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Factors affecting energy sector efficiency in OECD countries

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Abstract Energy efficiency is an important concept for ensuring sustainable development and reducing energy consumption. Efficiency means using a minimal amount of energy to complete a process. Considering the amount of energy needed by OECD countries, we aimed to analyze the energy efficiency of 37 OECD countries in different sectors, such as transport, industry, trade, and agriculture for 2015. The analysis involves modeling the efficiency results obtained using multivariate adaptive regression splines to explore linear and nonlinear relationships. We examined the effects of various factors, such as Gross National Income (GNI), population density, Gross Fixed Capital Formation (GFCF), Gross Floor Area (GFA), CO2 density, and Total Primary Energy Supply (TPES). The results showed that the energy efficiency of OECD countries varies greatly between different sectors, with transport and industry being the least productive. In addition, this study revealed that the nonlinear effects of the GNI of the energy mix, population density, and CO2 density significantly affect energy efficiency. The findings show that policies aiming to promote energy efficiency in different sectors should consider the non-linear effects of various factors that can lead to more efficient and sustainable energy use. In addition, increasing energy efficiency has many benefits, including environmental protection, cost savings, and improved economic performance.

Keywords Data Envelopment Analysis · Second Stage Analysis · Energy Efficiency · OECD · MARS

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1. Introduction

Energy is defined as "the capacity to move or be active" or "available power" (Energy, 2020). Since no energy source is infinite, reducing energy use is of utmost importance. Careless use of energy can cause environmental damage, and the ongoing war between Ukraine and Russia and the emerging energy crisis underscore the importance of energy (Prisecaru, 2022; Hutter and Weber, 2022; Kuzemko et al., 2022). Two ways to address these issues are through efficient energy use and the adoption of renewable energy sources.

In the European Union (EU), energy efficiency is a key factor in reducing energy consumption and greenhouse gas emissions (GHG) (European Commission, 2021). According to the International Energy Agency's (2021) report on Turkey, increasing the energy efficiency of commercial buildings can significantly reduce energy consumption and carbon emissions. The report also highlights the residential sector, commercial buildings, and transportation as important factors influencing energy consumption and CO2 emissions. Edenhofer et al. (2014) demonstrated that transportation is one of the main sources of energy consumption and CO2 emissions in modern society. As the demand for transportation increases, so do energy consumption and its associated emissions. Creutzig et al. (2015) argued that as transportation increases, carbon emissions rise, posing a significant challenge to sustainable development. Energy efficiency requires the most efficient use of energy to produce specific products and services, which are influenced by various product-related factors. By grouping and classifying these factors into inputs and outputs, optimum energy efficiency can be achieved by reducing positive inputs and increasing negative outputs.

We aimed to examine the energy efficiency of the transport, industry, trade, and agriculture sectors in OECD countries. We used Data Envelopment Analysis (DEA) to determine energy efficiency scores for each sector and then conducted a second-stage analysis to assess the impact of various factors, such as GNI, population density, GFCF, GFA, CO2 intensity, and TPES. In the second stage, we used Multivariate Adaptive Regression Splines (MARS) to explore both linear and non-linear relationships simultaneously.

The importance of energy efficiency is critical not only because of its impact on climate change and fossil fuel depletion but also because it promotes sustainable development by increasing countries' energy security.

2. Related work

As a key strategy for sustainable development, energy efficiency plays an important role in combating climate change, ensuring energy security, and increasing economic welfare. In this context, extensive research on the determinants and impacts of energy efficiency has focused on different regions and sectors around the world.

