-market based instruments are collected in two groups: emissions standards and R&D subsidies. However, the statistics of OECD do not provide data on deposit & refund scheme; therefore, they are not included in our analysis. The data covers 27 OECD countries over the period from 1990 to 2015. After checking the absence of multi-collinearity problem in the regressions, by using the correlation matrix and variance inflation factor test, the econometric analysis of panel data was based on several steps. First, the results Breusch and Pagan LM (Lagrange Multiplier) test (Breusch and Pagan 1980), Pesaran CD test (Pesaran 2004) and Pesaran, Ullah, and Yamagata bias-adjusted LM test (Pesaran et al., 2008) showed the existence of cross-sectional dependence in the models. Second, the CIPS second-generation unit root test developed by Pesaran (2007) demonstrated that all the variables used in this study are stationary. Third, the estimation results of the two-step system GMM method developed by Arellano et Bover (1995) and Blundell and Bond (1998) showed a positive association between EPS and REC. Market and non-market environmental policy index also had a positive influence on REC. However, the non-market environmental policy appears relatively more effective than market-based policy. Furthermore, the analysis demonstrated that not all the environmental policy instruments are efficient in stimulating green energy use.

According to the findings, R&D subsidies and trading schemes have a positive and signifiant impact on REC, while taxes, feed-in-tariff and emission standards have not a significant effect. In addition, R&D subsidies are more effective than trading schemes in stimulating the use of clean energy. These findings are robust across three alternative panel estimators (panel-corrected standard errors, multilevel mixed-effects and random effects).

Funding: this research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Conflicts of interest

We confirm that this manuscript has not been published elsewhere and is not under consideration by another journal. We are agree with submission to the Ecological Economics Journal, and there are no conflicts of interest to disclose. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Footnotes

1. See:https://ec.europa.eu/info/strategy/priorities-2019-2024/european-green-deal/energy-and-green-deal_en

2. See : https://www.iea.org/reports/net-zero-by-2050

3. Marra et Colantonio (2021) have used only 12 EU countries in their analysis

4. See :https://www.oecd.org/environment/environment-at-a-glance/Climate-Change-Archive-February-2020.pdf

5. Implemented in Stata with the package xtdpdgmm (Kripfganz, 2020)

6. Hansen test is the alternative test of the Sargan test when using the system GMM estimator.

7. Note : the OECD statistics have no data of Deposit& Refund Scheme (DRS), that is way we did not show its statistics.

References

Akella, A. K., R. P. Saini, et M. P. Sharma. 2009. « Social, Economical and Environmental Impacts of Renewable Energy Systems ». *Renewable Energy*, Renewable Energy for Sustainable Development in the Asia Pacific Region, 34 (2): 390-96. https://doi.org/10.1016/j.renene.2008.05.002.

Apergis, Nicholas, James E. Payne, Kojo Menyah, et Yemane Wolde-Rufael. 2010. « On the Causal Dynamics between Emissions, Nuclear Energy, Renewable Energy, and Economic Growth ». *Ecological Economics*, Special Section - Payments for Ecosystem Services: From Local to Global, 69 (11): 2255-60. https://doi.org/10.1016/j.ecolecon.2010.06.014.

Arellano, Manuel, et Stephen Bond. 1991. « Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations ». *The Review of Economic Studies* 58 (2): 277-97. https://doi.org/10.2307/2297968.

Arellano, Manuel, et Olympia Bover. 1995. « Another Look at the Instrumental Variable Estimation of Error-Components Models ». *Journal of Econometrics* 68 (1): 29-51. https://doi.org/10.1016/0304-4076(94)01642-D.

Bae, Hyunhoe, et Sanguk Yu. 2018. « Information and Coercive Regulation: The Impact of Fuel Mix Information Disclosure on States' Adoption of Renewable Energy Policy ». *Energy Policy* 117 (juin): 151-59. https://doi.org/10.1016/j.enpol.2018.03.010.

Bashir, Muhammad Farhan, Benjiang MA, Muhammad Adnan Bashir, Magdalena Radulescu, et Umer Shahzad. 2021. « Investigating the role of environmental taxes and regulations for renewable energy consumption: evidence from developed economies ». *Economic Research-Ekonomska Istraživanja* 0 (0): 1-23. https://doi.org/10.1080/1331677X.2021.1962383.

