




# “The interplay between technological innovation, energy efficiency, and economic growth: Evidence from 30 European countries”

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# THE INTERPLAY BETWEEN TECHNOLOGICAL INNOVATION, ENERGY EFFICIENCY, AND ECONOMIC GROWTH: EVIDENCE FROM 30 EUROPEAN COUNTRIES

## **Abstract**

It is assumed that technological progress plays a vital role in energy efficiency improvements when the effects of industrial restructuring, infrastructure, environmental challenges, and economic shocks seem more dubious. However, a limited number of studies have been conducted to examine the impact of technological innovation on countries' energy efficiency levels. This study aims to explore the relationship between energy efficiency, technological innovation, and economic growth in 30 European countries by utilizing data from 2012 to 2020. To this end, a two-stage analysis is carried out. The first step involves estimating the total factor energy efficiency (TFEE) by the countries to illustrate the effects of energy parameters on economic growth and the environment, and technological innovation (TI) to estimate the innovation capability of each country by using data envelopment analysis (DEA) methodology. The second step includes a panel regression model to explore how technological innovation affects energy efficiency, considering the degree of government intervention, industrial structure, infrastructure, and economic openness.

The results indicate that the bottom-15 countries, whose TFEE scores were the lowest, are mainly countries of Central and Eastern Europe. Regarding the countries' technological capability, the results were similar, but the score was lower than the TFEE.

Moreover, the regression analysis shows that a one percent increase in innovation activity contributes to an increase in energy efficiency by 0.27 percent. Hence, it confirms the notion of a positive impact of new technology on energy efficiency.

## **Keywords**

economic growth, energy efficiency, innovation capability, data envelopment analysis

## **JEL Classification**

O11, O32, Q43

## **INTRODUCTION**

According to the Environmental Kuznets Curve (EKC), pollution increases with economic growth until a certain level of wealth and thereafter starts to decrease as the economic growth continues. This development is first seen in marginal pollution rates, which means that pollution rates first increase with economic growth and, after that, fall under continuous economic growth. Several research papers have traced EKCs empirically. However, admittedly, the evidence is significantly weaker for absolute pollution than marginal pollution rates (Grytten et al., 2020). The EKC can basically be explained in three ways: an income approach, a political approach, and a technological approach (Koilo, 2019).

In the first place, the income approach argues that economic growth gives higher income, and income over a certain level gives demand for clean and sustainable products because consumers can afford to pay the potentially higher price. Secondly, the political approach argues

that economic growth gives a wealthier electorate and subsequently wealthier states that at a certain level will require and can afford a cleaner environment. Finally, the technological approach argues that economic growth gives more advanced economies with more advanced technology. This technology can consume energy more efficiently, thus resulting in less pollution, which offers a cleaner environment and a more sustainable development.

It is well known that during the last decades, energy efficiency as a tool to solve the overconsumption of fossil fuels has become an increasingly central issue. One can argue that energy efficiency improvement can be attributed to two main factors. Firstly, there are industrial restructuring and enhancing energy substitution from low- to high-productivity industries, e.g., manufacturing to services. Secondly, it is worth noting improvement in the utilization of production factor efficiency by technological progress (Jin & Kim, 2019).

With industrialization, economic growth, and increased living standards worldwide, demand for energy consumption is increasing, making energy shortage a considerable problem. Indeed, energy is one of the primary drivers of socio-economic development (Olsson, 1994). Thus, combining increasing energy efficiency, which promotes economic growth, and sustainable green economic development is a significant challenge. However, as global energy consumption continues to grow, it will drive investments into cleaner and more sustainable energy production to limit global emissions. Digital technology disruption offers new communication solutions enabling industries to become more data-driven, optimizing and improving asset efficiencies. Nowadays, energy efficiency is difficult to improve through industrial restructuring, and more advanced technologies are needed to solve the issues of high pollution and high energy consumption in industrial development (Shao et al., 2019).

As a result, innovation-oriented development strategies have become a relevant method of reducing energy intensity. Technological innovation capability and energy efficiency have become significant indicators for measuring the success of a strategy (H. Wang & M. Wang, 2020).

Continuously, more advanced technology is needed to develop more energy-efficient technology (Shao et al., 2019). Consequently, innovation-driven development strategies are relevant to obtain energy efficiency, reduced energy intensity, sustainable development, and economic growth. Technology innovation capability and energy efficiency are important indicators for measuring the success of such a strategy. Then this question stands out: What factors drive development towards higher energy efficiency?

Based on an empirical study of 30 European economies, the present paper suggests the importance of central parameters for developing energy efficiency. The econometric tests suggest that economic growth and real GDP levels per capita seem to be the most critical factors for the development of TFEE. This means that the empirical tests suggest that economic growth leads to energy efficiency, which might lead to less pollution. This again suggests evidence for the Environmental Kuznets Curve (EKC), where energy efficiency might be an important contributor to less pollution and a more sustainable pattern of economic development.

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## 1. LITERATURE REVIEW

### 1.1. Model departure in literature

The global trend of assessing energy efficiency and its connection to technological innovation and economic growth has gained popularity over the past few years.

The Solow model was initially used to explain how real income growth can be determined by technological progress. Solow (1957) referred to total factor productivity (TFP) as the rate of residual output growth caused by technological change, and it is not described by any rise in costs. In fact, the Solow residual assesses the influence of neutral technological progress and, in addition, shows the impact

of technological progress on the productivity of all production factors (H. Wang & M. Wang, 2020).

Many studies use value creation and economic growth based on the Solow model in economic literature. In neoclassical theory, an important role of a company is to transform inputs into useful outputs. The activities of the economy are described by the Cobb-Douglas function, which expresses the relationship between the production results and the productive resources (Bassanini et al., 2000):

$$Y = F(C, L, N), \tag{1}$$

where  $Y$  – Production = Value creation;  $F$  – Function = Composition of the production factors;  $C$  – Capital;  $L$  – Labor;  $N$  = Natural resources.

Natural resources are often considered part of the capital. Thus,  $N$  is a sub-size of  $C$ . One then arrives at which leads to a simplified production function:

$$Y = F(C, L). \tag{2}$$

The contribution of the factors to production can be operationalized by:

$$Y = C^a L^{(1-a)}, \tag{3}$$

where  $a$  – rate of return on investments, with a value of  $0 < a < 1$ .

Since output depends not only on the volume of input resources, but also on their combination and the way they are organized, technology is of significant importance. This is highlighted in the Solow-Swan model: it predicts that economies converge to their steady state in the long run and that permanent growth is achieved by technological progress (Carlin & Soskice, 2015). To prove this, the model is also based on a Cobb-Douglas function:

$$Y = AC^a L^{(1-a)}. \tag{4}$$

This function is concave, reflecting diminishing returns to scale for capital.  $A$  is total factor productivity, and  $(\alpha)$  is capital share of income. Thus, the labor share of income is  $(1-\alpha)$ . Therefore, output per worker will depend on capital per worker and total factor productivity (Figure 1).  $A$  will capture the technology, the efficiency with which technology and capital are used, and the management quality. Hence,  $A$  represents multi-factor productivity (MFP), which is the same as total factor productivity (TFP) (Carlin & Soskice, 2015).

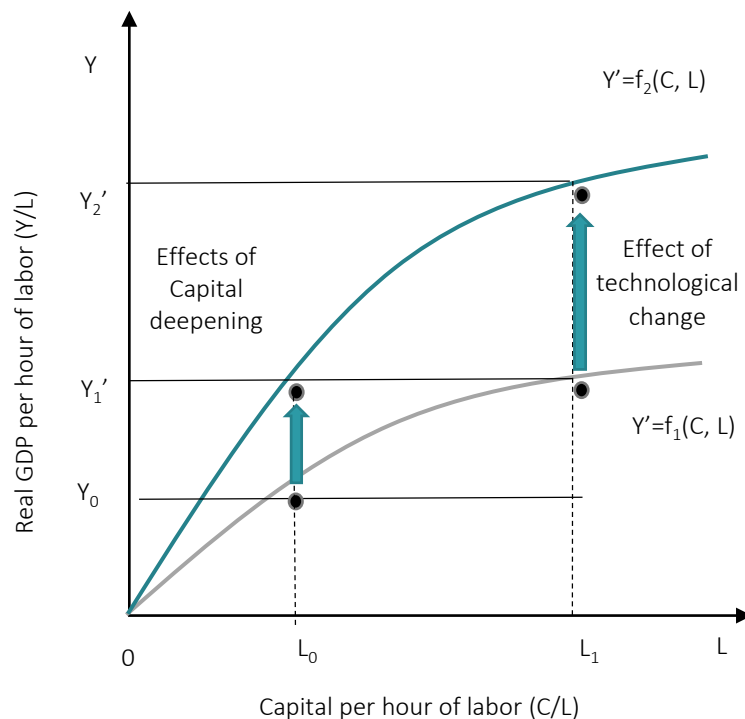


Figure 1. Effects of technological change on the neoclassical production function

## 1.2. Conceptual framework in the literature

Research on the impact of technological progress on energy consumption and energy efficiency has obtained considerable attention.

