Environmental effect of production, energy prices and innovativeness: The role of onshore wind energy in top five contributors to the EU economy.

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Renewable energy represents a key element in achieving environmental targets set by the European Union. However, the level of implementation of certain environmental directives is not equal among all of the member states. This paper provides an analysis of the effect of onshore wind energy consumption (which is a major part of renewable energy supply), levelized costs of onshore energy production, spending on research and development, and industrial production on CO_2 emission in five largest EU economies. Subject literature provides significant evidence on positive relation between energy consumption and economic development. Most of the developed countries have decoupled their economic performance from energy consumption (hence increasing their efficiency), however, industrial production and manufacturing play a significant part in the economic performance of the EU member states. This paper tests the significance of those processes on environment degradation.

Purpose of this paper is confirm to whether developing new wind energy sources and spending on various research and development is drastically decreasing the negative influence of those economies on climate change.

This paper employs two three step analysis. First, it checks current trends of the influence of the European Union on climate change it will investigate current time trends. Second, it develops learning curves that present relation between innovativeness and cost and capacity of the wind energy. Third, it runs a GMM estimation to capture statistical relationships between examined data. All investigated economies are subjected to the analysis for period from 1990 till 2018. Data are sourced from four databases – OECD data, World Development Indicators, Eurostat, and International Energy Agency.

This paper encompasses five logically structured sections. Section 1 is the Introduction and presents general background of the study, as well as it sets its major aims and scope. Section 2 presents context of this research; it provides the reader with extensive discussion on the role of the energy consumption, price of energy and innovation in environment degradation. Sections 3 and 4 presents methodological setting and data explanation. Section 5 presents and interprets results of empirical analysis. Finally, Section 6 discusses results and concludes.

1. Introduction

Results of the contemporary research provide a proof that pollution released to the atmosphere increased significantly in the last two centuries in comparison to the pre-industrial era. Furthermore, in the last decades warming climate has been recognized as one of the most important problems of the globe. This challenge combines three significant areas – economy, environment, and energy. It has created a conundrum; energy sector is responsible for the emission of 65% of carbon dioxide to the atmosphere while long-term empirical research provides unquestionable evidence economic development is directly correlated with the amount of energy used. Emission from a country's energy sector depend both on the amount of energy supplied and primarily on the source of the energy.

European Union (EU) as a whole is one of the biggest producers of greenhouse gasses (GHG) responsible for 22% of the global CO_2 emission. This negative human influence on the climate change has spurred EU governing bodies to issue a set of environmental policies where majority of them focus on CO_2 emission. To reduce the negative effects since 1997 EU is introducing new policies which main assumptions are: to decrease share of fossil fuels in energy mix, to improve energy efficiency of the EU member states, and to cover energy gap with renewables. These endowments of the EU member states resulted with increase of the supply of energy from the renewables by over 330% and decrease of energy sourced from fossil fuels by over 12% in the last three decades. At the same time total energy supply remained on the same level while the EU economy increased over two times.

Increasing use of renewables in global energy mix has countless potential benefits among which most important is reducing emission of greenhouse gases and increasing energy safety by diversification of the main sources of the energy. EU has introduced policies that obligate its members to increase the share of the renewables in their energy mix. In 2019 over a third of the electricity sourced from renewables is sourced from wind power. It is one of the most feasible renewable energy sources. However, market is often unfavourable for the new energy sources representing new technologies. Main reason for that is the overall cost which is higher than price of conventional – not environmentally friendly-energy sources. Such effect may be mitigated with set of policies and subsidies for innovation. Such actions are justified based on the "technological learning". This phenomenon relies on decreasing cost of the technology in result of increasing cumulative installation (or capacity in case of renewables) (Dosi, 1988; Arrow, 1962; Argote and Epple, 1990; Dutton and Thomas, 1984). These policies can stimulate innovation and up-front costs could be recovered in the long run as technological learning occurs.

In this paper we focus on the wind energy as it is one of the most important renewable energy sources in the EU energy mix. We are comparing the levelized costs of wind energy and the resources allocated to the research and development (R&D) in the field of renewables. We are applying Goddard learning curve to present the correlation between R&D, capacity of the wind power installed and levelized costs of wind energy. Further, we apply generalized method of moments (GMM) to test the impact of those variables on the overall CO_2 emission. In this paper we focus on five largest economies of the EU (Germany, France, Spain, Netherlands, and Italy) that represent 70% of the overall EU GDP and 61% production of the energy from renewables.