Hamilton and Turton (2002) investigated the factors contributing to the growth of energy-related GHG emissions in OECD countries during the period 1982–1997. Employing a decomposition approach, this study dissects the impacts of various factors, including changes in population, economic growth, production energy intensity, primary energy use in final energy consumption, the proportion of fossil fuels in the energy mix, and the carbon intensity associated with fossil fuel combustion. The results suggest that the primary drivers of emission growth are economic expansion and an increased demand for primary energy to meet final energy consumption. However, these effects are partially mitigated by reductions in energy intensity and a decrease in reliance on fossil fuels. Shi et al. (2010) considered the energy efficiency of China regions

at the macro-economy level and used DEA to consider undesirable output variables. They claim that the energy consumption cannot be minimized without considering undesirable outputs into consideration. Song et al. (2013) used a super-slacks-based measure (SBM) and Bootstrap DEA to determine the efficiency of BRIC countries. They showed an improvement in the efficiency through years and the effect of energy structures on the relationship between the factors and efficiency. Wang et al. (2013) highlighted the varying economic, structural, and development characteristics of China's provinces. This leads to bias when determining energy efficiency. China's rapid growth has increased their demand for energy, so biased efficiency is the last thing they need. Energy consumption also increases the harmful consequences for the environment. Industry, transport, and fuel combustion cause air pollution. Wu et al. (2014) analyzed the total factor energy of Chinese regions considering both technical efficiency and the technology progress rate. They found that even though the Chinese government's efforts were insignificant, overall energy efficiency improvement was low. Cui and Li (2014) defined the transportation energy efficiency and proposed a three-staged DEA model to evaluate the transportation energy efficiency in China regions for years approximately 2003-2012. Xie et al. (2014) used a Malmquist approach to determine the efficiency of the BRIC and OECD countries. In the second stage, Tobit regression is used to show that economic factors influence efficiency. Apergis et al. (2015) study in OECD countries between 1995 and 2011 and found that productivity has declined over time. In addition, focus on the importance of cost minimization and CO2 emissions. Liu and Wang (2015) proposed another modified DEA model based on network DEA and determined the energy efficiency in China industry. Sineviciene et al. (2017) investigated the determinants of energy efficiency and consumption in 11 post-communist countries in Eastern Europe over the period 1996-2013. The study analyzes long-term dynamic relationships using a stochastic frontier function approach and comparative analysis. The results show that Gross Domestic Product (GDP) growth is the main driver of both energy efficiency and consumption. Other important factors for energy efficiency include CO2 emissions per capita, fixed capital and the share of industry in the economy. Park et al. (2018) used an SBM-DEA model to investigate energy efficiency in transportation in the United States between 2004 and 2012. CO2 was used as an undesirable output, and the results showed that most states are favorable for development. However, energy efficiency is a concern in developing countries. He et al. (2019) conducted a comprehensive analysis of energy efficiency levels in 32 OECD countries between 1995 and 2016 using the epsilon-based measurement (EBM) DEA model. This study compares how energy efficiency is affected by environmental factors through efficiency and forecast value analyses. Fidanoski et al. (2021) investigated energy efficiency through an integrated model that connects energy, environment, technology, and urbanization. They assessed how efficiently developed countries use primary energy and electricity (secondary energy). Using DEA, they calculated efficiency scores for minimizing energy consumption, losses, and environmental emissions in a sample of 30 OECD member countries from 2001 to 2018. They found that countries had mean inefficiency margins of 16.1% for primary energy and 10.8% to 13.5% for electricity. Piling et al. (2021) identify a noteworthy influence of environmental tax policies on energy efficiency in OECD countries between 1995 and 2016. Their research delves deeper, revealing that taxes targeting energy use, vehicles, and the environment all contribute significantly to improved energy efficiency. Kazemzadeh et al. (2022) used data from 16 emerging countries in the years approximately 1990-2014 and estimated the energy efficiency. They used SBM-DEA for the first stage and quantile regression for the second stage. They found that Turkey and Hungary were better in efficiency and showed a relationship between energy efficiency and the ecological footprint. Paramati et al. (2022) used a dataset from 28 OECD countries for the years between 1990 and 2014 and proved the positive effect of environmental technology on energy efficiency. Bertoldi's (2022) study underlined that academic

recommendations are not implemented on a large scale. The results also demonstrated the positive impact of energy efficiency policies and recommended that OECD citizens reduce their energy demand.