A substantial number of studies have explored energy-saving technologies in different industries and sectors. For example, Hritonenko and Yatsenko (2013) argued that “technological progress refers to a combination of all effects that lead to increased productive output without increasing the amounts of the productive inputs (e.g., capital, labor, and resources).” Moreover, they concluded that technical progress affects not only the economy’s efficiency but also the natural environment.

Dasgupta and Roy (2015) presented a comprehensive analysis of the energy demand behavior of seven energy-intensive industrial and manufacturing sectors in India from 1973 to 2011. They focused on two main drivers of energy demand: technological progress and energy prices. Their findings show that the contribution of technological progress differed substantially among industries and varied over the period. In general, they summarized that productivity growth in energy consumption was driven by both technological progress and higher energy prices.

Ouyang and Lin (2015) applied a co-integration analysis to investigate a long-run equilibrium relationship between sectoral energy demand and several explanatory variables, such as economic growth, energy prices, technological progress, and per capita productivity. Their results indicate that technological progress ensures continuous improvement in sectoral energy efficiency. Additionally, they concluded that if economic growth rates were higher, the sectoral energy savings could be improved.

Zhu et al. (2019) employed a model based on a Cobb-Douglas production function to examine the role technological progress might have on energy savings in China’s construction industry. The results indicate a positive relationship between technological progress and energy efficiency, which improved by an average of 7.1% per year from 1997 to 2014.

Zeraibi et al. (2020) applied the non-linear autoregressive distributive lag (NARDL) econometric approach to investigate an asymmetric relationship between technological innovation, energy consumption, and economic growth for the period 1980–2018 in China. According to their study, a 1% energy consumption reduction would significantly reduce economic growth. In addition, increasing the number of patent applications improves economic growth significantly.

Another study was conducted by Karali et al. (2017) by implementing Industrial Sector Energy Efficiency Modeling (ISEEM) and the learning curve formula for 24 energy efficiency technologies, which were selected from the US metallurgical sector. The results reveal the importance of technological learning, and they should be included in optimization-based energy models. Moreover, they conclude that learning could further reduce emissions and costs.

Shang et al. (2020) proposed a SBM-DEA model to measure the total factor energy efficiency in different regions of China. The conclusion is that the average annual measured value of total factor energy in China from 2005 to 2016 was less than 0.5 when 1.0 is max considering environmental constraints. However, with existing technology and a constant return to scale on investment, this value still increases by 50%. This provides a theoretical advantage for further transformation and modernization of China’s energy capacity and supply reform.

Li et al. (2019) analyzed the energy and economic efficiencies of Chinese provinces and cities by applying radial (CCR or BCC) and non-radial SBM (Slacks Based Measures) models. The results indicated huge energy efficiency differences between the cities. However, the CO<sub>2</sub> efficiencies showed that around half the cities had sustained improvements in an economy with a significant technology gap between cities.

Other researchers employed a two-stage procedure to examine how technological progress affects energy efficiency from the perspective of technological innovation and technology introduction (Zhang & Fu, 2022). Their analysis is conducted at the industrial level in Guangdong (China) from 2000 to 2018. They concluded that independent innovations have a

significant negative impact on the energy efficiency of the manufacturing industry due to the rebound effect. On the other hand, in terms of interaction, independent innovations contribute to increasing energy efficiency with the help of transferred technology by the emergence of competition.

The findings of previous studies reveal a lack of studies on the effects of technological progress on energy efficiency on national and international levels. The present study seeks to fill that gap.

## 2. METHODOLOGY

The paper proposes a two-step analysis. Firstly, a data envelopment analysis (DEA) is used to measure efficiency indicators, such as total factor energy efficiency (TFEE), to illustrate the effects of the energy factors on economic growth and the environment, and technological innovation (TI), to estimate the innovation capability of each country. Secondly, the study explores the impacts of technological progress on energy efficiency by using panel data analyses.

### 2.1. Data and variable selection

The units of the study are 30 European countries: 27 EU countries, the EEA countries Iceland and Norway (Liechtenstein is not included due to lack

of available data), and finally, the United Kingdom. The sample data cover the period from 2012 to 2020. The data were obtained from Eurostat (2022) and the European Patent Office (2022).

### 2.2. DEA analysis

To arrive at objective measurements of TFEE and TI, it is crucial to solve the issue of constructing relevant parameters. One of the advanced methods of analyzing production efficiency is the DEA method (data envelopment analysis), in which the country that provides the maximum output per unit of resources serves as a “benchmark.” All other countries are compared to this country according to the degree of utilization of their resources. Furthermore, an efficient country creates a so-called “production efficiency frontier” known as a “data envelope.” This “data envelope” sets the limit of production possibilities, i.e., the maximum possible output of products for any combination of resources. Thus, an efficiency measurement determines the distance between the analyzed indicators and the efficiency limit.

Thus, energy efficiency is characterized by the degree to which a country utilizes a given number of resources (capital, labor input, and energy consumption) to achieve the maximum production (GDP per capita), including undesirable output such as CO2 emissions from the energy sector.

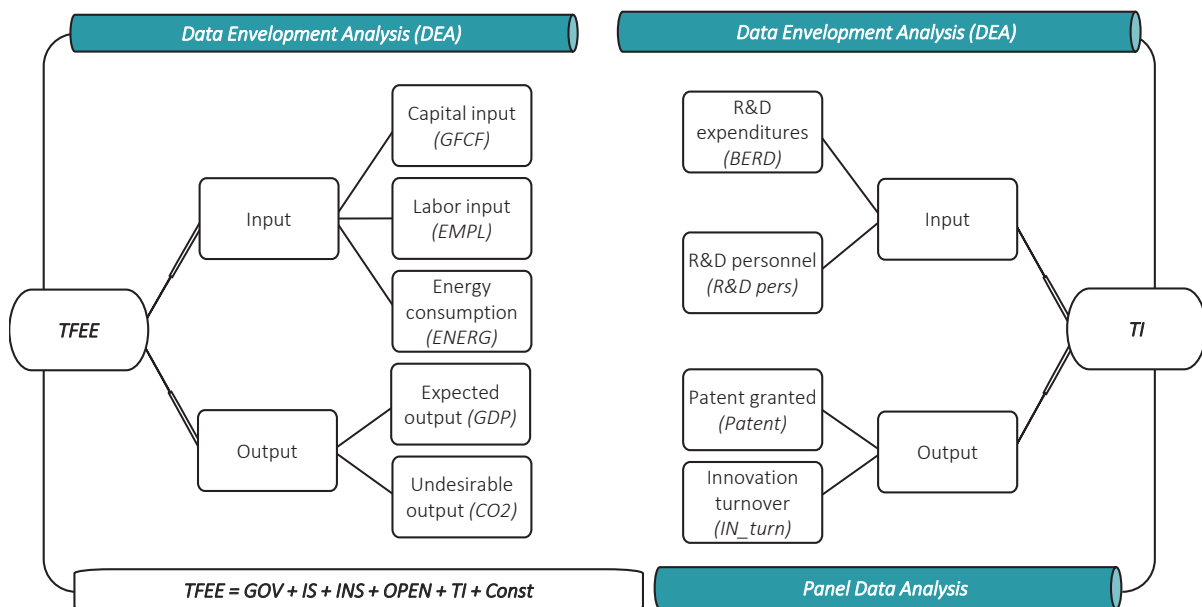


Figure 2. Relationship between total factor energy efficiency (TFEE) and technological innovation (TI)



Therefore, input and output factors are also considered in determining efficiency indicators (TI).