Section 2 of this paper presents literature review concerning the subject, section 3 and 4 introduces methodology and data review, section 5 presents results of the econometric analysis, section 6 concludes and discusses the results obtained.

2. Literature Review

Studies on negative influence of human activity on environment in the field of energy dates back to the 18th century (Malthays 1798). However, the majority of the empirical analysis has been published in this century. In the field of economy three main fields can be distinguished, all of which divide the scientists with mixed results. First, describing correlation between energy consumption and economic growth, results show no consensus. Second, focusing on economic growth and pollution, which verifies hypothesis on existence of the environmental Kuznets curve. This research assumes that at some point of development economies decrease their pollution with further growth. (Grossman and Krueger, 1991; Arouri et al., 2012; Shahbaz et al., 2012; Pérez-Suárez and López-Menéndez, 2015). However, this theorem has been challenged in various publications. Main charge against it is the lack of robustness of the analysis at which environmental Kuznets curve is based on (Stern 2004, Dasgupta et al. 2002). Third field combines both previously described. It examines the correlation between economic growth, pollution, and energy consumption. However, results of those analyses vary between countries. The mixed findings reflect several factors, including country differences, model specification and methodological approach.

More recent research takes into focus application of the renewable energy technologies in fight with progressing global warming and degradation of the environment. However, there is a very limited amount of research investing correlation between emission of greenhouse gases, innovation and production of energy from renewables. Klaasen et al. (2005) examines impact of the subsidies and public R&D expenditures on cost reducing innovation for wind turbine farms in Denmark, Germany, and the United Kingdom. They applied two-factor learning curve (Kouvaritakis et al. 2000) based on the fixed effect model. Their results support the two-factor learning curve hypothesis that states cost reductions are explained by increase in cumulative increase of the power capacity and the R&D knowledge stock. Ding et al. (2020) validate the efficiency of the governmental policies concerning photovoltaics and the R&D in selected countries. They confirmed the efficiency of the policies in driving PV costs down with learning-by-research rate presented at single factor learning curve (Argote and Epple 1990). Soderholm and Klaassen (2007) examined the influence of various economic and political factors on innovation activities and diffusion in the wind energy sector. Their research suggests that a number of factors are significant for determining innovation patterns in this industry where most important are price subsidies and fixed feed-in price systems. Wang et al. (2018) evaluate effect of technological learning on industrial air pollution in China. They have applied multi-factor environmental learning curve to test relationship between technological learning and intensity of industrial air pollutants. Based on simple mediating effect model they have decomposed the overall effect into direct and indirect effects. Their results showed that learning-by-doing, learning-by-researching, and learning-by-importing can significantly- in the same proportion reduce industrial air pollutants intensity through energy efficiency. To estimate the offset of the GHG in result of substitution of the fossil fuels generators with the wind farms in Texas Cullen (2013) applied fixed effect model. Obtained results shows that one MWh of wind power production offsets half a ton of CO_2, almost one pound of NOx, and no discernible amount of SO2. What is more, he has estimated that to outweigh costs of subsidies, social costs of CO_2 must be grater than 42USD/ton. Similar research has been run by Kaffine et al. (2013). They have applied fixed effect model to estimate the decrease in CO_2 emission as a result of substitution of the energy sourced from fossil fuels with wind farms in Texas. Their results specified the amount of the savings which depends on the type of the fuel substituted.

Industry energy efficiency is very often associated with proses of decoupling of the economic performance from the energy demand. Main concept of decoupling has been challenged by many researchers (Moreau and Vuille 2018, Voigt et al. 2013, Fiorito 2013, Peters et al. 2008). Key allegation against its success is doubt whether deindustrialization and moving the least efficient processes abroad may be called a decoupling, and as a result should energy use of the foreign country be assigned to the deindustrializing country (Moreau and Vuille 2018).

3. Methodology

This paper presents three step analysis. First, we describe the data and present time trends for each of the investigated economies. Second, we estimate and plot the learning curve for five top economies of the EU. Third, we run GMM estimation with all necessary tests.

