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# Economic Sanctions, Energy Efficiency, and Environmental Impacts: Evidence from Iranian Industrial Sub-Sectors

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**Abstract**

Improving energy efficiency is vital for curtailing energy consumption and can have substantial impacts on alleviating carbon emissions. This study investigates the impact of sanctions on Iran's energy efficiency across different industrial sub-sectors from 2015 to 2019. We compute a sanctions index for each industrial sub-sector by using Principal Component Analysis (PCA). This index measures how much each sub-sector has been affected by sanctions. Additionally, energy efficiency is measured using the Directional Distance Function (DDF) method, considering the environmental impacts as undesirable outputs. We examine the effect of the degree of the sanctions indicator on energy efficiency using feasible generalized least squares (FGLS) estimation, controlling for other drivers of efficiency. Our results show a one standard deviation increase in sanctions index results in a decline of about 3% in sub-industrial energy efficiency.

**Keywords:** Energy Efficiency; Directional Distance Function; Sanctions; Sectoral effects; FGLS; Iran.

**JLE classification:** Q410; C190; D240; F51; L90

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## 1. Introduction

In recent years, industrialization has played a vital role in the economic development of numerous nations, including Iran (Li and Shi, 2014). The industrial sector in Iran has witnessed growth from 14% of GDP in 2006 to more than 16% of GDP in 2019 (SCI, 2022a). However, this growth has brought about heightened energy consumption and environmental challenges, underscoring the necessity for enhanced energy efficiency (Ashena and Hossein Abadi, 2020; Gholami et al., 2019). The imperative to improve energy efficiency arises from its pivotal role in energy conservation, the reduction of greenhouse gas emissions, and the promotion of sustainable industrial development (IEA, 2023; Jalo et al., 2021). Moreover, energy efficiency serves as a financial tool, aiding in the reduction of fossil fuel consumption and ensuring sustainable industrial growth (Apeaning and Thollander, 2013; Wang et al., 2020).

Policymakers in Iran have strategically prioritized initiatives to enhance energy efficiency, aligning with goals to safeguard the environment and preserve fossil fuel resources amid ongoing economic development. Despite these efforts, the energy efficiency of Iran's industrial sector lags that of other nations (Mohammadi et al., 2022). The impact of economic sanctions on energy efficiency in Iran is a complex issue, intertwined with factors such as reduced GDP and restricted access to energy-saving technologies (Balali et al., 2023; Chen et al., 2019; Madani, 2021).

Only a limited number of studies specifically investigate the impact of sanctions on energy efficiency and there is a lack of focus on the sub-sector level. For instance, Chen et al. (2019) report that unilateral sanctions diminished energy efficiency, while plurilateral sanctions exhibited an opposite effect across multiple target countries. In a qualitative exploration, Vakili et al. (2022) scrutinized energy efficiency barriers within the Iran Shipping Company, revealing that sanctions act as a major obstacle by limiting access to capital and subsequently lowering power efficiency. Furthermore, Kazemi and Kazemi (2022) probed the financial impediments to enhancing the energy efficiency of buildings in Iran, concluding that sanctions heightened concerns about hidden costs and diminished investor motivation for energy efficiency projects. While Fu et al. (2020) indirectly address energy efficiency in their exploration of the environmental effects of sanctions, revealing that sanctions can detrimentally impact energy efficiency, a comprehensive investigation specifically focused on the intricate relationship between sanctions and energy efficiency is warranted.

This study aims to explore the effects of sanctions on the energy efficiency of Iran's industrial sub-sector while considering their environmental impacts as undesirable outputs. Additionally, the study investigates other factors influencing energy efficiency, including technological progress, labor productivity, energy consumption structure, capital-labor structure, trade openness, enterprise scale, and industrial concentration. This paper makes contributions to the existing literature in three distinct ways.

Firstly, it addresses a gap in the research by examining how sanctions affect the energy efficiency of industrial sub-sectors. As per data from the Central Bank of Iran, the industrial sector boasted the largest capital stock among all economic sectors, reaching 33,964 billion IRR in 2022. In comparison, other sectors recorded lower capital stocks. Specifically, the physical capital stocks for the transportation, mining, communication, agriculture, oil and gas, and water and electricity sectors were 31,460, 2,070, 4,418, 14,766, 14,663, and 19,810 billion IRR, respectively (see Figure $I_a$ in Appendix I). Considering the capital-intensive character of this sector and the constrained flow of capital and manufacturing equipment resulting from sanctions, it is expected that the impact on energy efficiency will be significant, making it worthy of investigation.