The capabilities of the DEA method for measuring and evaluating efficiency are immense. The basis of the DEA is the construction of a curve (boundary), based on the performance of the best countries.

There are different variations of DEA models (Lissitsa & Babićeva, 2003):

- 1) with direct and double input or output orientation and without orientation;
- 2) with a constant return to scale (CRS) or variable return to scale (VRS);
- 3) piecewise linear or piecewise non-linear type of production function.

It should be noted that models with a constant return to scale (CRS) can be considered CCR-Output and CCR-Input models. On the other hand, the basis of BCC models is input- or output-oriented models of efficiency, which differ from CCR models by adopting variable returns to scale (VRS).

There are also models where input- (costs) and output-oriented (profits) efficiency can be applied. These models are called input- and output-oriented or non-oriented models (ADD). Furthermore, in parallel with piecewise linear models, so-called “multiplicative models” or piecewise non-linear types of models were created without a similar orientation, such as VarMult and InvMult. These include a partially logarithmic or Cobb-Douglas production function instead of a partially linear function of the CCR, BCC, and ADD models.

This study uses a DEA-CCR model (primal CCR model) proposed by Charnes et al. (1978). In mathematical terms, the basic model that this study refers to would be:

Maximize

$$E_0 = \frac{\sum_{j=1}^s w_j y_{j0}}{\sum_{i=1}^r v_i x_{i0}} \tag{5}$$

Subject to

$$\frac{\sum_{j=1}^s w_j y_{jm}}{\sum_{i=1}^r v_i x_{im}} \leq 1, \quad m = 1, 2, \dots, n, \tag{6}$$

$$w_j \geq 0, \quad j = 1, 2, \dots, s,$$

$$v_i \geq 0; \quad i = 1, 2, \dots, r,$$

where  $y_{j0}$  – output  $j$  of the DMU<sub>0</sub>;  $x_{i0}$  – input  $i$  of the DMU<sub>0</sub>;  $w_j$  – weight of the output  $j$ ;  $v_i$  – weight of the output  $i$ ;  $n$  – number of the DMU;  $s$  – number of the inputs;  $r$  – number of the outputs.

This equation can be transformed into a conventional linear programming model by setting the denominator in the objective function equal to a constant (usually 1) and maximizing the numerator (Melao, 2005):

Maximize

$$E_0 = \sum_{j=1}^s w_j y_{j0} \tag{7}$$

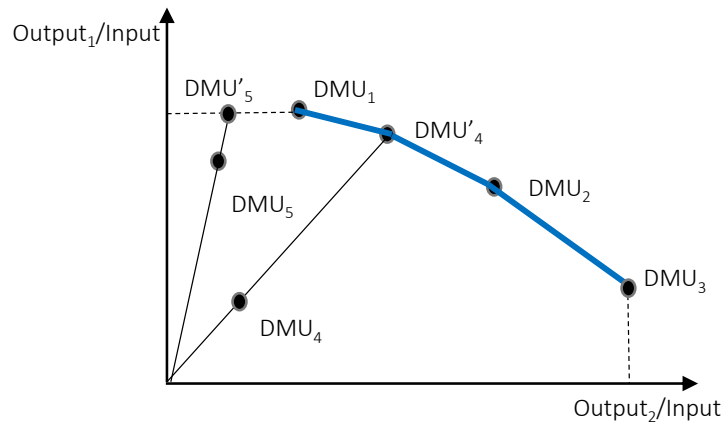
Subject to

$$\sum_{i=1}^r v_i x_{im} = 1, \tag{8}$$

$$\sum_{j=1}^s w_j y_{j0} - \sum_{i=1}^r v_i x_{im} \leq 0. \tag{9}$$

The data program Solver was used to calculate the unknown weights  $w_j$  and  $v_i$  for DEA. According to equation (5), the current CCR model contains several inputs and outputs, and it looks for a set of values for  $w_j$  and  $v_i$ , which aims to maximize  $E_0$ . The results of the maximum efficiency ( $E_0$ ) of DMU<sub>0</sub> will be  $0 < E_0 < 1$  due to the restrictions in (6). Therefore,  $E_0 = 1$  represents the maximum efficiency, when  $E_0 < 1$  indicates that DMU is inefficient.

As mentioned earlier, there are two ways to apply DEA: one is focused on input (costs), at which a certain level of output is achieved with a minimum amount of resources (investment minimization); the other is output-oriented (profits), in which output is maximized for a certain level of input (Paço & Pérez, 2013).



**Figure 3.** The DEA case with one input and two outputs

Figure 3 illustrates the DEA methodology for the output-oriented model with single input and two-output cases.

The line which connects all extreme DMUs is called “the efficiency frontier.” It defines the maximum combinations of outputs obtained from a given set of inputs. In the case of  $E_0 = 1$ , DMU is relatively efficient and, therefore, it becomes a “best practice” unit. Nevertheless, it does not mean that this unit is efficient in an absolute sense: there are no other DMUs (or combinations of DMUs) in the study that are more efficient. On the other hand,  $E_0 < 1$  signifies that the unit is relatively inefficient, which means that other DMUs (or combinations of DMUs) display higher efficiency. Hence, there is room for improvement (Melao, 2005).

**2.2.1. Total factor energy efficiency (TFEE)**

The model’s input parameters are capital, labor, and energy consumption (as technological progress parameters, assuming improvement of energy efficiency through technological progress); the expected output is GDP, and the undesirable output is carbon dioxide emission from the energy sector.

Input variables:

- Capital input (GFCF): gross capital formation (euro per capita).
- Labor input (EMPL): total employment (percent of the total population).

- Energy consumption (ENERG): primary energy consumption (tones of oil equivalents (TOE) per capita).

Output variables:

- Expected output (EO) the GDP of countries (euro per capita).
- Undesirable output (UO): energy-related carbon dioxide emission (tons CO2 per capita).

**2.2.2. Technological innovation (TI)**

Input variables:

- R&D expenditures (BERD): business enterprise R&D expenditure (ml. euro).
- R&D personnel and researchers (R&D pers): number of scientific researchers (full-time equivalent).

Output variables:

- Patents granted (Patent): European patent granted by the European patent office (number)
- Innovation turnover (IN\_turn): turnover from innovation core activities (ml. euro).

**2.3. Regression analysis**

A panel regression model is used to illustrate the effect of technological progress on improvement of energy efficiency. This paper proposes a linear model described by:



$$TFEE = GOV + IS + INS + OPEN + TI + Const. \quad (10)$$

The methodology includes Total factor energy efficiency (*TFEE*) as a dependent variable and technological innovation (*TI*) as a core influence variable. The model also includes five additional control variables, i.e., the degree of government intervention, industrial structure, infrastructure, and economic openness:

- Government intervention (*GOV*): final consumption expenditure of the general government (percent of the gross domestic product).
- Industrial structure (*IS*): manufacturing value added (percent of the gross domestic product).
- Infrastructure (*INF*): construction value added (percent of the gross domestic product).
- Economic openness (*OPEN*): Sum of imports and exports of goods and services (percent of the gross domestic product).

### 3. RESULTS AND DISCUSSION

#### 3.1. Results of DEA analysis

Based on the data envelope analysis, the indicators were ranged, and countries were divided into categories: top 15 (frontier) and bottom 15 (less efficient). The results are presented in Table 1. It shows that the bottom 15 countries, whose *TFEEs* were the lowest, are mainly countries of Central and Eastern Europe,

i.e., Slovenia, Czechia, Bulgaria, Romania, Estonia, Latvia, Lithuania, Hungary, Croatia, Austria, Poland (except the last year, where it showed an improvement in energy efficiency), and Finland as well.

The efficiency of Luxembourg, Portugal, Italy, United Kingdom, Sweden, Denmark, Malta, Ireland, Spain, Greece, France, Germany, Norway, and Iceland is almost at the frontier (except for some years for the last four countries).