Multi-stage DEA models are now preferred over classical DEA (Wang et al., 2017; Wang and Wang, 2022; Wang et al., 2022; Zhang and Chen, 2022; Zuo et al., 2022; Zhu et al., 2022). This study makes an important contribution to the existing literature. First, it enables the development of specific strategies on a sectoral basis by analyzing in detail the factors affecting energy efficiency in different sectors. Second, it analyzes non-linear relationships using the MARS method and reveals significant non-linear effects of GNI and CO2 intensity on energy efficiency. The effects of other factors, such as population density, GFCF, GFA, and TPES, were also analyzed.

3. Methodology

3.1. Data envelopment analysis

In DEA, organizational units such as enterprises, institutions, firms, and companies that produce similar outputs using similar inputs are called decision-making units (DMUs) (Aydemir, 2002). DEA is a non-parametric efficiency measurement technique designed to assess the relative efficiency of these DMUs in converting inputs into outputs. This method enables the determination of how to efficiently use available resources to produce output (Ramanathan, 2003). The process starts with the identification of appropriate DMUs, followed by the determination of inputs and outputs for the relative efficiency measurement of these units.

Let n denote the number of DMUs, indexed by $j = 1, ..., n$, where each DMU utilizes a distinct combination of inputs x_{ij} (for $i = 1, ..., m$) to produce a set of outputs y_{rj} (for $r = 1, ..., s$). Specifically, the $j-th$ DMU generates an output y_{rj} corresponding to the $r-th$ output while consuming an input x_{ij} associated with the $i-th$ input. It is assumed that $x_{ij} \geq 0$ and $y_{rj} \geq 0$, with the condition that each DMU has at least one positive input and one positive output. In the context of DEA, the efficiency of a given DMU is evaluated by the ratio of its total output to its total input, where the "effectiveness" of inputs and outputs is determined in relation to the observed data. The efficiency score reflects the relative ability of a DMU to convert inputs into outputs and is derived from the comparison of each DMU's performance to that of the best-performing units (Luptacik, 2010).

Let θ_k be efficiency score for DMU_k. Then, the input-oriented CCR model (Charnes, 1978) can be expressed as follows:

$$\min g_0(\theta, s^-, s^+) = \theta_k - \varepsilon \left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right)$$

$$constraints\ \theta_k x_{ik} - \sum_{j=1}^{n} x_{ij}\lambda_j - s_{ik}^- = 0$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j - s_{rk}^+ = y_{rk}$$

$$\lambda_j \geq 0, s_i^- \geq 0, s_r^+ \geq 0$$

$$i = 1, ..., m, j = 1, ..., n, r = 1, ..., s.$$

In the input-oriented CCR model, the objective function shows how much the inputs of the relevant DMU can be reduced radially (circularly) for a certain output level. In this model, DMUs with an efficiency value of 1 are efficient.

Here λ_j, is the density value of DMU_j and indicates whether the DMU_j will be in the reference group. The s_i^- in the model represents the excess amount used by the i-th input, in other words, the idle value of the i-th input, to produce the observed outputs of the DMU. s_r^+, on the other hand, represents the difference between the amount of output to be achieved and the observed output of the r-th output of the DMU, in other words, the idle value of the r-th output (Sözen and Cengiz, 2022).

3.2. Multivariate Adaptive Regression Splines (MARS)

The MARS model comprises basis functions and model parameters. The general MARS model is expressed as follows.

$$Y = \beta_0 + \sum_{k=1}^{K} a_k B_k(x_t) + \varepsilon_i$$

Here, k is the number of nodes, K is the number of basis functions, β_0 is the constant term, α_k is the coefficient for k-th basis function and B_k is k-th basis function for t-th independent variable. Basis functions are defined as follows:

$$B_k(x) = \prod_{j=1}^{J_k} \left[S_{kj}(x_{wkj} - t_{kj}) \right]_+, k = 1, 2, ..., K.$$

J_k is the number of splits and is used to obtain B_k. $[\cdot]_+$ is $\max[0, \cdot]_+$ and can be expressed as a hinge function, $h(.)$. $S_{kj} \in [\pm 1]$ and it defines the direction of B_k. t_{kj} is the split point and x_{wkj} is corresponding value of variable.