3.1 Learning curve

Formerly learning curves described only narrow area, work study and cost control while focusing mainly on labour costs. One of the first curves were showed by Wright (1936). He presented the correlation between unit cost and cumulative production where learning was assumed to be the main driver. Further function has been renamed as experience curve to reflect the technological change (Goddard 1982). However, more recently, learning and experience were used interchangeably to describe the curve. We are applying Goddard equation presented in fig. 1 to present the relation between R&D spending's on renewables, wind energy capacity and levelized costs of the wind energy.

$$\log Y_t = a \ \log X_t + b + n(t)$$

Where, Y_t stands for spending on cumulative R&D at time t, X_t stands for wind power capacity or levelized cost of wind energy at time t, a b stands for constant, and n(t) stands for noise term.

3.2 Tests

Econometric analysis of panel data is divided into three parts. First, Im-Pesaran and Shin test (IPS) has been employed to test for the stationarity of the variables. Null hypothesis of this test states presence of the unit root (not-stationarity of series) while alternative hypothesis assumes lack of unit root in at least a fraction of dataset. Next variables concerning industry, wind power capacity, R&D spending, wind LCOE and CO_2 are tested for cointegration to which Westerlund test was employed. There are many cointegration tests, among which the most recognizable is Pedroni test (Pedroni 1999 and 2004) which considers heterogeneity and independence. However, in this specific case it was not plausible to implement it as it does not control for cross-sectional dependence which was confirmed with Pesaran test (Eberhardt and Presbitero 2013, Pesaran 2007). Westerlund test estimates four statistics – $G\theta$, $G\alpha$, (which perform under alternative that the panel is co-integrated as a whole) and $\rho\theta$, $\rho\alpha$ (which alternative is that there is at least one element of the panel which is co-integrated) (Westerlund 2007, Jaunky 2010). In all cases H_0 of no-cointegration is tested. In case of co-integration, then causality must run in at least one direction (Engle and Granger, 1987).

To account for the fact that greenhouse gas emission at time t might be determined by its past values and to resolve potential problem with endogeneity we estimate a linear dynamic panel data model using a system GMM estimator (Blundell and Bond 1998). Following equation is estimated:

$$\Delta CO2_{it} = \Delta CO2_{it-1} + \beta_1 \Delta IND + \beta_2 \Delta WC_{it} + \beta_3 \Delta RDR_{it} + \beta_4 \Delta LCOE_{it} + \Delta X'_{it} \beta_5 + \Delta \mu_{it}$$

To decrease number of the instruments we restrict estimation up to seven lags and we instrument variables to collapse in a single vector of instrument per each variable and lag distance. (Roodman, 2009). To assess for first order serial correlation in the first-order residuals and lack of second-order serial correlation (necessary condition for system GMM estimation) we employ Arellano-Bond test for serial correlation. We use Sargan-Hansen (1988) test to check for over-identifying restrictions.

4. Data

This paper is based on panel data of five top economies of the EU. Data was sourced from various databases – free (Eurostat, Worldbank, IREAN, EIA) and paid ones (OECD). Used variables were described and summarized in Table 1. This research is limited to the period between 1990 and 2018. Limitation results from lack of data and lack of significant spending on research and development in the field of renewable energy. For the econometrical estimations, all variables except EFF were transformed into first difference.

Table 1. Definitions and descriptive statistics of data used in the study.

Var	Definition	Source	N	mean	SD	Min	Max
CO2	Greenhouse gas emissions, Thousands of tons of CO2 equivalent	Eurostat	145	392,093.40	223,926.10	147,774.80	940,007.70
WC	Net maximum electrical capacity for wind in Megawatt	Eurostat	145	7,521.23	11,406.00	0.00	58,721.00
FOSS	Gross available fossil energy in thousands of TOE	Eurostat	145	151,851.10	70,882.58	71,869.84	312,196.60
EFF	Primary energy consumption, Million tons of oil equivalent in TOE	Eurostat	145	178.71	90.18	58.50	332.75
GDP	Gross domestic product per capita in EUR	WDI	145	31,392.43	10,064.88	13,487.77	57,899.82
OIL	Brent spot prices in USD	EIA	145	48.65	32.40	12.76	111.63
LCOE	Levelized cost of energy sourced from wind in EUR	IRENA	145	1,855.30	469.88	1,311.60	2,744.66
IND	Industry (including construction) in EUR	WDI	145	101.09	14.66	67.07	134.41
RDR	Governmental spending on research and development of the renewable sources of energy in EUR	OECD	145	90.86	73.42	4.16	341.98
RDT	Total governmental spending on research and development in field of energy in EUR	OECD	145	519.94	393.94	59.26	1,498.57