When it comes to the technological capability of the countries, the results were similar, but the score was lower compared to the *TFEE* (Table 2).

Again, Central and Eastern European countries are inefficient according to the results of the DEA analysis, i.e., Hungary, Lithuania, Croatia, Latvia, Portugal, Romania, Bulgaria, Slovenia, Estonia, Greece, Malta, Cyprus (since 2016, the situation has decreased), Iceland, Denmark (except the last year), and Poland (showed an improvement in the last year, when it ended up among the top 15).

The main values of the *TFEEs* range from 0.37 to 1 in 2012, and 0.51 to 1 in 2020, reporting an overall positive trend in energy efficiency, as shown in Figure 4.

The countries displaying a decreasing trend during the period 2012–2020 are Norway, the Netherlands, Malta, Italy, Croatia, Greece, Spain, France, Germany, and Belgium.

The countries displaying an overall increasing trend but having some fluctuations during the period are Bulgaria, Czechia, Estonia, Latvia,

**Table 1.** The top 15 and bottom 15 (*TFEE*)

	2012	2014	2016	2018	2020
Top 15	Norway, Italy, Luxembourg, Greece, Denmark, United Kingdom, Ireland, Sweden, Spain, Cyprus, Netherlands, France, Germany, Austria, Portugal	Sweden, Denmark, United Kingdom, Norway, Luxembourg, Greece, Iceland, Ireland, Italy, Portugal, Cyprus, Malta, Netherlands, Spain, France	Iceland, Norway, Greece, Ireland, Sweden, Luxembourg, Denmark, United Kingdom, Italy, Portugal, Malta, Spain, Germany, Netherlands, Cyprus	Norway, Denmark, Malta, Sweden, Ireland, Luxembourg, Greece, Iceland, United Kingdom, Italy, Netherlands, Portugal, France, Germany, Spain	Sweden, Iceland, Lithuania, United Kingdom, Luxembourg, Ireland, Denmark, Greece, Italy, Malta, Cyprus, Germany, Poland, Spain, Portugal
Bottom 15	Lithuania, Belgium, Iceland, Finland, Slovakia, Malta, Slovenia, Poland, Croatia, Latvia, Czechia, Bulgaria, Hungary, Romania, Estonia	Germany, Austria, Belgium, Finland, Lithuania, Slovenia, Croatia, Slovakia, Latvia, Poland, Romania, Bulgaria, Czechia, Hungary, Estonia	France, Lithuania, Austria, Slovenia, Latvia, Belgium, Finland, Bulgaria, Poland, Croatia, Romania, Slovakia, Hungary, Czechia, Estonia	Cyprus, Austria, Lithuania, Slovenia, Belgium, Romania, Poland, Latvia, Slovakia, Finland, Bulgaria, Croatia, Czechia, Estonia, Hungary	Netherlands, Slovenia, Slovakia, France, Austria, Belgium, Norway, Finland, Bulgaria, Latvia, Romania, Czechia, Croatia, Hungary, Estonia

**Table 2.** The top 15 and bottom 15 (TI)

	2012	2014	2016	2018	2020
Top 15	Germany, Italy, Luxembourg, Norway, United Kingdom, Cyprus, Ireland, Poland, Belgium, Sweden, Netherlands, France, Spain, Slovakia, Austria	Norway, Germany, Luxembourg, Italy, Ireland, Sweden, Belgium, Cyprus, United Kingdom, Netherlands, France, Spain, Austria, Slovakia, Poland	Luxembourg, Germany, United Kingdom, Ireland, Italy, Sweden, France, Netherlands, Norway, Spain, Romania, Belgium, Poland, Finland, Slovakia	Belgium, Germany, Luxembourg, United Kingdom, Sweden, Norway, Netherlands, Ireland, Italy, France, Spain, Romania, Finland, Slovakia, Poland	Sweden, United Kingdom, Germany, Luxembourg, Norway, Netherlands, France, Italy, Ireland, Finland, Romania, Spain, Austria, Denmark, Belgium
Bottom 15	Romania, Czechia, Finland, Greece, Hungary, Malta, Croatia, Bulgaria, Latvia, Lithuania, Denmark, Portugal, Estonia, Slovenia, Iceland	Finland, Czechia, Portugal, Denmark, Greece, Malta, Hungary, Lithuania, Croatia, Latvia, Iceland, Romania, Bulgaria, Slovenia, Estonia	Austria, Latvia, Czechia, Denmark, Malta, Cyprus, Hungary, Greece, Portugal, Lithuania, Croatia, Bulgaria, Estonia, Iceland, Slovenia	Austria, Czechia, Latvia, Denmark, Malta, Portugal, Cyprus, Lithuania, Hungary, Greece, Bulgaria, Croatia, Estonia, Iceland, Slovenia	Poland, Slovakia, Czechia, Latvia, Cyprus, Greece, Malta, Hungary, Bulgaria, Lithuania, Portugal, Croatia, Iceland, Estonia, Slovenia

Lithuania, Hungary, Malta, Poland, Portugal, Romania, Slovenia, Slovakia, and Finland.

Denmark and Luxembourg were absolute leaders; Ireland, Sweden, and the United Kingdom were frontier counties during almost the entire period, except for some years. Norway and Greece just lost their position in the last year.

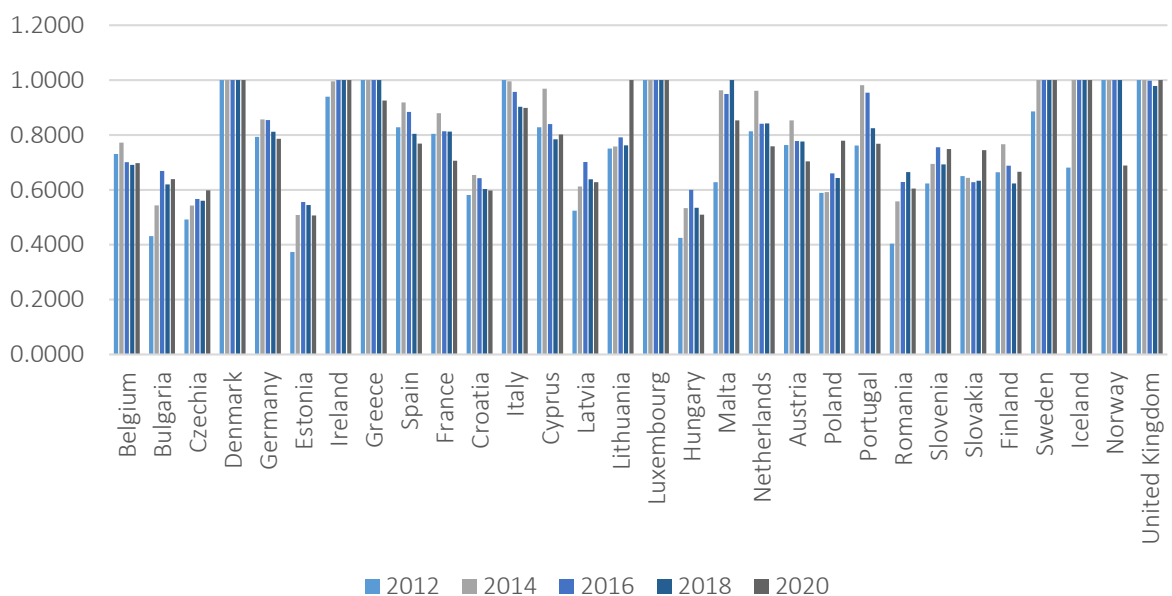
Overall, for most countries, 2014 was the most successful year in terms of energy efficiency, when the score was at its recorded maximum.

The TI indicator varies from 0.10 to 1.00 in 2012, and from 0.11 to 1.00 in 2020, which indicates lower score levels of innovation capability of the countries compared to the energy efficiency results (Figure 5).