The structural model constructed using MARS employs a piecewise linear basis function expansion of the form $(x-t)_+$ and $(t-x)_+$. Here, the subscript "+" denotes the positive part, meaning that the basis function equals zero if the specified condition is not met. This definition is defined as follows (Friedman, 1991):

$$\begin{cases} (x-t)_+ = \{x-t, \;\; x > t \, 0 \, , otherwise \\ (t-x)_+ = \{t-x, \;\; x < t \, 0 \, , otherwise \;\;)) \end{cases}$$

Thus, "t" is the node value, and each function is piecewise linear at "t". The basis functions $(x-t)_+$ and $(t-x)_+$ are known as a mirrored pair, representing the right and left regions of the knot "t" respectively (Sevimli, 2009). The independent variable value at which the relationship form changes is called a node. In other words, the node value is the last value of the independent variable that does not alter the slope of the line within the defined intervals.

The MARS model uses the weighted sum of piecewise linear basis functions to construct a nonparametric regression model that includes nonlinear functions and interactions of estimators (Leblanc and Crowley, 1999).

The model building process consists of two stages. These two stages are called forward and backward passes. In the forward pass process, as the name suggests, an overfit model is built as much as possible by adding the basis functions of the nodes that minimize the sum of the error squares to the initial constant model. Then, in the backward pass process, the basis functions are subtracted one by one, giving the lowest generalized cross-validation (GCV) value. GCV is calculated using

$$GCV = \frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{(1 - (r + \lambda z)/N)^2}.$$

z is the number of nodes and r is the number of basis functions in the model. The value of λ is constant and is generally chosen as 3 in regression models with multiplicative terms and 2 in additive regression models (Friedman et al., 2001).

4. Results

Energy efficiency is a multifaceted and intricate concept that poses challenges in measurement and evaluation. Therefore, it is advantageous to dissect it into subfactors aligned with various sectors or domains of operation. Previous research has identified a large number of potential sub-factors covering areas such as transport, industry, commercial enterprises, agriculture, fisheries, forestry, residential areas, and others (Perez et al., 2008; Bowden and Payne, 2009; Zachariadis, 2007; Jobert and Karanfil, 2007). In this study, we focus on four main sectors: transport, industry, commercial enterprises, and agriculture. These sectors were selected due to their important role in energy consumption, GHG emissions, and data availability. The analysis uses data from all OECD countries for 2015. Analyzing energy efficiency in these sectors can provide important insights into the overall energy efficiency landscape in OECD countries and highlight potential areas for improvement. In addition, using data from different sectors provides a comprehensive understanding of energy efficiency trends and dynamics in various fields of activity. This knowledge can ultimately inform policymakers and stakeholders about creating more effective strategies and policies aimed at promoting energy efficiency and sustainability in OECD countries and around the world. Datasets were obtained from different sources, such as WorldBank, OECD, World Energy Council, and Energy Information Administration. Table 1. gives input and output variables for energy subsectors. The DEA models constructed using the variables in Table 1 determined the efficiencies for each subsector.

Table 1

Inputs and Outputs of Subsectors

Subsector	Inputs	Outputs
Transport	• Energy consumption (ktoe) Employment	• GDP (US million $) CO2 emissions (million ton)
Industry	• Energy consumption (ktoe) Employment	• GDP (US million $) CO2 emissions (million ton)
Commercial	• Energy consumption (ktoe) Employment	• GDP (US million $) CO2 emissions (million ton)
Agriculture	• Energy consumption (ktoe) Employment	• GDP (US million $) CO2 emissions (million ton)

According to Table 2:

- Iceland, Japan, Luxembourg, Switzerland, and the United States are efficient in transportation energy consumption.
- Estonia, Germany, Ireland, Japan, Luxembourg, Switzerland, and the United States have efficient industrial energy consumption.
- Iceland, Italy, Japan, Luxembourg, Mexico, Switzerland, the United Kingdom, and the United States are efficient in their commercial energy consumption.

- Australia, Germany, Iceland, Japan, Luxembourg, Norway, and the United States are efficient producers of agricultural energy consumption.