Secondly, the study introduces a novel and more accurate approach to quantifying the presence of sanctions. Previous studies (e.g., Dizaji and Farzanegan, 2021; Ebrahimi, 2022; Ghasseminejad et al., 2021; and Zamanialaei et al., 2023) often relied on a binary variable to indicate the presence of sanctions. However, the current analysis contributes to the literature by using a sanctions index calculated quantitatively using the Principal Component Analysis (PCA) method. This index is based on multiple variables influenced by sanctions across various industrial sub-sectors, offering a more comprehensive and statistically robust approach compared to a binary variable. A dummy variable represents only the presence or absence of the sanctions, without capturing the degree of their intensity.

Thirdly, the study takes a holistic approach to measuring energy efficiency by incorporating both the efficiency and undesirable environmental effects of production. While traditional energy efficiency assessments often focus solely on productive outputs, the current study acknowledges the importance of considering undesirable outputs in the production process. Industrial enterprises produce goods and services, but they also consume resources and energy and generate waste and emissions. These environmental impacts affect the well-being of nearby residents. Therefore, enterprises should balance their economic goals with environmental responsibility. However, traditional energy efficiency analyses that ignore undesirable outputs, such as CO2 emissions, may lead to inaccurate assessments of the energy efficiency of industrial sub-sectors (Liao and Lee, 2023).

The paper is organized as follows: Section 2 presents a brief overview of existing research on the impact of sanctions on energy efficiency dynamics. In Section 3, the methodology and data are explained. Section 4 presents the empirical results. Section 5 concludes the study with some policy implications.

## 2. Literature Review

Enhancing energy efficiency is vital for sustainable development goals (Xu et al., 2020). However, barriers such as lack of information, regulatory obstacles, financial constraints, uncertainties, limited access to capital, and external factors, including international sanctions, impede investments in energy efficiency projects (Vakili et al., 2022; Howarth and Anderson, 1992; Eyre, 1997). Langlois-Bertrand et al., (2015) emphasize the crucial role of political and institutional actors as fundamental barriers to energy efficiency. According to their argument, even if other barriers are eliminated, the improvement of energy efficiency is contingent on addressing these political and institutional obstacles. Kazemi and Kazemi (2022) emphasize the apprehension of hidden costs linked to efficiency development projects, attributing a significant role to sanctions. Various studies, including those by Le and Hoang (2021), Wen et al. (2021), Fu et al. (2020), and Chen et al. (2019), affirm that unilateral and multilateral sanctions adversely affect energy efficiency. Therefore, the following paragraphs explore how sanctions significantly hinder achieving energy efficiency. It explains how financial sanctions impact this aspect.

Sanctions affect energy efficiency through three primary variables: economic performance, technological progress, and foreign direct investment. Understanding these mechanisms is essential to developing effective strategies to mitigate the negative impact of sanctions and promote energy efficiency initiatives in Iran. Recent studies have highlighted the adverse effects of sanctions on economic performance. Notably, Gurvich and Prilepskiy (2015) have demonstrated that sanctions can lead to a decline in the GDP of the target country by negatively impacting consumption and investment, causing a contraction in sectors dependent on imported components, and diminishing the overall productivity potential of production factors. Additionally, Neuenkirch and Neumeier (2015) argue that sanctions affect the economic performance of countries through multiple channels, including declines in both imports and exports, a loss of bargaining power in international markets, reduced foreign direct investment, and a decrease in international aid. Consequently, it is evident that sanctions typically result in a reduction in the GDP of the target countries. This in turn may lead to an increase in energy consumption per unit of GDP, diminishing energy efficiency.