Source: Own elaboration

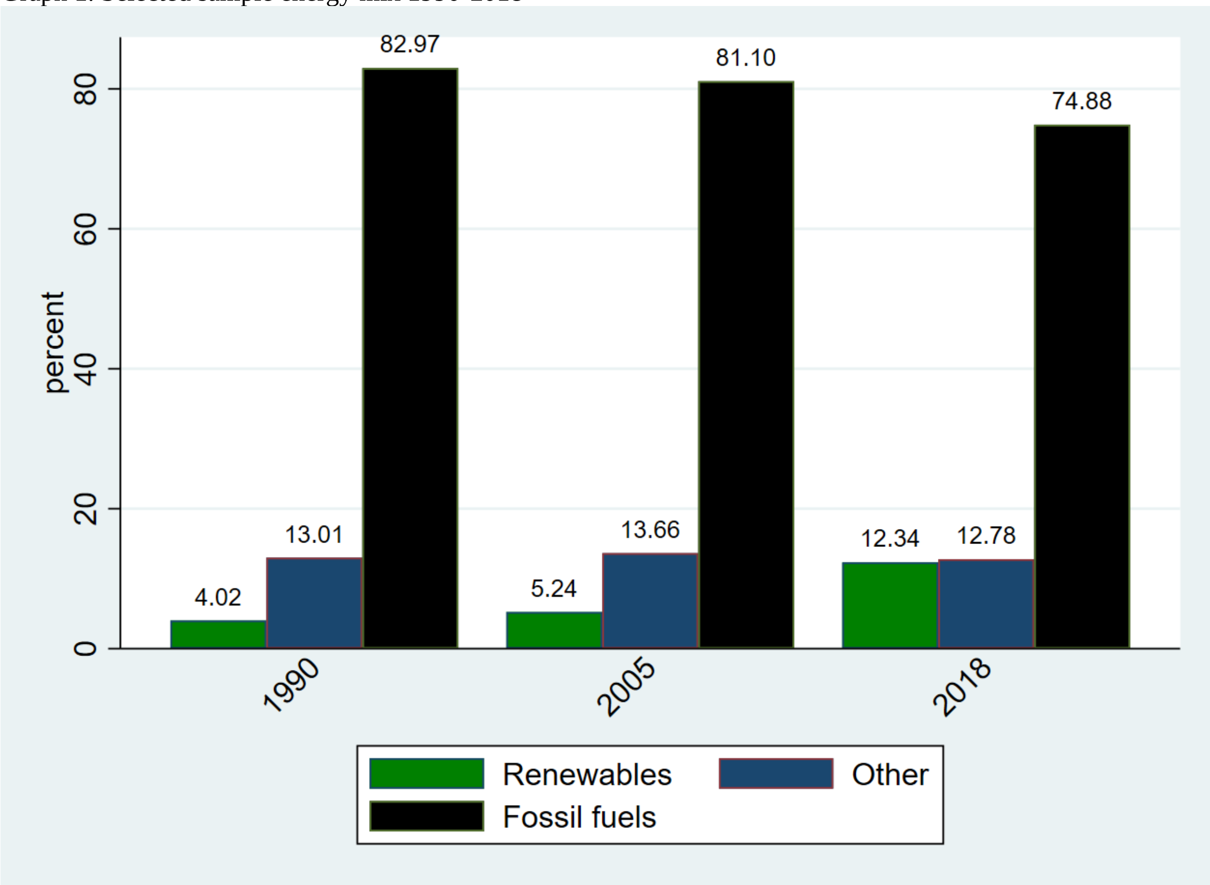
Note: Presented statistics were obtained before any transformation

5. Empirical analysis

5.1 Time trends

Total energy produced in 2018 within the selected sample equalled to 958.8 MTOE which was 5.37% more than in 1990 but 11.1% less then pick in 2006. In the same time GDP per capita within selected economies rose on average over three times. This suggests on process of decoupling economic performance from energy use which relies on increasing efficiency within economy by increasing units of produced output per unit of energy. In the EU, 21 out of 28 members reached absolute decoupling in 2005 (EEA 2016).