Table 2

DEA Eefficiency Scores of Each Subsector for OECD Countries

Countries	Transport	Industry	Commercial	Agriculture
Australia	0.610	0.662	0.872	**1.000**
Austria	0.591	0.289	0.897	0.288
Belgium	0.496	0.288	0.599	0.422
Canada	0.919	0.480	0.223	0.758
Chile	0.225	0.161	0.508	0.222
Colombia	0.232	0.187	0.828	0.092
Czech Republic	0.257	0.230	0.333	0.247
Denmark	0.659	0.588	0.745	0.534
Estonia	0.478	**1.000**	0.908	0.262
Finland	0.404	0.322	0.459	0.443
France	0.781	0.630	0.977	0.697
Germany	0.760	**1.000**	0.808	**1.000**
Greece	0.364	0.306	0.577	0.250
Hungary	0.240	0.219	0.323	0.245
Iceland	**1.000**	0.408	**1.000**	**1.000**
Ireland	0.623	**1.000**	0.798	0.420
Israel	0.458	0.475	0.782	0.756
Italy	0.921	0.758	**1.000**	0.643
Japan	**1.000**	**1.000**	**1.000**	**1.000**
Korea	0.335	0.707	0.357	0.361
Latvia	0.416	0.656	0.722	0.195
Lithuanian	0.376	**1.000**	0.790	0.260
Luxembourg	**1.000**	**1.000**	**1.000**	**1.000**
Mexico	0.396	0.366	**1.000**	0.262
Netherlands	0.722	0.339	0.651	0.732
New zealand	0.450	0.238	0.743	0.721
Norway	0.586	0.690	0.563	**1.000**
Poland	0.237	0.175	0.353	0.104
Portugal	0.371	0.227	0.637	0.204
Slovakia	0.301	0.224	0.404	0.391
Slovenia	0.385	0.500	0.940	0.346
Spain	0.741	0.443	0.970	0.642
Sweden	0.529	0.358	0.621	0.768
Switzerland	**1.000**	**1.000**	**1.000**	0.473
Turkey	0.350	0.203	0.409	0.659
United Kingdom	0.785	0.757	**1.000**	0.551

Countries	Transport	Industry	Commercial	Agriculture
United states	**1.000**	**1.000**	**1.000**	**1.000**

High efficiency in the transport sector can be attributed to improved public transportation systems, stringent fuel efficiency standards and significant investments in sustainable transport infrastructure. High industrial energy consumption efficiency suggests the use of advanced production technologies and energy management practices. Efficiency in the commercial sector indicates the implementation of energy-saving technologies and sustainable building practices. Efficiency in agriculture refers to the use of modern agricultural techniques, efficient irrigation systems, and sustainable practices.

For the second stage, we selected a set of variables that may have a linear or non-linear effect on energy efficiency: GNI, Population density, GFCF, GFA, CO2 intensity of the energy mix, and TPES. Before the second stage, we used missing data imputation because not every GFA value was available for the different countries. To impute missing data, we used the CubistR function on decision trees in the imputeR package in the R software. After imputation, the efficiencies were modeled with the given variables using MARS regression.

Table 3 provides a summary of the transport sector results. We found significant effects of GNI, GFA and TPES. In the transport sector, GNI has a positive impact on transport efficiency for levels above 38,570. Economic growth at this level supports improved infrastructure and technology, enhancing efficiency. However, between 42,010 and 47,480, a significant negative impact is observed. This suggests that higher income levels may lead to inefficiencies due to increased transport demand and energy consumption beyond this threshold. For levels above 47,480, there is a positive impact once again, reinforcing the trend that very high-income levels support energy-efficient transport systems through advanced technologies and infrastructure investments. For GFA in the transport sector, there is a negative impact on transport efficiency for levels above 4.30344, indicating that excessive investments in fixed assets may not yield proportional efficiency gains, possibly due to diminishing returns. Conversely, a positive effect is observed for levels between 1.41103 and 4.30344, suggesting an optimal investment range for infrastructure that maximizes efficiency gains. Additionally, a positive effect is also seen for levels below 4.30344, indicating that investments in infrastructure contribute positively to efficiency up to a certain point. For TPES, there is a positive influence on transport efficiency for levels above 4.3, implying that a higher energy supply supports more efficient energy use through better energy management and the integration of renewable energy sources.