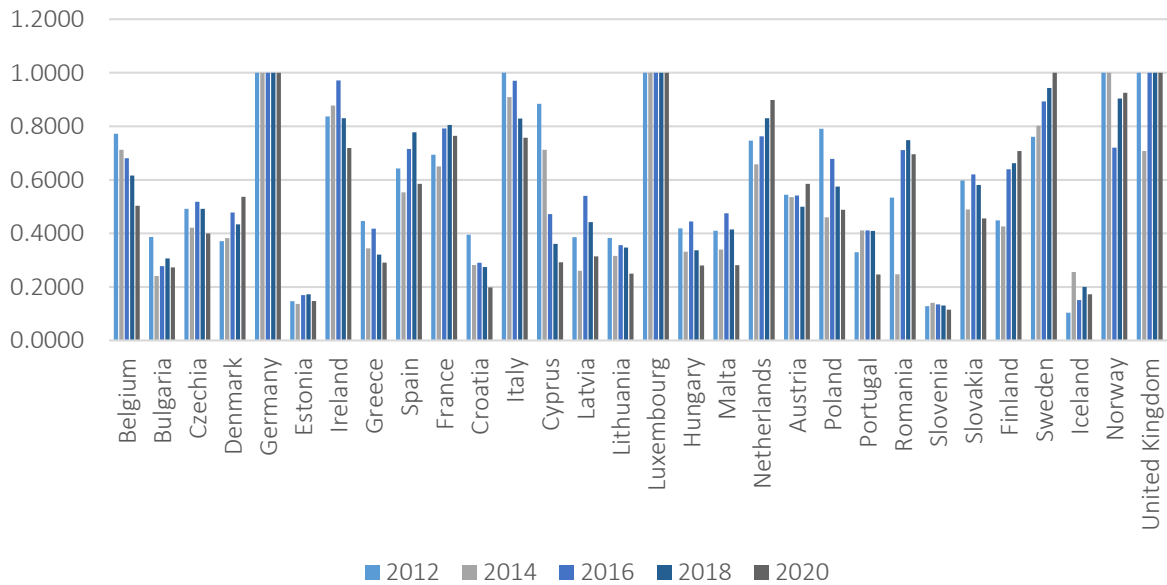
The TI of Denmark, France, Estonia, Lithuania, the Netherlands, Austria, Finland, Sweden, and Iceland gradually increased after 2012. Regarding the other countries, there was a decreasing trend in the last years compared to the early years of the observation period. It should be noted that only Germany and Luxembourg were absolute frontier countries during the entire period, 2012–2020.

Figures 6 and 7 indicate a higher energy efficiency level than innovation capability and a significantly decreasing TI trend for most countries.

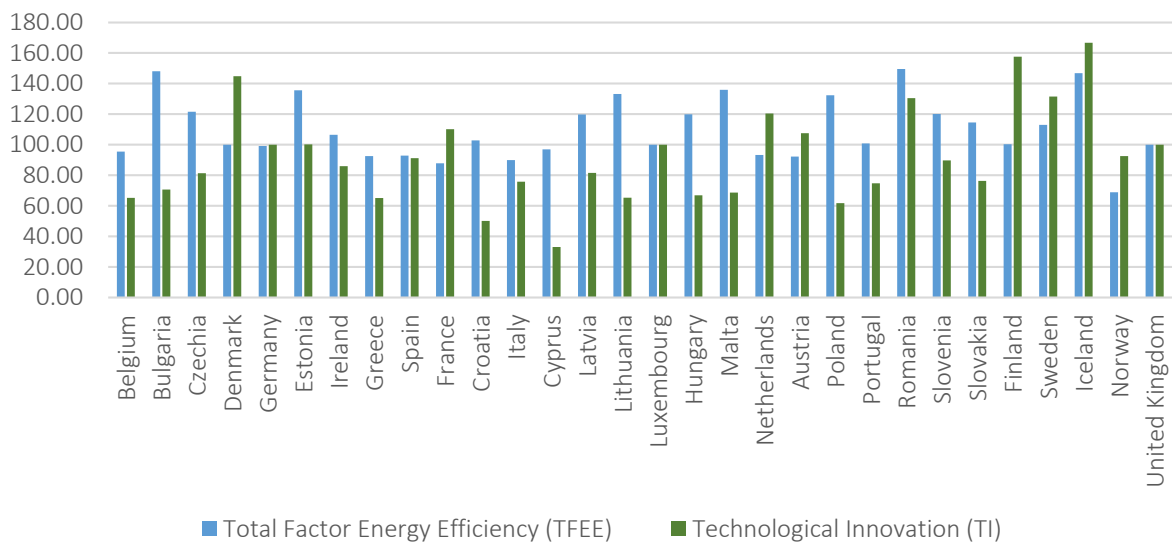
It is essential to highlight that for most countries, the average level of TI was lower during the investigated period compared to the average TFEE. The exceptions are Romania and



**Figure 4.** Estimated bi-annual values of TFEE, 2012–2020



**Figure 5.** Estimated bi-annual values of TI, 2012–2020



**Figure 6.** Growth rates of TFE and TI, 2012–2020

Germany, especially the last country that has a significantly better technological capability, which is max = 1, while energy efficiency still has room for improvement (Figure 7).

In addition, there is a traced correlation trends between the analyzed indicators. The total correlation during the period was positive and with a coefficient of an impressive 0.87 (Figure 8).

Moreover, correlation analyses for each country were conducted (Table 3). The results reveal an interesting feature: positive correlations were

observed in 14 countries, some of which were Central and Eastern European countries, some Western ones. Even countries with a high level of negative correlation had high levels of energy efficiency and innovation capabilities, such as Denmark, Norway, the United Kingdom, and Luxembourg.

Hence, the calculated indicators allow performing a last step in the analysis and investigating the relationship between energy efficiency and innovation capability by applying regression analyses.