Technological progress is crucial for improving energy efficiency, as discussed in recent studies (e.g., Chen et al., 2019; Wang and Wang, 2020; Zhang and Fu, 2022; Moteng et al., 2023). Zhang and Fu (2022) suggest that the adoption of advanced technologies by production units reduces production costs, leading to lower product prices and increased competitiveness. This motivates other units to implement energy-saving technologies, optimizing their resource utilization and enhancing energy efficiency. Furthermore, Wang and Wang (2020) emphasize that the use of new technologies optimizes fossil fuel consumption, promotes clean energy adoption, and reduces emissions without compromising economic output. Considering the role of technological progress in energy efficiency, it becomes clear that sanctions hinder the importation of modern equipment and technologies, forcing target countries to rely on outdated equipment. This reliance on obsolete technologies inevitably leads to a decline in energy efficiency (Chen et al., 2019). Sanctions lead to a lack of affordable access to renewable energy and green technologies and decrease energy efficiency (Moteng et al., 2023). Moreover, economic sanctions can devalue a country's currency via several channels, such as restricting export income, subsiding oil revenues, and freezing assets (Laudati and Pesaran, 2023; Zamani et al., 2021). Due to this, sanctions lower purchasing power for energy-saving technologies (Madani, 2021). Consequently, sanctions may contribute to reduced energy efficiency by impeding the availability of energy-saving technologies to the manufacturing sector. Cheratian et al. (2023) show that under sanctions, one of the strategies which Iranian small and medium-sized businesses choose to increase their resilience is cutting spending on research and development. While such strategies may help them survive under sanctions, they have long-term negative impacts on the sustainable development of the country.

The imposition of sanctions has a detrimental impact on new foreign direct investment, including investments aimed at improving efficiency, as foreign investors opt to withdraw from the target country for various reasons, such as asset freezes and restrictions on financial transactions (Chen et al., 2019). Consequently, in such circumstances, some foreign companies may choose to renounce their commitments to energy efficiency projects in the target country or even cease operations entirely. For instance, when sanctions were imposed on Iran in 2018, Quercus, an investor in Iran's renewable energy resources, discontinued its activities in the country (Madani, 2021). Biglaiser and Lektzian (2011) and Mirkina (2018) report that sanctions diminish international incentives to invest in diverse production and service sectors, hampering scientific advancements and efforts to improve efficiency in these sectors. Farzanegan and Batmanghelidj (2023) provide a survey of the economic effects of sanctions in Iran, suggesting that while numerous studies have examined the impact of economic sanctions on macroeconomic conditions, the microeconomic effects of the sanctions imposed on Iran have been less studied. We contribute by using data on 24 industrial sub-sectors in Iran and focusing on environmental effects of sanctions.

## 3. Methodology and Data

### 3.1. Model Specification

Our analytical framework encompasses a range of methods to examine the impact of sanctions on energy efficiency (see Figure 1). To assess the relative energy efficiency among various entities, we use a modified version of Data Envelopment Analysis (DEA)[1] that calculates an efficiency indicator. Additionally, we employ the Principal Component Analysis (PCA) to derive a sanctions indicator, which captures the overall effect of sanctions across different dimensions. The feasible generalized least squares (FGLS) estimation (Parks, 1967; Kmenta, 1986), which controls for panel heteroscedasticity and panel correlation (Yu et al., 2014), is used to evaluate the potential impact of the sanctions indicator on energy efficiency.

Following the literature, specifically the studies of Liao and He (2018), Li and Shi (2014) and Zhang and Fu (2022), the empirical model to evaluate the effects of sanctions on the energy efficiency of Iranian industrial sub-sectors is specified as follows:

$$\begin{aligned}\mathrm{eff}_{i,t} = {} & \alpha_{i,t} + \beta_1 \mathrm{san}_{i,t} + \beta_2 \mathrm{rltp}_{i,t} + \beta_3 \mathrm{goc}_{i,t} + \beta_4 \mathrm{gc}_{i,t} + \beta_5 \mathrm{oc}_{i,t} + \beta_6 \mathrm{open}_{i,t} + \beta_7 \mathrm{rlp}_{i,t} \\ & + \beta_8 \mathrm{cl}_{i,t} + \beta_9 \mathrm{res}_{i,t} + \beta_{10} \mathrm{ec}_{i,t} + \beta_{11} \mathrm{res}_{i,t}^2 + \beta_{12} \mathrm{hhi}_{i,t} + \varepsilon_{i,t}\end{aligned} \tag{1}$$