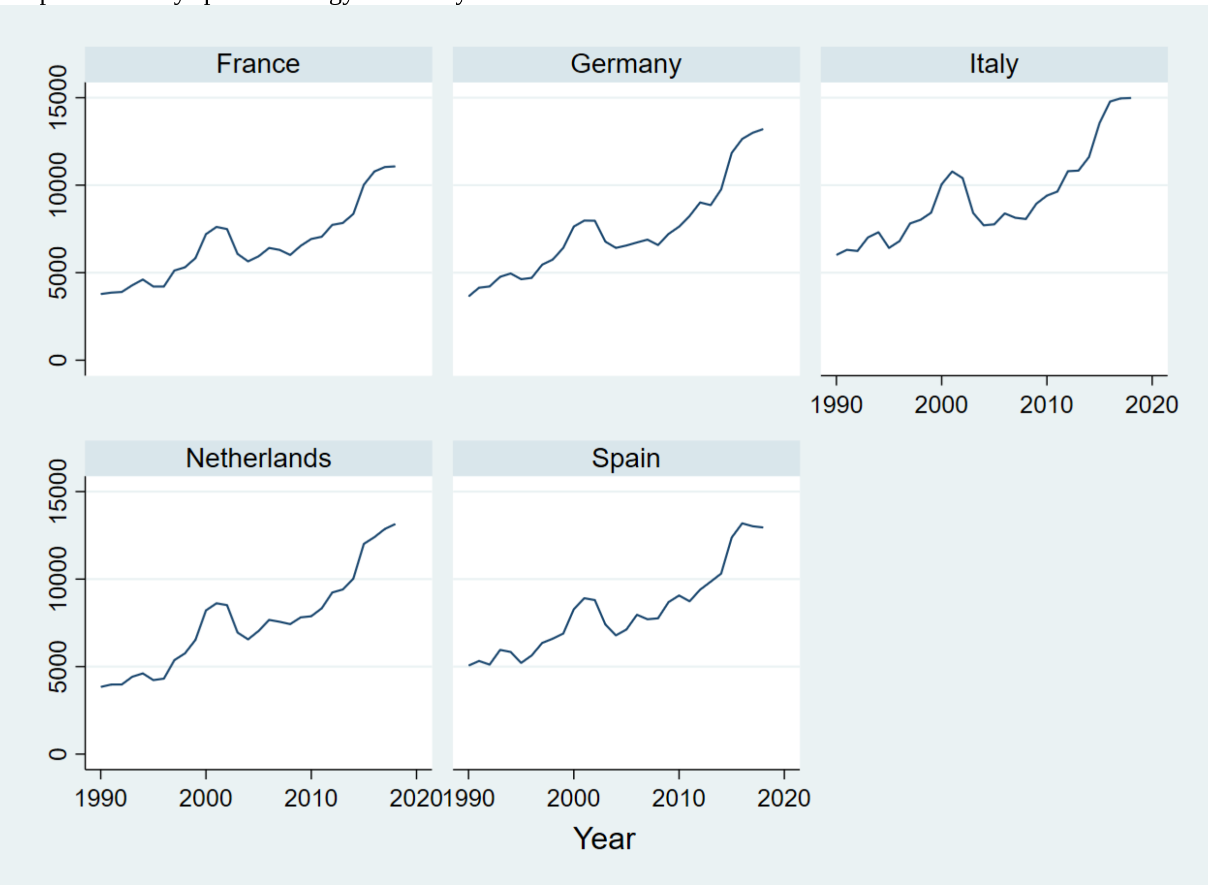
Graph 1. Selected sample energy mix 1990-2018



Source: Own elaboration based on Eurostat

Energy produced using fossil fuels equalled to 688.50MTOE, 6.77% less than in 1990 and 17.44% less than in 2006. 123.68MTOE was sourced from renewables. Energy mix of the selected sample has been presented in Graph 1. European Union's energy structure is strongly diversified because of differences in economies and populations of each member state. This is why it is important to analyse not only the volume of the energy used but how efficiently it was used. In all of investigated countries there is a visible upward trend in efficiency of the use of energy. Graph 2 presents the ratio of GDP to used energy. Efficiency of selected countries rose from 220% in case of Italy up to 312% in case of Germany between 1990 and 2018.