Baye, Richmond Silvanus, Allesandro Olper, Albert Ahenkan, Issa Justice Musah-Surugu, Samuel Weniga Anuga, et Samuel Darkwah. 2021. « Renewable Energy Consumption in Africa: Evidence from a Bias Corrected Dynamic Panel ». *Science of The Total Environment* 766 (avril): 142583. https://doi.org/10.1016/j.scitotenv.2020.142583.

Bigerna, Simona, Maria Chiara D'Errico, et Paolo Polinori. 2020. « Heterogeneous Impacts of Regulatory Policy Stringency on the EU Electricity Industry:A Bayesian Shrinkage Dynamic Analysis ». *Energy Policy* 142 (juillet): 111522. https://doi.org/10.1016/j.enpol.2020.111522.

Blundell, Richard, et Stephen Bond. 1998. « Initial Conditions and Moment Restrictions in Dynamic Panel Data Models ». *Journal of Econometrics* 87 (1): 115-43. https://doi.org/10.1016/S0304-4076(98)00009-8.

Bond, Stephen Roy, Anke Hoeffler, et Jonathan Temple. 2001. « GMM Estimation of Empirical Growth Models ». 3048. *CEPR Discussion Papers*. CEPR Discussion Papers. C.E.P.R. Discussion Papers. https://ideas.repec.org/p/cpr/ceprdp/3048.html.

Botta, Enrico, et Tomasz Koźluk. 2014. « Measuring Environmental Policy Stringency in OECD Countries ». OECD Economics Department Working Papers 1177. http://www.oecd-ilibrary.org/economics/measuring-environmental-policy-stringency-in-oecd-countries_5jxrjnc45gvg-en.

Bourcet, Clémence. 2020. « Empirical Determinants of Renewable Energy Deployment: A Systematic Literature Review ». *Energy Economics* 85 (janvier): 104563. https://doi.org/10.1016/j.eneco.2019.104563.

Breusch, T. S., et A. R. Pagan. 1980. « The Lagrange Multiplier Test and its Applications to Model Specification in Econometrics ». *The Review of Economic Studies* 47 (1): 239-53. https://doi.org/10.2307/2297111.

Can Şener, Şerife Elif, Julia L. Sharp, et Annick Anctil. 2018. « Factors Impacting Diverging Paths of Renewable Energy: A Review ». *Renewable and Sustainable Energy Reviews* 81 (janvier): 2335-42. https://doi.org/10.1016/j.rser.2017.06.042.

Chen, Chaoyi, Mehmet Pinar, et Thanasis Stengos. 2021. « Determinants of Renewable Energy Consumption: Importance of Democratic Institutions ». *Renewable Energy* 179 (décembre): 75-83. https://doi.org/10.1016/j.renene.2021.07.030.

Cheng, Cheng, Xiaohang Ren, Zhen Wang, et Cheng Yan. 2019. « Heterogeneous Impacts of Renewable Energy and Environmental Patents on CO2 Emission - Evidence from the BRIICS ». *Science of The Total Environment* 668 (juin): 1328-38. https://doi.org/10.1016/j.scitotenv.2019.02.063.

Chudik, Alexander, M. Hashem Pesaran, et Elisa Tosetti. 2011. « Weak and strong cross-section dependence and estimation of large panels ». *The Econometrics Journal* 14 (1): C45-90. https://doi.org/10.1111/j.1368-423X.2010.00330.x.

Conley, T. G. 1999. « GMM Estimation with Cross Sectional Dependence ». *Journal of Econometrics* 92 (1): 1-45. https://doi.org/10.1016/S0304-4076(98)00084-0.

Destek, Mehmet Akif, et Alper Aslan. 2017. « Renewable and Non-Renewable Energy Consumption and Economic Growth in Emerging Economies: Evidence from Bootstrap Panel Causality ». *Renewable Energy* 111 (octobre): 757-63. https://doi.org/10.1016/j.renene.2017.05.008.

Greene, William H. 2012. *Econometric analysis*. 7th ed. Boston: Prentice Hall.

Hassan, Mahmoud, et Damien Rousselière. 2021. « Does increasing environmental policy stringency lead to accelerated environmental innovation? A research note ». *Applied Economics* 0 (0): 1-10. https://doi.org/10.1080/00036846.2021.1983146.

Hájek, Miroslav, Jarmila Zimmermannová, Karel Helman, et Ladislav Rozenský. 2019. « Analysis of Carbon Tax Efficiency in Energy Industries of Selected EU Countries ». *Energy Policy* 134 (novembre): 110955. https://doi.org/10.1016/j.enpol.2019.110955.