In equation 1, *san* is an explanatory variable that represents economic sanctions. In this study, various control variables have been used to represent important economic and technological aspects. The abbreviations used are as follows: *rltp*, *rlp*, *cl*, *open*, *hhi*, and *res*, which respectively stand for technological progress, labor productivity, capital-labor structure, degree of trade openness, industrial concentration, and enterprise scale. Following Li and Shi (2014), we use *oc*, *goc*, *gc*, and *ec* to include the energy consumption structure. Specifically, *oc* represents the ratio of fuel oil to the total consumed energy, *goc* represents the ratio of diesel fuel to the total consumed energy, *gc* represents the ratio of natural gas to the total consumed energy, and *ec* represents the ratio of electricity consumption to the total energy consumed by industrial sub-sectors. Furthermore, the symbol $\varepsilon$ indicates the idiosyncratic error terms, while *eff* represents the energy efficiency and is the dependent variable.

[1] A discussion of the Directional Distance Function (DDF) inefficiency index is provided in Appendix IV.

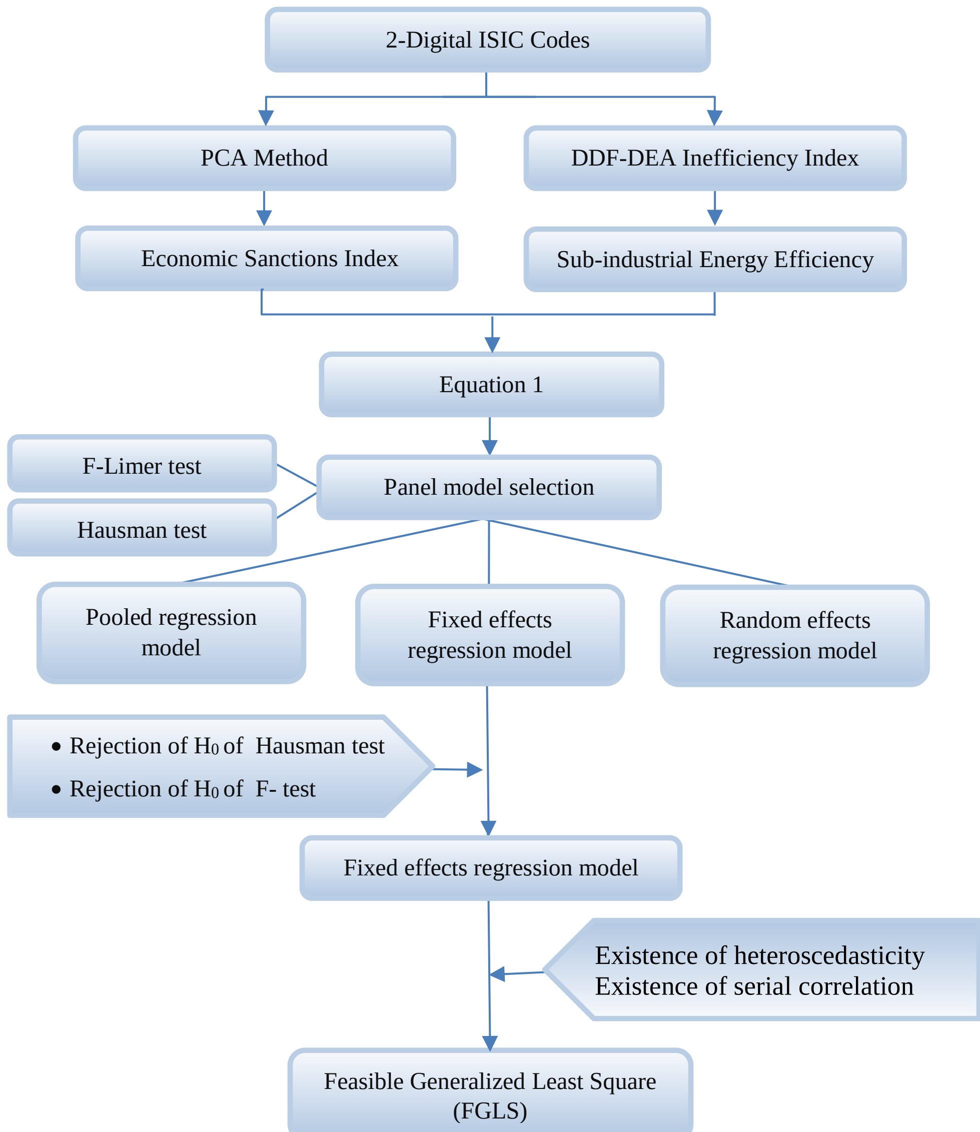



**Figure 1.** Analysis Framework.

Source: Own illustration.