Graph 2. Country specific energy efficiency 1990-2018



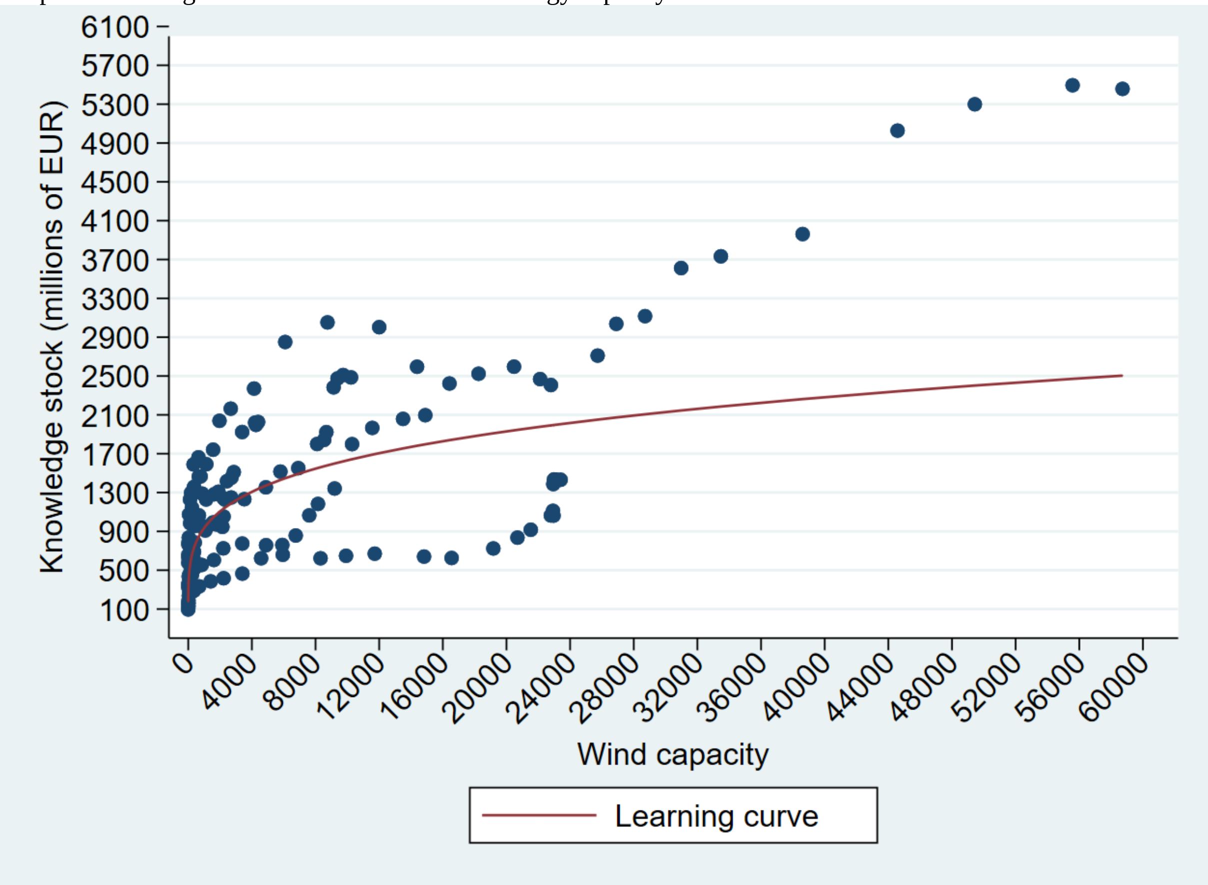
Source: Own elaboration based on Eurostat

5.2 Learning curve

Spending on R&D of renewable energy in the last decades rose even by 1,300% in case of France. However, in term of real values, those are not significant amounts. The highest amounts are spent by Germany with 280mEUR. At the same time, total capacity of installed turbines reached 111,649MW in the researched sample[1]. During this period LCOE has fallen by over 52%. Graph 3 presents the relation of the R&D cumulative stock and wind power capacity.