Hille, Erik, Wilhelm Althammer, et Henning Diederich. 2020a. « Environmental Regulation and Innovation in Renewable Energy Technologies: Does the Policy Instrument Matter? » *Technological Forecasting and Social Change* 153 (avril): 119921. https://doi.org/10.1016/j.techfore.2020.119921.

Hille, Erik, Wilhelm Althammer, et Henning Diederich. 2020b. « Environmental Regulation and Innovation in Renewable Energy Technologies: Does the Policy Instrument Matter? » *Technological Forecasting and Social Change* 153 (avril): 119921. https://doi.org/10.1016/j.techfore.2020.119921.

Holtz-Eakin, Douglas, Whitney Newey, et Harvey S. Rosen. 1988. « Estimating Vector Autoregressions with Panel Data ». *Econometrica* 56 (6): 1371-95. https://doi.org/10.2307/1913103.

Kennedy, Peter. 1992. *A Guide to Econometrics*. Oxford: Blackwell.

Kilinc-Ata, Nurcan. 2016. « The Evaluation of Renewable Energy Policies across EU Countries and US States: An Econometric Approach ». *Energy for Sustainable Development* 31 (avril): 83-90. https://doi.org/10.1016/j.esd.2015.12.006.

Kripfganz, Sebastian. 2020. *XTDPDGMM: Stata Module to Perform Generalized Method of Moments Estimation of Linear Dynamic Panel Data Models*. *Statistical Software Components*. Boston College Department of Economics. https://ideas.repec.org/c/boc/bocode/s458395.html.

Le, H., et S. A. Sarkodie. 2020. « Dynamic linkage between renewable and conventional energy use, environmental quality and economic growth: Evidence from Emerging Market and Developing Economies ». https://doi.org/10.1016/j.egyr.2020.04.020.

Le, Hoang Phong, et Samuel Asumadu Sarkodie. 2020. « Dynamic Linkage between Renewable and Conventional Energy Use, Environmental Quality and Economic Growth: Evidence from Emerging Market and Developing Economies ». *Energy Reports* 6 (novembre): 965-73. https://doi.org/10.1016/j.egyr.2020.04.020.

Li, Raymond, et Guy C. K. Leung. 2021a. « The Relationship between Energy Prices, Economic Growth and Renewable Energy Consumption: Evidence from Europe ». *Energy Reports* 7 (novembre): 1712-19. https://doi.org/10.1016/j.egyr.2021.03.030.

Li, Raymond, et Guy C. K. Leung. 2021b. « The Relationship between Energy Prices, Economic Growth and Renewable Energy Consumption: Evidence from Europe ». *Energy Reports* 7 (novembre): 1712-19. https://doi.org/10.1016/j.egyr.2021.03.030.

Marques, António Cardoso, et José Alberto Fuinhas. 2012. « Are Public Policies towards Renewables Successful? Evidence from European Countries ». *Renewable Energy* 44 (août): 109-18. https://doi.org/10.1016/j.renene.2012.01.007.

Marra, Alessandro, et Emiliano Colantonio. 2021. « The Path to Renewable Energy Consumption in the European Union through Drivers and Barriers: A Panel Vector Autoregressive Approach ». *Socio-Economic Planning Sciences* 76 (août): 100958. https://doi.org/10.1016/j.seps.2020.100958.

Menyah, Kojo, et Yemane Wolde-Rufael. 2010. « CO2 Emissions, Nuclear Energy, Renewable Energy and Economic Growth in the US ». *Energy Policy*, The Role of Trust in Managing Uncertainties in the Transition to a Sustainable Energy Economy, Special Section with Regular Papers, 38 (6): 2911-15. https://doi.org/10.1016/j.enpol.2010.01.024.

Menz, Fredric C., et Stephan Vachon. 2006. « The Effectiveness of Different Policy Regimes for Promoting Wind Power: Experiences from the States ». *Energy Policy* 34 (14): 1786-96. https://doi.org/10.1016/j.enpol.2004.12.018.

Nguyen, Kim Hanh, et Makoto Kakinaka. 2019. « Renewable Energy Consumption, Carbon Emissions, and Development Stages: Some Evidence from Panel Cointegration Analysis ». *Renewable Energy* 132 (mars): 1049-57. https://doi.org/10.1016/j.renene.2018.08.069.