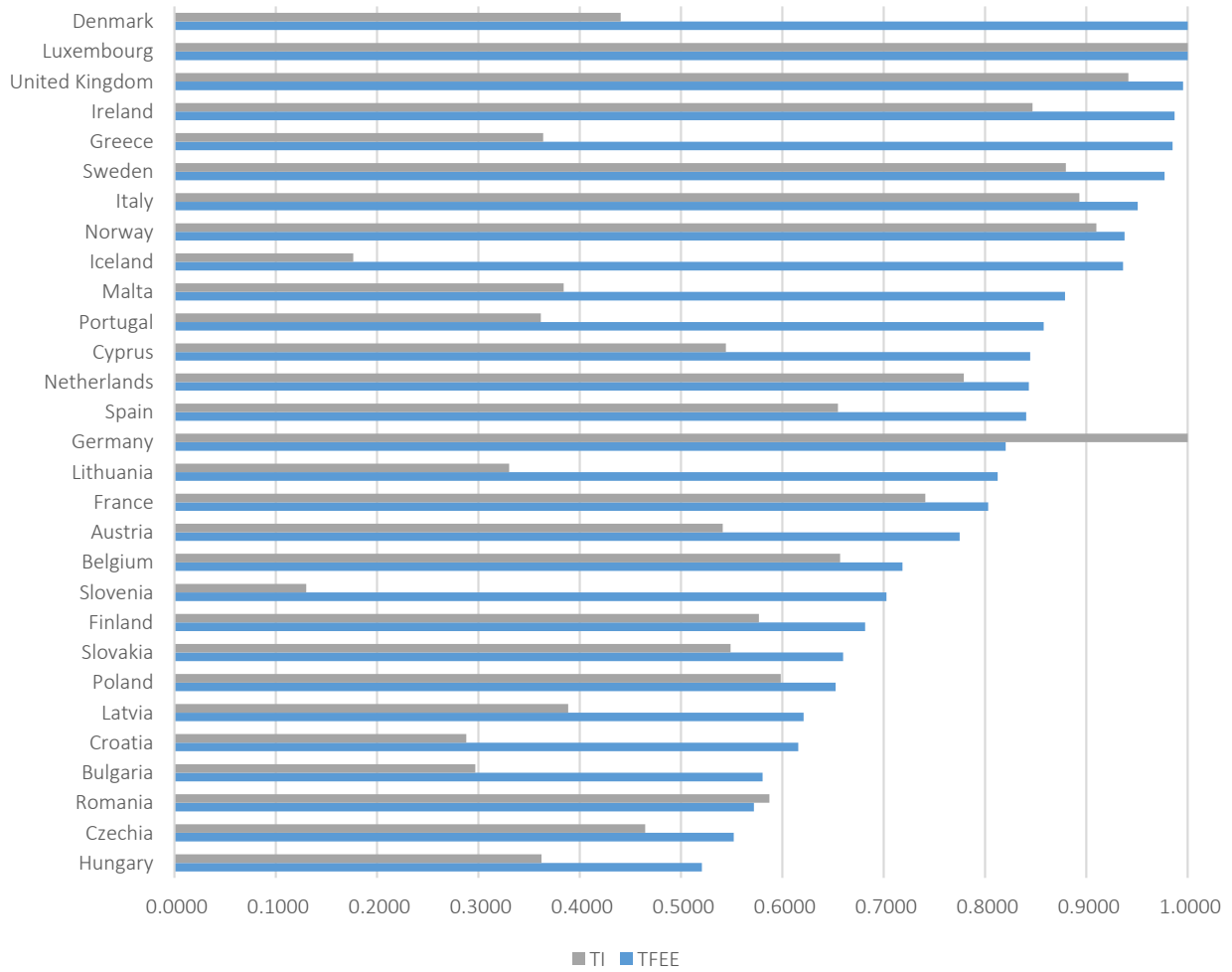


Figure 7. Average values of TFEE and TI, 2012–2020

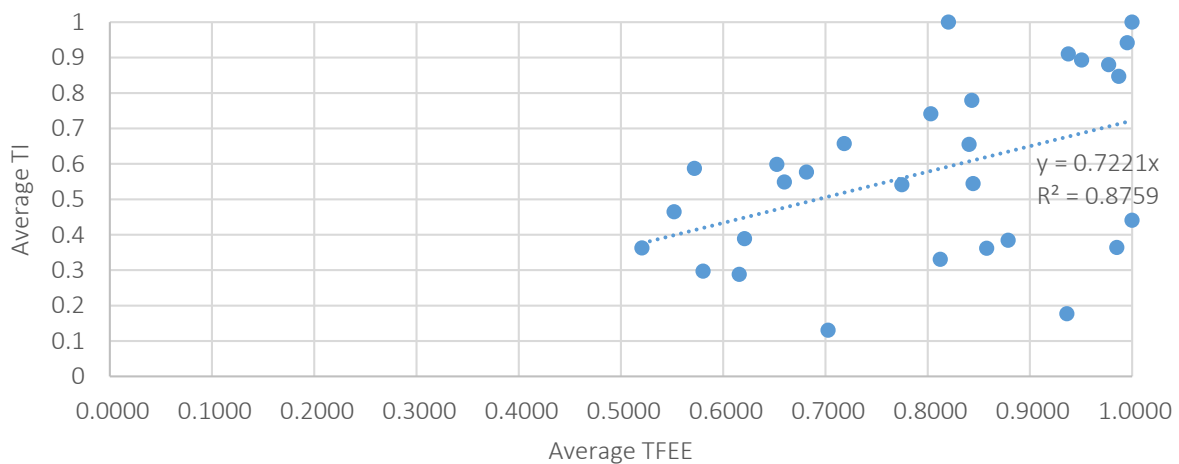


Figure 8. Correlation between TFEE and TI for 30 European economies, 2012–2020

**Table 3.** Correlation between TFEE and TI bi-annually, 2012–2020

Country	Positive	Country	Negative
Italy	0.8520	Norway	-0.0742
Portugal	0.7477	Slovenia	-0.1941
Iceland	0.7201	Spain	-0.2038
Sweden	0.6758	Croatia	-0.2326
Greece	0.6226	Luxembourg	-0.2503
Belgium	0.6002	United Kingdom	-0.2778
Estonia	0.5249	Denmark	-0.3742
Cyprus	0.5172	Czechia	-0.3981
Latvia	0.5038	Poland	-0.4001
Romania	0.4677	France	-0.4888
Hungary	0.0738	Austria	-0.5657
Malta	0.0575	Finland	-0.6254
Ireland	0.0497	Bulgaria	-0.6638
Germany	0.0023	Slovakia	-0.7580
		Netherlands	-0.8713
		Lithuania	-0.8764

### 3.2. Regression analysis

Based on the adjusted R<sup>2</sup> value, one can conclude that the model can explain 71% of the variation in total factor energy efficiency (TFEE). The results are reliable, with an F-value of less than 5%. According to the regression analysis results for 30 countries, 2012–2020 (Table 4), the estimated coefficient of the TI variable is significantly positive at the 1% level, while other control variables are estimated to have a negative impact on TFEE.

**Table 4.** Regression results, 2012–2020

Variable	Coefficient	t-ratio	Std. err
Dependent variable	113.92*	4.78	23.83
GOV	-0.14	-0.50	0.27
IS	-1.07*	-2.67	0.40
INS	-4.37*	-2.44	1.79
OPEN	-0.02	-0.61	0.03
TI	0.27*	2.99	0.09
R-squared		0.71	
F-statistic		5.05	
F-criteria		0.00	

Note: \* 1% significance level.

Similar results were observed while conducting time series cross-section regression analysis with five years of data from the 30 countries, i.e., only the technological innovation indicator was significantly positive (Table 5).

**Table 5.** Panel data (time series cross-section) analysis, 2012–2020

Variable	Coefficient	t-ratio	Std. err
Dependent variable	116.16*	10.96	10.59
GOV	-0.16**	-1.36	0.12
IS	-1.07*	-5.76	0.19
INS	-4.17*	-5.31	0.79
OPEN	-0.02**	-1.43	0.02
TI	0.24*	5.93	0.04
R-squared		0.65	
F-statistic		22.09	
F-criteria		0.00	

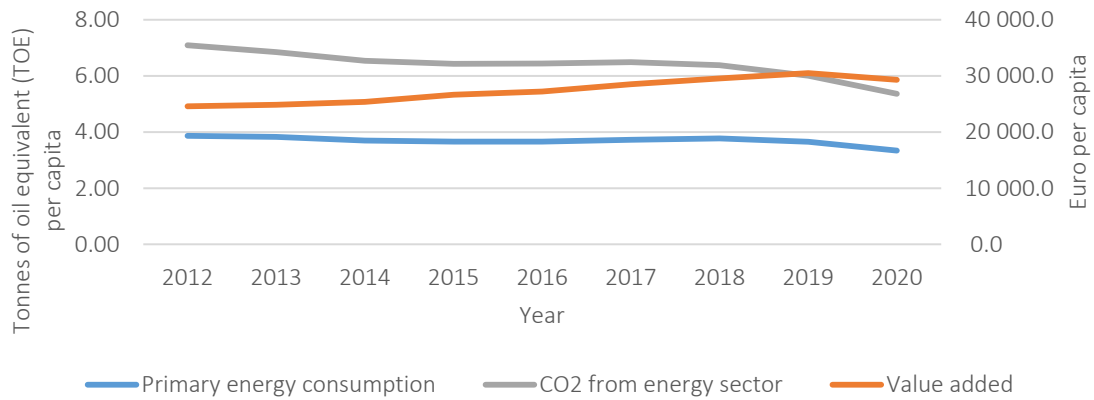
Note: \* 1% significance level; \*\* 10% significance level.

However, estimates of the cross-sectional data analysis for 2020 show that economic openness and innovation indicators also had a positive impact on TFEE (Table 6).

**Table 6.** Cross-sectional data analysis, 2020

Variable	Coefficient	t-ratio	Std. err
Dependent variable	123.31*	4.11	29.99
GOV	-0.50**	-1.57	0.32
IS	-0.61	-1.26	0.48
INS	-2.89**	-1.37	2.11
OPEN	0.004	0.09	0.04
TI	0.15**	1.53	0.10
R-squared		0.50	
F-statistic		1.65	
F-criteria		0.18	

Note: \* 1% significance level; \*\* 10% significance level.



**Figure 9.** Energy consumption, GDP growth, and CO2 emissions from the energy sector, average for 30 European countries, 2012–2020

Hence, the achieved results confirm the positive relationship between energy efficiency and the technological capability of the European countries.

### 3.3. Discussion

This study suggests that during the last decade, energy consumption per capita decreased (Figure 9) because of structural changes in the economies, the energy sector, and through additional improvements in energy efficiency due to new technology. This is also mainly because different energy sources produce different amounts of emissions. Therefore, energy consumption and intensity do not necessarily indicate environmental degradation (Grytten et al., 2020).