Table 3

MARS Regression Summary Rresults for the Transport

	Coef.	SE	t	p
(Intercept)	−0.150	0.158	−0.946	0.352
h(GNI-42010)	0.000	0.000	−5.644	0.000*
h(GFA-4.30344)	−0.197	0.055	−3.564	0.001*
h(4.30344-GFA)	0.137	0.046	2.985	0.006*
h(TPES-4.3)	0.026	0.010	2.768	0.010*
h(GFA-1.41103)	0.200	0.055	3.650	0.001*
h(GNI-38570)	0.000	0.000	6.396	0.000*
h(GNI-47480)	0.000	0.000	4.129	0.000*

*p<0.05

Table 4 provides a summary of the results for the industry sector. The effects of GNI, Population density, GFA, and TPES were significant. For GNI levels below 53,490, there is a negative impact on industrial energy efficiency, implying that lower GNI levels are associated with less efficient industrial practices due to limited access to advanced technologies and infrastructure. Population Density has a positive effect on industrial energy efficiency above 113.129, suggesting that higher population density leads to more efficient energy use due to economies of scale and optimized industrial processes. Conversely, population densities below 35.5276 result in a negative effect, indicating that lower population densities may lead to less efficient industrial practices due to dispersed infrastructure and less optimized resource use. Regarding GFA, investments above 3.14895 have a positive effect on industrial energy efficiency, indicating that such investments contribute to more efficient industrial operations through modernization and improved infrastructure. Even moderate investments below 3.14895 positively affect efficiency, although to a lesser extent. However, GFA levels above 4.30344 have a negative impact, indicating that excessive investment in fixed assets may lead to diminishing returns, where additional infrastructure does not translate into proportional efficiency gains. Finally, TPES levels above 2.7 have a negative impact on industrial energy efficiency, suggesting that higher energy supply levels may lead to inefficiencies due to overreliance on abundant energy resources without implementing energy-saving technologies.

Table 4

MARS Regression Summary Results for Industry

	Coef.	SE	t	p
(Intercept)	0.460	0.098	4.706	0.000*
h(53490-GNI)	0.000	0.000	−6.702	0.000*
h(GFA-3.14895)	0.573	0.101	5.654	0.000*
h(3.14895-GFA)	0.284	0.046	6.212	0.000*
h(Population density-113.129)	0.004	0.001	3.437	0.002*
h(TPES-2.7)	−0.069	0.016	−4.407	0.000*
h(GFA-4.30344)	−0.566	0.104	−5.463	0.000*
h(Population density-35.5276)	−0.004	0.001	−3.426	0.002*

*p<0.05

Table 5 provides summary results for the MARS regression for the commercial sector. We found that regression found the effects of GNI, TPES, and GFCF to be significant. GNI levels above 32,560 have a positive impact on commercial energy efficiency, implying that higher income levels support better energy practices due to more resources for energy-efficient technologies and infrastructure. However, GNI levels above 42,010 show a negative impact, suggesting that beyond a certain threshold, the positive effects of increasing GNI on energy efficiency may diminish or reverse because higher consumption patterns offset efficiency gains. TPES levels below 4.3 have a positive effect on commercial energy efficiency, indicating that lower energy supply levels encourage more efficient energy use through prudent management and conservation practices. Regarding GFCF, levels above 136,023 have a negative impact, implying that very high levels of fixed capital formation may not contribute proportionally to efficiency due to over-investment in areas with diminishing returns. Conversely, GFCF levels below 136,023 have a positive effect, suggesting that moderate investment in fixed capital is beneficial for commercial energy efficiency. Additionally, GFCF levels above 46,945.9 have a positive effect, indicating that initial increases in fixed capital formation positively contribute to efficiency through investments in energy-efficient infrastructure and technology.