Omri, Anis, et Duc Khuong Nguyen. 2014. « On the Determinants of Renewable Energy Consumption: International Evidence ». *Energy* 72 (août): 554-60. https://doi.org/10.1016/j.energy.2014.05.081.

Pesaran, M. Hashem. 2004. « General Diagnostic Tests for Cross Section Dependence in Panels ». Working Paper. Faculty of Economics. https://doi.org/10.17863/CAM.5113.

Pesaran, M. Hashem. 2007. « A Simple Panel Unit Root Test in the Presence of Cross-Section Dependence ». *Journal of Applied Econometrics* 22 (2): 265-312. https://doi.org/10.1002/jae.951.

Pesaran, M. Hashem, Aman Ullah, et Takashi Yamagata. 2008. « A Bias-Adjusted LM Test of Error Cross-Section Independence ». *The Econometrics Journal* 11 (1): 105-27. https://doi.org/10.1111/j.1368-423X.2007.00227.x.

Polzin, Friedemann, Michael Migendt, Florian A. Täube, et Paschen von Flotow. 2015. « Public Policy Influence on Renewable Energy Investments—A Panel Data Study across OECD Countries ». *Energy Policy* 80 (mai): 98-111. https://doi.org/10.1016/j.enpol.2015.01.026.

Sadorsky, Perry. 2009. « Renewable Energy Consumption, CO2 Emissions and Oil Prices in the G7 Countries ». *Energy Economics* 31 (3): 456-62. https://doi.org/10.1016/j.eneco.2008.12.010.

Salim, Ruhul A., et Shuddhasattwa Rafiq. 2012. « Why Do Some Emerging Economies Proactively Accelerate the Adoption of Renewable Energy? » *Energy Economics* 34 (4): 1051-57. https://doi.org/10.1016/j.eneco.2011.08.015.

Schleich, Joachim, Rainer Walz, et Mario Ragwitz. 2017. « Effects of Policies on Patenting in Wind-Power Technologies ». *Energy Policy* 108 (septembre): 684-95. https://doi.org/10.1016/j.enpol.2017.06.043.

Shahzad, Umer, Magdalena Radulescu, Syed Rahim, Cem Isik, Zahid Yousaf, et Stefan Alexandru Ionescu. 2021. « Do Environment-Related Policy Instruments and Technologies Facilitate Renewable Energy Generation? Exploring the Contextual

Evidence from Developed Economies ». *Energies* 14 (3): 690. https://doi.org/10.3390/en14030690.

Su, Chi-Wei, Muhammad Umar, et Zeeshan Khan. 2021. « Does Fiscal Decentralization and Eco-Innovation Promote Renewable Energy Consumption? Analyzing the Role of Political Risk ». *Science of The Total Environment* 751 (janvier): 142220. https://doi.org/10.1016/j.scitotenv.2020.142220.

Tong, Tingting, et T. Edward Yu. 2018. « Transportation and Economic Growth in China: A Heterogeneous Panel Cointegration and Causality Analysis ». *Journal of Transport Geography* 73 (décembre): 120-30. https://doi.org/10.1016/j.jtrangeo.2018.10.016.

Tugcu, Can T. 2018. « Chapter 8 - Panel Data Analysis in the Energy-Growth Nexus (EGN) ». In *The Economics and Econometrics of the Energy-Growth Nexus*, édité par Angeliki N. Menegaki, 255-71. Academic Press. https://doi.org/10.1016/B978-0-12-812746-9.00008-0.

Wang, Qiang, Shuyu Li, et Zhanna Pisarenko. 2020. « Heterogeneous Effects of Energy Efficiency, Oil Price, Environmental Pressure, R&D Investment, and Policy on Renewable Energy -- Evidence from the G20 Countries ». *Energy* 209 (octobre): 118322. https://doi.org/10.1016/j.energy.2020.118322.

Wang, Qiang, et Shasha Wang. 2020. « Is Energy Transition Promoting the Decoupling Economic Growth from Emission Growth? Evidence from the 186 Countries ». *Journal of Cleaner Production* 260 (juillet): 120768. https://doi.org/10.1016/j.jclepro.2020.120768.

Windmeijer, Frank. 2005. « A Finite Sample Correction for the Variance of Linear Efficient Two-Step GMM Estimators ». *Journal of Econometrics* 126 (1): 25-51. https://doi.org/10.1016/j.jeconom.2004.02.005.