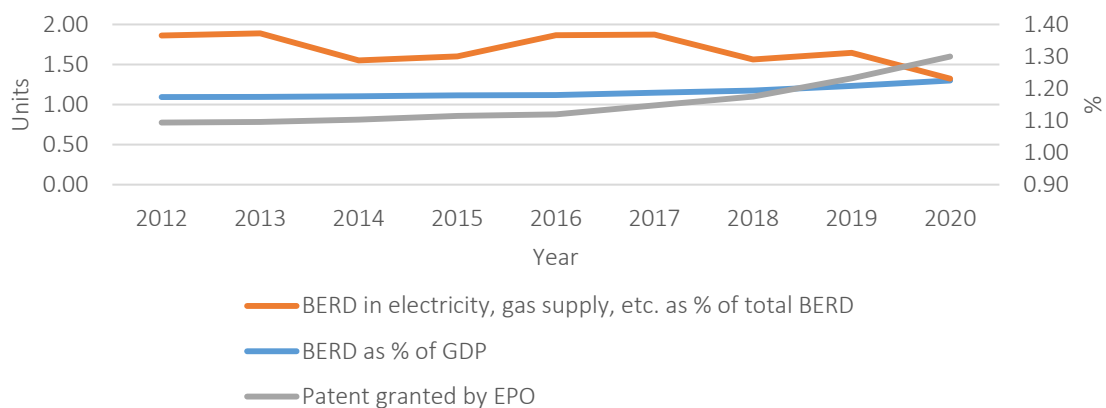
However, the current pace of energy efficiency improvement is not enough to overcome the other factors that increase energy consumption. Hence, the main challenge is further decoupling

of energy use and related CO2 emissions from economic growth (Konan & Aklobessi, 2021).

Another issue is that through outsourcing of energy intensive industries, Europe has reduced its emissions without necessarily having made any real improvements. The global energy consumption grew in the period of 2012-2020 by 6% primarily driven by China to which much of European manufacturing activities has been outsourced.

According to OECD (2011), the development and diffusion of clean technologies are crucial for moving towards energy efficiency and low-carbon economies. However, while the share of R&D expenditures in GDP is slightly increasing, the share of BERD in the electricity supply of total BERD has fluctuated and, during recent years, fallen to a low level (Figure 10).

Hence, the results show that science, technology, and innovation capabilities are essential for meet-



**Figure 10.** R&D expenditures and patents granted, average for European countries, 2012–2020



ing the challenges of climate change, increased need for energy consumption, and sustainability in general. Indeed, according to Petrushenko et al. (2021), technological development should be determined in the plane of “knowledge-innovation,” particularly regarding the transition to sustainability through simultaneous development of socially oriented and ecological activities.

At the same time, the need for significant financing on the way to a green economy as part of sustainable development remains undeniable (Versal & Sholoiko, 2022).

According to the “Fit for 55” package, the EU aims to align the climate and energy legislative framework with its 2050 climate neutrality objective. Thus, the European Council agreed to reduce the energy consumption of the EU by 36% for final consumption and 39 % for primary consumption by 2030. A significant challenge is to make transportation more energy efficient. Significant progress has been made in this field internationally, where Norway aims to take a leading role within the important maritime sector. These developments must go on.

Even though energy efficiency has improved over the past five years, energy demand is still increasing. This is one of the main reasons for environmental concerns. On the other hand, new technologies are believed to be the most promising, fastest, cheapest, and safest means to mitigate climate change. Moreover, technological innovation capability and energy efficiency are proclaimed as essential indicators to measure the success of the energy strategy. The present study suggests this is possible, but probably not without reducing the impact of factors increasing energy consumption.

The suggested Cobb-Douglas production function can be improved by adding foreign capital inflows (FDI) to the model. This variable can better explain the level of technology productivity (total factor productivity) and show how it accelerates economic development (Nthangu & Bokana, 2022).

Moreover, there is also the methodological shortcoming of energy numbers that do not use thermodynamics as a basis for unifying the various primary energy sources (Giampietro and Sorman, 2012). This can give errors in the range of 20-30%, so in a future study this problem can be overcome by using several other sources.

In addition, the proposed framework can be used to examine the effects of energy factors on economic growth and the environment considering industrial and firm levels. For example, accelerating technological progress has made digital tools viral, especially in the maritime industry. Using digital technology enables one to do things in less time and with less employees, which can reduce costs and optimize energy and emission efficiency.

The SFI MOVE project fosters innovation in close collaboration between R&D-performing companies and prominent research groups. It aims to support research and development activities that help to increase value creation within a sustainable framework. Hence, it is important to examine how new technologies in different industries address the issue of climate change, contribute to achieving the climate target on the way to climate neutrality, and enhance companies’ profitability and competitiveness. Hence, new investigations should consider technological innovation’s effects on energy efficiency at sectoral and firm levels.

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## CONCLUSION

This study represents a novel step towards enhancing the understanding of the impact of technological progress on energy efficiency and economic growth. It is based on an empirical study of 30 European economies. The results highlight the importance of further research and concentration at a sectoral level.

The paper proposes a two-step analysis. Firstly, a data envelopment analysis is used to measure efficiency indicators and illustrate the effects of energy factors on economic growth and the natural environment. In addition, the same methodology was compiled to assess the innovation capability of each country. Secondly,

the study explores the relationship between energy efficiency as a response variable and five explanatory variables: government intervention expressed as R&D expenditures, industrial structure, infrastructure, openness of the economy, and technological innovations. The data sample is collected from 30 European countries for the period 2012–2020 to run a quantitative econometric analysis.

The calculations of energy efficiency indicators revealed that Luxembourg, Portugal, Italy, the United Kingdom, Sweden, Denmark, Malta, Ireland, Spain, Greece, France, Germany, Norway, and Iceland are considered frontier countries almost every year (except for some years for the last four countries). Overall, for most countries, 2014 was the most successful year in terms of energy efficiency.

The technological indicator shows a lower innovation score than the energy efficiency results. The TI of Denmark, France, Estonia, Lithuania, the Netherlands, Austria, Finland, Sweden, and Iceland gradually increase after 2012. As for the other countries in the sample, there was a decreasing trend in the last years compared to the beginning of the observation period. It should be noted that only Germany and Luxembourg were absolute frontiers during the entire period, 2012–2020.

According to the applied regression analyses, the paper found that science, technology, and innovation capability are essential factors for increasing energy consumption when technology efficiency makes it possible to reduce energy consumption.

Hence, it can be concluded that technological progress plays a vital role in energy efficiency improvements; however, it is not sufficient alone to reverse the increasing demand for energy.

## AUTHOR CONTRIBUTIONS

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Formal analysis: Viktoriia Koilo.

Investigation: Viktoriia Koilo.

Methodology: Viktoriia Koilo.

Resources: Viktoriia Koilo.

Software: Viktoriia Koilo.

Validation: Viktoriia Koilo, Ola Honningdal Grytten, Jan Emblemsvåg.

Visualization: Viktoriia Koilo.

Writing – original draft: Viktoriia Koilo.

Writing – review & editing: Ola Honningdal Grytten, Jan Emblemsvåg.