Table 5
MARS Regression Summary Results for the Commercial

	Coef.	SE	t	p
(Intercept)	−0.925	0.328	−2.823	0.008*
h(GNI-32560)	0.000	0.000	4.295	0.000*
h(4.3-TPES)	0.187	0.043	4.368	0.000*
h(GNI-42010)	0.000	0.000	−3.669	0.001*
h(GFCF-136023)	0.000	0.000	−3.460	0.002*
h(136023-GFCF)	0.000	0.000	4.109	0.000*
h(GFCF-46945.9)	0.000	0.000	3.494	0.002*

*p<0.05

Table 6 gives summary results for Agriculture sector. The effects of GNI, Population density, and GFA were significant. Population Density above 69.7835 has a negative impact on agricultural energy efficiency, suggesting that high population density may lead to inefficiencies in agricultural energy use due to increased demand and strain on resources. In contrast, a population density below 69.7835 has a positive effect, indicating that a lower population density facilitates more efficient energy use due to less pressure on resources and more sustainable practices. Additionally, population density above 35.5276 has a positive impact, indicating a threshold effect where moderate levels of population density positively influence efficiency through optimized resource use and better management practices. GNI levels above 53,490 have a positive effect on agricultural energy efficiency, suggesting that higher national income levels support better energy practices in agriculture through increased investments in efficient technologies and infrastructure. Finally, GFA levels above 1.41103 have a positive impact on agricultural energy efficiency, suggesting that higher levels of fixed assets contribute to more efficient energy use through improved infrastructure and equipment.

Table 6
Regression Summary Results for Agriculture

	Coef.	SE	t	p
(Intercept)	−0.737	0.218	−3.389	0.002*
h(Population density-69.7835)	−0.030	0.007	−4.577	0.000*
h(69.7835-Population density)	0.025	0.004	5.940	0.000*
h(GNI-53490)	0.000	0.000	3.471	0.002*
h(Population density-35.5276)	0.031	0.007	4.701	0.000*
h(GFA-1.41103)	0.021	0.004	6.000	0.000*

*p<0.05

5. Conclusion

This study aims to identify the key factors affecting energy efficiency in 37 OECD countries using data from 2015. This research provides a detailed examination of the variables affecting energy efficiency in different sectors by calculating energy efficiency scores for the transport, industry, trade, and agriculture sectors using DEA and analyzing these scores with MARS.

The findings show significant differences in energy efficiency across sectors and countries. In particular, the transport and industrial sectors are the least efficient in terms of energy use. Our analysis shows that GDP and CO2 intensity have significant non-linear effects on energy efficiency. Other factors such as population density, GFCF, GFA, and TPES also affect energy efficiency, but their effects are smaller than those of GNI and CO2 intensity. These results underscore the need to adopt a multifaceted approach when developing energy policies. Policymakers and stakeholders should consider the non-linear effects of various factors to create more effective and sustainable strategies to maximize energy efficiency. Moreover, recognizing that GDP can have both positive and negative impacts on energy efficiency depending on its level can help economic and energy policies to maximize efficiency gains while minimizing potential inefficiencies. The significant impact of CO2 intensity on energy efficiency also highlights the critical need for policies aimed at reducing carbon emissions. This could include promoting cleaner technologies, investing in renewable energy sources, and improving energy management practices to reduce the environmental impact of energy consumption. In the transport sector, policies could focus on improving infrastructure and technology to increase efficiency, while in the industrial sector, efforts could be directed toward modernizing equipment and industrial processes. The trade sector can make balanced investments in fixed capital and ensure that these investments lead to tangible productivity gains. In agriculture, strategies that consider population density and resource management practices can lead to more sustainable energy use. By taking into account the non-linear effects of factors such as GDP and CO2 intensity, countries can achieve more sustainable and efficient energy use, leading to reduced environmental impact, cost savings, and a more sustainable future. These are essential to contribute to the overall well-being of the planet and its inhabitants by enabling the global community to achieve its environmental and economic goals.

In conclusion, this study analyzes the importance of sector-specific approaches to improving energy efficiency and highlights the need for comprehensive and nuanced policies that take into account the existing complex, non-linear relationships between economic, demographic, and energy-related variables. OECD countries can use this knowledge to improve their energy efficiency, reduce greenhouse gases, and move toward a more sustainable and resilient energy future.

Peer Review Externally peer-reviewed.
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