Zhang, Mingming, Shichang Zhang, Chien-Chiang Lee, et Dequn Zhou. 2021. « Effects of Trade Openness on Renewable Energy Consumption in OECD Countries: New Insights from Panel Smooth Transition Regression Modelling ». *Energy Economics* 104 (décembre): 105649. https://doi.org/10.1016/j.eneco.2021.105649.

Supplementary material

Supplementary material, Appendix (A)

A.1. Data description and sources

Variable	Proxy	Measure	Source
Renewable energy consumption (REC_{it})	Renewable energy consumption (% of total final energy consumption) denoted by REC	%	WDI
Environmental policy stringency ($LogEPS_{it}$)	Environmental Policy Stringency Index, denoted as EPS	Index	OECD
Market Based policies ($LogMB_{it}$)	The index of Market Based instruments of Environmental policy, denoted by MB	Index	OECD
Non-Market Based policies ($LogNMB_{it}$)	The index of Non-Market Based instruments of environmental policy, denoted as NMB	Index	OECD
Taxes ($Log\mathrm{TAXES}_{it}$)	The index of taxes of environmental policy, denoted as TAXES	Index	OECD
Trading schemes ($Log\mathrm{TRADSCH}_{it}$)	The index of Trading schemes of environmental policy, denoted as TRADSCH	Index	OECD
Feed-in-tariffs ($Log\mathrm{FIT}_{it}$)	The index of Feed-in-tariffs of environmental policy, denoted as FIT	Index	OECD
Emissions standards ($Log\mathrm{STAND}_{it}$)	The index of emissions standards of environmental policy, denoted as STAND	Index	OECD
R&D subsidies ($Log\mathrm{RD}_{it}$)	The index of R&D subsidies of environmental policy, denoted as RD	Index	OECD
Environmental innovation ($EINNOV_{it}$)	Development of environment-related technologies, % all technologies. denoted as EINNOV	%	OECD
Emissions ($LogCO2_{it}$)	Total CO2 emissions from fuel combustion, denoted as CO2	Million tonnes of CO2	IEA

Table A.1. Data description and sources.

A.2. Data Statistics

Variable	Unit	Mean	Std. Dev.	Min	Max
REC	%	12.849	12.312	0.441	61.378
EPS	Real number between 0 and 6	1.762	0.912	0.208	4.133
MB	Real number between 0 and 6	1.187	0.813	0.001	3.983
NMB	Real number between 0 and 6	2.338	1.218	0.001	5.5
TAXES	Real number between 0 and 6	1.519	0.648	0.001	4
TRADSCH	Real number between 0 and 6	0.658	1.088	0.001	5.2
FIT	Real number between 0 and 6	1.389	1.825	0.001	6
STAND	Real number between 0 and 6	2.545	1.655	0.001	6
RD	Real number between 0 and 6	2.131	1.294	0.001	6
EINNOV	%	9.201	3.715	0	25.86
CO2	Million tonnes	435.480	991.108	1.859	5729.875

Table A.2. Descriptive Statistics (before taking logarithm), 1990–2015.

Supplementary material, Appendix (B)

	1	2	3	4	5	6	7	8	9	10	11	12
1.REC	1.00											
2.Lag1REC	0.99	1.00										
3.LogEPS	0.14	0.12	1.00									
4.LogMB	0.00	-0.01	0.70	1.00								
5.LogNMB	0.16	0.14	0.89	0.45	1.00							
6.LogTAXES	-0.01	-0.02	0.27	0.75	0.13	1.00						
7. LogTRADSCH	0.08	0.06	0.63	0.46	0.54	0.12	1.00					
8.LogFIT	0.01	0.00	0.61	0.62	0.39	0.12	0.27	1.00				
9.LogSTAND	0.03	0.02	0.70	0.33	0.74	0.04	0.41	0.34	1.00			
10.LogRD	0.15	0.14	0.49	0.19	0.63	0.16	0.18	0.12	0.27	1.00		
11.EINNOV	0.23	0.21	0.32	0.19	0.29	-0.02	0.41	0.21	0.15	0.13	1.00	
12.LogCO2	-0.34	-0.33	-0.02	-0.01	-0.04	-0.02	-0.01	-0.04	-0.04	-0.08	0.04	1.00

Table B1. Correlation matrix

Variable	**VIF**
Lag1REC	1.20
LogEPS	1.13
EINNOV	1.18
LogCO2	1.15

Table B2. VIF values of predictors in the equation (4)