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## REFERENCES

1. Bassanini, A., Scarpetta, S., & Visco, I. (2000). *Knowledge, Technology and Economic Growth: Recent Evidence from OECD Countries* (OECD Economics Department Working Papers No. 259). Paris: OECD Publishing. <https://doi.org/10.1787/536435460443>
2. Carlin, W., & Soskice, D. (2015). *Macroeconomics: Institutions, Instability, and the Financial System* (1st ed.) (638p.). Oxford.
3. Charnes A., Cooper, W.W., & Rhodes, E.L. (1978). Measuring the Efficiency of Decision Making Units. *European Journal of Operational Research*, 2, 429-444.
4. Dasgupta, S., & Roy, J. (2015). Understanding technological progress and input price as drivers of energy demand in manufacturing industries in India. *Energy Policy*, 83, 1-13. <https://doi.org/10.1016/j.enpol.2015.03.024>

5. European Patent Office. (2022). *European patent granted 2012-2021 per country of residence of the first named applicant*. Retrieved from <https://www.epo.org/about-us/annual-reports-statistics/statistics.html>
6. Eurostat. (2022). *Data Browser*. Retrieved from [https://ec.europa.eu/eurostat/databrowser/explore/all/all\\_themes?lang=en&display=list&sort=category](https://ec.europa.eu/eurostat/databrowser/explore/all/all_themes?lang=en&display=list&sort=category)
7. Giampietro, M., & Sorman, A. H. (2012). Are energy statistics useful for making energy scenarios? *Energy*, 37, 5-17. <http://dx.doi.org/10.1016/j.energy.2011.08.038>
8. Grytten, O. H., Lindmark, M., & Minde, K. B. (2020). The wealth of nations and sustainable development: energy intensity and the environmental Kuznets curve. *Environmental Economics*, 11(1), 110-123. [http://dx.doi.org/10.21511/ee.11\(1\).2020.10](http://dx.doi.org/10.21511/ee.11(1).2020.10)
9. Hritonenko, N., & Yatsenko, Y. (2013). Modeling of Technological Change. In *Mathematical Modeling in Economics, Ecology and the Environment* (pp. 53-88). Boston, MA: Springer. [https://doi.org/10.1007/978-1-4614-9311-2\\_3](https://doi.org/10.1007/978-1-4614-9311-2_3)
10. Jin, T., & Kim, J. (2019). A comparative study of energy and carbon efficiency for emerging countries using panel stochastic frontier analysis. *Scientific Reports*, 9, 6647. <https://doi.org/10.1038/s41598-019-43178-7>
11. Karali, N., Park, W. Y., & McNeil, M. (2017). Modeling technological change and its impact on energy savings in the U.S. iron and steel sector. *Applied Energy*, 202, 447-458. <https://doi.org/10.1016/j.apenergy.2017.05.173>
12. Koilo, V. (2019). Evidence of the Environmental Kuznets Curve: Unleashing the Opportunity of Industry 4.0 in Emerging Economies. *Journal of Risk and Financial Management*, 12(3), 122. <https://doi.org/10.3390/jrfm12030122>
13. Konan, Y. S., & Aklobessi, K. (2021). Revisiting the environmental Kuznets curve: Evidence from West Africa. *Environmental Economics*, 12(1), 64-75. [https://doi.org/10.21511/ee.12\(1\).2021.06](https://doi.org/10.21511/ee.12(1).2021.06)
14. Lestari, D., Lesmana, D., Yudaruddin, Y. A., & Yudaruddin, R. (2022). The impact of financial development and corruption on foreign direct investment in developing countries. *Investment Management and Financial Innovations*, 19(2), 211-220. [https://doi.org/10.21511/imfi.19\(2\).2022.18](https://doi.org/10.21511/imfi.19(2).2022.18)
15. Li, Y., Chiu, Y., & Lin, T. (2019). Energy and Environmental Efficiency in Different Chinese Regions. *Sustainability*, 11(4), 1216. <https://doi.org/10.3390/SU11041216>
16. Li, Y., Sun, L., Feng, T., & Zhu, C. (2013). How to reduce energy intensity in China: A regional comparison perspective. *Energy Policy*, 61, 513-522. <https://doi.org/10.1016/j.enpol.2013.06.007>
17. Lissitsa, A., & Babićeva, T. (2003). *Data Envelope Analysis (DEA) – Modern Method of Determination Production Efficiency* (Discussion Paper No. 50). Institute of Agricultural Development in Central and Eastern Europe (IAMO). (In Russian). Retrieved from <https://digital.bibliothek.uni-halle.de/pe/urn/urn:nbn:de:gbv:3:2-23263>
18. Melao, N. (2005). Data envelopment analysis revisited: a neophyte's perspective. *International Journal of Management and Decision Making*, 6(2), 158-179. <http://dx.doi.org/10.1504/IJMDM.2005.006029>
19. Nthangu N. D., & Bokana, K. G. (2022). Foreign capital inflows, trade openness and output performance in selected sub-Saharan African countries. *Investment Management and Financial Innovations*, 19(1), 236-246. [https://doi.org/10.21511/imfi.19\(1\).2022.18](https://doi.org/10.21511/imfi.19(1).2022.18)
20. OECD. (2011). *Towards Green Growth: Monitoring Progress. OECD Indicators*. New York. Retrieved from <https://millenniumindicators.un.org/unsd/envAccounting/ceea/meetings/UNCCEA-6-11.pdf>
21. Olsson, L. E. (1994). Energy-Meteorology: A new Discipline. *Renewable Energy*, 5(5-8), 1243-1246. [https://doi.org/10.1016/0960-1481\(94\)90157-0](https://doi.org/10.1016/0960-1481(94)90157-0)
22. Ouyang, X., & Lin, B. (2015). Analyzing energy savings potential of the Chinese building materials industry under different economic growth scenarios. *Energy and Buildings*, 109, 316-327. <https://doi.org/10.1016/j.enbuild.2015.09.068>
23. Paço, C. L., & Pérez, J. M. C. (2013). The use of DEA (Data Envelopment Analysis) methodology to evaluate the impact of ICT on productivity in the hotel sector. *Via Tourism Review*, 3. <https://doi.org/10.4000/viatourism.1005>
24. Petrushenko, M., Burkynskiy, B., Shevchenko, S., & Baranchenko, Y. (2021). Towards sustainable development in a transition economy: The case of eco-industrial parks in Ukraine. *Environmental Economics*, 12(1), 149-164. [https://doi.org/10.21511/ee.12\(1\).2021.13](https://doi.org/10.21511/ee.12(1).2021.13)
25. Shang, Y., Liu, H., & Lv, Y. (2020). Total factor energy efficiency in regions of China: An empirical analysis on SBM-DEA model with undesired generation. *Journal of King Saud University – Science*, 32(3), 1925-1931. <https://doi.org/10.1016/j.jksus.2020.01.033>
26. Shao, S., Yang, Z., Yang, L., & Ma, S. (2019). Can China's Energy Intensity Constraint Policy Promote Total Factor Energy Efficiency? Evidence from the Industrial Sector. *The Energy Journal*, 40(4), 101-128. <https://doi.org/10.5547/01956574.40.4.ssha>
27. Solow, R.M. (1957). Technical Change and the Aggregate Production Function. *Review of Economics and Statistics*, 39, 312-320. <https://doi.org/10.2307/1926047>
28. Versal, N., & Sholoiko, A. (2022). Green bonds of supranational financial institutions: On the road to sustainable development. *Investment Management and Financial Innovations*, 19(1), 91-105. [https://doi.org/10.21511/imfi.19\(1\).2022.07](https://doi.org/10.21511/imfi.19(1).2022.07)

29. Wang, C.-N., Le, A. L., & Hou, C.-C. (2019). Applying Undesirable Output Model to Security Evaluation of Taiwan. *Mathematics*, 7(11), 1023. <https://doi.org/10.3390/math7111023>
30. Wang, H., & Wang, M. (2020). Effects of technological innovation on energy efficiency in China: Evidence from a dynamic panel of 284 cities. *Science of The Total Environment*, 709, 136172. <https://doi.org/10.1016/j.scitotenv.2019.136172>
31. Zeraibi, A., Balsalobre-Loren-te, D., & Shehzad, K. (2020). Examining the Asymmetric Nexus between Energy Consumption, Technological Innovation, and Economic Growth; Does Energy Consumption and Technology Boost Economic Development? *Sustainability*, 12(21), 8867. <https://doi.org/10.3390/su12218867>
32. Zhang, R., & Fu, Y. (2022). Technological progress effects on energy efficiency from the perspective of technological innovation and technology introduction: An empirical study of Guangdong, China. *Energy Reports*, 8, 425-437. <https://doi.org/10.1016/j.egy.2021.11.282>
33. Zhu, W., Zhang, Z., Li, X., Feng, W., & Li, J. (2019). Assessing the effects of technological progress on energy efficiency in the construction industry: A case of China. *Journal of Cleaner Production*, 238, 117908. <https://doi.org/10.1016/j.jclepro.2019.117908>