[1] In 1990 cumulative power capacity of wind turbine in researched sample was 103MW

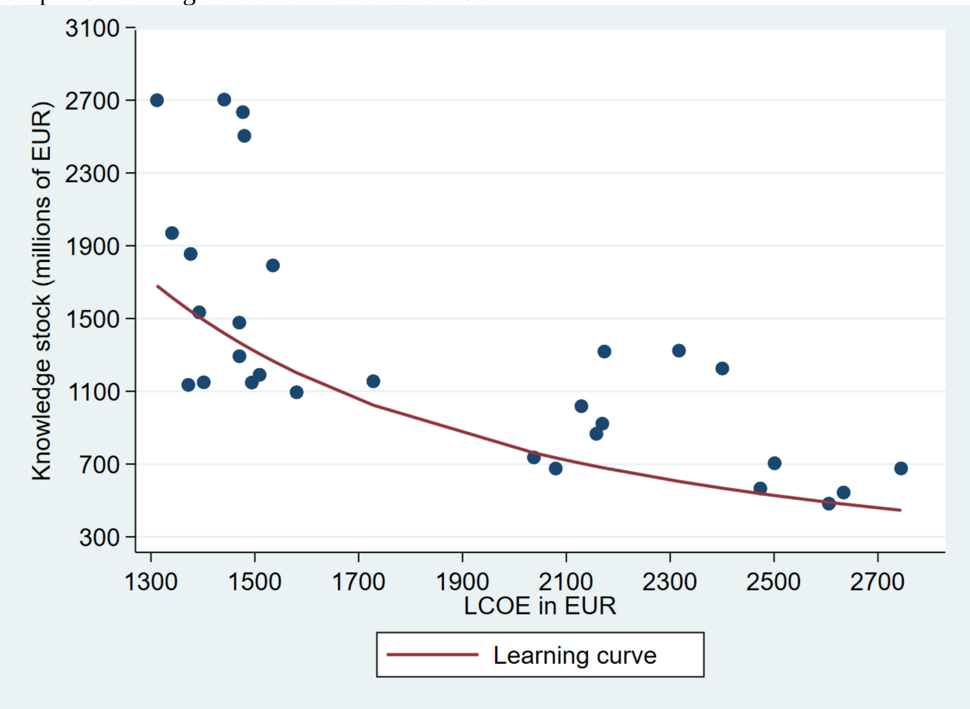
Graph 3. Learning curve R&D stock and wind energy capacity



Source: Own elaboration

Learning curve as well as real data suggests that relation between knowledge stock and the capacity of power produced with wind turbine is fairly linear. However, as it is presented in Graph 4, increase in knowledge stock significantly decreases levelized cost of energy sourced from wind.

Graph 2. Learning curve R&D stock and LCOE



Source: Own elaboration

5.3 Results of the econometric estimation

Tables 2-4 present the result of the empirical analysis. First step of the empirical analysis was to test for stationarity. To do so, Im-Pesaran and Shin test (IPS) was employed. Null hypothesis of this test states presence of the unit root (not-stationarity of series) while alternative hypothesis assumes lack of unit root in at least a fraction of dataset. Table 2 shows results of Im-Pesaran-Shin test for unit root. In all tests, time trend was included. In eleven out of twelve cases, H0 of unit root was rejected at 1% which resulted in stationarity of at least some panels. Only in case of variable ESUP H0 has been rejected at 10% level.

Table 2. Unit root test

Im-Pesaran-Shin (2003) unit root test			
Variable	Statistic	p-value	Options included
CO2	-7.1317	0.0000	Time trend
WC	-2.9808	0.0014	Time trend
FOSS	-6.7787	0. 0000	Time trend
EFF	-6.5646	0. 0000	Time trend
GDP	-5.1130	0.0000	Time trend
OIL	-5.9489	0.0000	Time trend
LCOE	-6.1148	0.0000	Time trend
IND	-5.0184	0.0000	Time trend
RDT	-7.9533	0.0000	Time trend
RDR	-7.2745	0.0000	Time trend
RDW	-7.9974	0.0000	Time trend
ESUP	-1.3594	0.0870	Time trend

Next, variables IND WC LCOE RDR and CO_2 were tested for cointegration for which Westerlund test was employed. There are many cointegration tests available, among which the most recognisable is Pedroni test (Pedroni 1999 and 2004) which considers heterogeneity and independence. However, in this specific case it was deemed as not plausible as it does not analyse cross-sectional dependence which was confirmed with Pesaran test (Eberhardt and Presbitero 2013, Pesaran 2007). Westerlund test estimates four statistics – $G\theta$, $G\alpha$, (which perform under alternative that the panel is co-integrated as a whole) and $\rho\theta$, $\rho\alpha$ (which alternative is that there is at least one element of the panel which is co-integrated) (Westerlund 2007, Jaunky 2010). In all cases, H_0 of no-cointegration is tested. In case of co-integration, then causality must run in at least one direction (Engle and Granger, 1987).