Variable	**VIF**
Lag1REC	1.22
LogMB	1.28
LogNMB	1.36
EINNOV	1.16
LogCO2	1.15

Table B3. VIF values of predictors in the equation (5)

Variable	**VIF**
Lag1REC	1.22
LogTAXES	1.06
LogTRADSCH	1.48
LogFIT	1.19
LogSTAND	1.38
LogRD	1.14
EINNOV	1.33
LogCO2	1.16

Table B4. VIF values of predictors in the equation (6)

Supplementary material, Appendix (C)

C1. The results of panel-corrected standard errors estmator

	Panel-corrected standard errors		
	(1)	(2)	(3)
Lag1REC	**0.988*** **	**0.989*** **	**0.990*** **
	(0.003)	(0.003)	(0.003)
LogEPS	**0.364*** **		
	(0.064)		
LogMB		**0.062* **	
		(0.035)	
LogNMB		**0.243*** **	
		(0.076)	
LogTAXES			0.032
			(0.030)
LogTRADSCH			**0.049*** **
			(0.012)
LogFIT			0.009
			(0.010)
LogSTAND			0.015
			(0.023)
LogRD			**0.089* **
			(0.050)
EINNOV	**0.055*** **	**0.058*** **	**0.048*** **
	(0.012)	(0.012)	(0.013)
LogCO2	**-0.083*** **	**-0.081*** **	**-0.074*** **
	(0.020)	(0.020)	(0.019)
Constant	0.132	0.095	**0.467** **
	(0.150)	(0.154)	(0.190)
Observations	675	675	675
Number of countries	27	27	27

Table C1. Regressions results of equations (4), (5) and (6); REC is the dependent variable

Note: *, **, and *** indicates the significance level at 10, 5, and 1% respectively based on the two-tailed test. Standard error estimates are in parentheses.

C2. The results of multilevel mixed-effects estimator

	Multilevel mixed-effects		
	(1)	(2)	(3)
Lag1REC	**0.989*** **	**0.989*** **	**0.990*** **
	(0.002)	(0.002)	(0.002)
LogEPS	**0.364*** **		
	(0.065)		
LogMB		**0.062** **	
		(0.027)	
LogNMB		**0.244*** **	
		(0.070)	
LogTAXES			0.032
			(0.025)
LogTRADSCH			**0.049*** **
			(0.011)
LogFIT			0.009
			(0.008)
LogSTAND			0.015
			(0.015)
LogRD			**0.088** **
			(0.041)
EINNOV	**0.055*** **	**0.058*** **	**0.047*** **
	(0.011)	(0.011)	(0.011)
LogCO2	**-0.082*** **	**-0.081*** **	**-0.074*** **
	(0.022)	(0.023)	(0.023)
Constant	0.126	0.090	**0.468*** **
	(0.111)	(0.128)	(0.170)
Observations	675	675	675
Number of countries	27	27	27

Table C2. Regressions results of equations (4), (5) and (6); REC is the dependent variable

Note: *, **, and *** indicates the significance level at 10, 5, and 1% respectively based on the two-tailed test. Standard error estimates are in parentheses.

C3. The results of random effect estimator

	Random Effect		
	(1)	(2)	(3)
Lag1REC	**0.989*** **	**0.989*** **	**0.990*** **
	(0.002)	(0.002)	(0.002)
LogEPS	**0.361*** **		
	(0.065)		
LogMB		**0.062** **	
		(0.027)	
LogNMB		**0.244*** **	
		(0.070)	
LogTAXES			0.031
			(0.026)
LogTRADSCH			**0.049*** **
			(0.010)
LogFIT			0.009
			(0.008)
LogSTAND			0.013
			(0.015)
LogRD			**0.084** **
			(0.039)
EINNOV	**0.055*** **	**0.058*** **	**0.047*** **
	(0.011)	(0.011)	(0.012)
LogCO2	**-0.082*** **	**-0.081*** **	**-0.075*** **
	(0.022)	(0.023)	(0.023)
Constant	0.130	0.090	**0.482*** **
	(0.111)	(0.128)	(0.170)
Observations	675	675	675
Number of countries	27	27	27

Table C3. Regressions results of equations (4), (5) and (6); REC is the dependent variable

Note: *, **, and *** indicates the significance level at 10, 5, and 1% respectively based on the two-tailed test. Standard error estimates are in parentheses.