Table 3. Westerlund cointegration test

Variables	Statistic	Value	Z-value	P-value	Robust P-value
Dependent:	Gθ	-2.859	-0.97	0.166	0.096
CO2	Gα	-14.739	-0.52	0.301	0.061
Independent:	Pθ	-6.73	-1.778	0.038	0.061
IND GDP WC LCOE RDR	Pα	-15.875	-1.937	0.026	0.04

Note: Westerlund cointegration test (2007) with a null hypothesis (H0) of non-cointegration

Cointegration test results were presented in Table 3. For transversal dependence, control robust values were generated through 800 simulations with bootstrapping regression. The H0 on no cointegration has been rejected in all cases.

There is potential endogeneity when relating energy prices, energy efficiency, use of fossil fuels and emission of greenhouse gases. This problem is addressed with application of the GMM estimation. Result of the estimation were presented in Table 4.

Table 4. Results of GMM estimation

Variable	Coefficient	
L1.CO2	0.0072884	
	(0.0218628)	
GDP	0.0094514	
	(0.0117926)	
IND	-0.0000000196	
	(0.0000000203)	
WC	-0.5358498	***
	(0.1798173)	
RDT	4.777146	
	(5.189502)	
RDR	-14.74779	
	(14.91148)	
LCOE	10.96704	*
	(6.267497)	
FOSS	2.789413	***
	(0.1281091)	
OIL	-30.82148	
	(97.43528)	
EFF	-5.642903	*
	(3.112824)	
Constant	-2527.768	
	(2155.844)	
N	140	
Sargan-Hansen	0.97	
AB1:	0.0373	
AB2:	0.8020	

Note: *p-value ≤ 0.10, **p-value ≤0.05, ***p-value ≤0.01; all variables except EFF were in first difference, estimation includes time effects

GMM estimation has been run to confirm hypothesis that emission of CO_2 is influenced not only by wind power capacity but also by prices of this energy and spending's on R&D in field of renewable energy. Second objective was to check whether decrease in CO_2 emission is not influenced by deindustrialization. Obtained results partially prove the initial hypothesis. Increase of wind power capacity results with decrease in emission of CO_2. In particular, we find that decrease in levelized cost of wind energy by 1EUR results with decrease in CO_2 emission by 10.96 tons. We find significance of the amount of used fossil fuels as well as prime energy consumption which are in line with subject literature. Finally, the AR and the Hansen J tests confirm that our instrumenting strategy is valid: the former confirms that the differenced residuals follow an AR(1) process, while the latter never rejects the null hypothesis of no over-identification. We conclude that our results are robust to unobserved heterogeneity and simultaneity.

6. Discussion and conclusion

Development of the renewable energy sources is crucial for achieving more sustainable economies and to reach the EU environmental targets. This paper presents that energy system of the EU is changing, and what is more important, tends to be more efficient in comparison to the 90's. Another conclusion is that the energy mix of the EU heads towards more sustainable energy economy, which constitutes one of main EU policies.

Further, we develop two learning curves that present the relation between R&D spending on renewables, levelized cost of wind energy and the capacity of the wind energy. Obtained results confirm that with increase of R&D spending on renewables, levelized cost of wind energy decreases and that cumulative capacity of wind energy generators increases as well. What can be observed is that eventhood relation seems to be linear, initial investment in R&D does not result with immediate increase of capacity.

Goal of this paper was to investigate whether innovation in energy sector represented by spending on R&D has influence on the emission of the greenhouse gases. GMM estimation provided evidence that ceteris paribus emission of CO_2 is influenced by the capacity of the wind energy and its levelized cost but not by the R&D spending. However, presented learning curve shows that R&D spending is related with wind power capacity and with the LCOE. Furthermore, results of the Westerlund cointegration test present evidence that value of the R&D of renewable energy is cointegrated with the CO_2 emission. Those results suggest that even though innovation is not directly influencing the amount of CO_2 emitted by the investigated countries it can decrease it indirectly by increasing capacity of the wind energy and decreasing its prices. What is more, obtained results suggests that current CO_2 emission is not influenced by its previous values.

Results obtained with this research should be a clue for the policy makers and the governing bodies that increase in spending on innovation have an indirect positive effect on the environment, and are worthy to be increased. However, it has to be noted that this research is based on a small sample and should be continued in future with much broader selection of countries.

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