### 3.2. Estimation Method

Before estimating the final empirical model, several tests are performed. Among them is the F-Limer test, employed to check the suitability of a pooled or panel model. The F-Limer test results rejects the null hypothesis favoring the pooled method, indicating that our model is best suited as a panel model (see Table 1). Additionally, the Hausman test also rejects the null hypothesis, supporting the use of a fixed effects model for estimating the model (Liao and He, 2018).

**Table 1.** Pre- requisite tests

| Test type | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| $Hausman\ test$ | 16.87** | 0.0131** | 14.82** | 18.75*** | 31.09 *** |
| $F-Limer\ test$ | 5.65*** | 5.65*** | 5.11*** | 5.28*** | 5.78*** |
| $Jochmans\ test$ | 13.36 | 15.16* | 13.072 | 11.979 | 16.284* |
| $Wald\ test$ | 10747.48 *** | 8494.71*** | 1.8e+05 *** | 1.9e+05*** | 11025.94 *** |

Note: *** p<0.01, ** p<0.05 and *** p<0.1.

Based on the above tests, the fixed effects model is chosen to examine the effects of sanctions on industrial efficiency. However, since the fixed effects model uses the OLS method, which might be sensitive to serial correlation and heteroscedasticity, a diagnostic test is conducted to address this issues. The study employs the Jochmans (2019) serial correlation test to investigate serial correlation, respectively (Table 1). The results show that the null hypothesis of no within-group correlation is not rejected in models (1), (3) and (4), indicating that the error terms are not serially correlated, but the null hypothesis of no within-group correlation is rejected in models (2) and (5), indicating that the error terms are serially correlated. The study employs the Wald heteroscedasticity test to investigate heteroscedasticity, respectively (Table 1). The results show that the null hypothesis of no heteroscedasticity is rejected in all models.

The 24 industrial sub-sectors in Iran have heterogeneity in production processes, technology, and other properties. Therefore, we considered a fixed effects model to analyze the impact of the sanctions on sub-sector energy efficiency. The Hausman test also shows these sub-sector heterogeneities. When we use a fixed effects model it is ideal to assume that the error term of the regression is homoscedastic and use Ordinary Least Squares (OLS) estimators that are consistent and unbiased. However, heteroscedasticity exists, which leads to in bias estimators (Wei et al., 2020; Xue et al., 2022; Thanh et al., 2024; Yu et al., 2014). We show that heteroscedasticity exists in our sub-industrial data in Table 1.

When heteroscedasticity exists in data, OLS estimators are less accurate in the face of heteroscedasticity because classical models assume the variance-covariance matrix of the error term is equal to a constant value of $\sigma^2 I$. The best alternative estimator is FGLS in these conditions. The FGLS estimator considers heteroscedasticity and serial correlation and solves the problem of fixed effects and multilevel regressions in the presence of heteroscedasticity or serial correlation.

(Hansen, 2007; Zakari et al., 2022 Therefore, to achieve this study's objective, we use the FGLS to analyze the effects of sanctions on Iranian sub-industrial energy efficiency.

### 3.3. Data

#### 3.3.1. Dependent Variable

In this study, energy efficiency is the dependent variable. We initially assess energy inefficiency utilizing the Directional Distance Function (DDF) method, where lower values indicate higher efficiency levels (for more details, refer to Appendix IV). Subsequently, to transform energy inefficiency into energy efficiency, we subtract the calculated values from 1. These adjusted values are then employed as the dependent variable in our estimations. Higher values of this transformed variable signify increased levels of energy efficiency within the industrial subsector.

To achieve study's objectives, a panel dataset spanning the years 2015 to 2019 is used, comprising data for each industrial sub-sector[2]. Our study investigates the energy efficiency of 24 selected industrial sub-sectors in Iran. Energy efficiency is evaluated by incorporating physical capital, labor force, and energy as inputs, while the output values of the industrial sub-sectors and carbon dioxide emissions are considered as desirable and undesirable outputs, respectively.

To calculate energy efficiency, data is collected from manufacturing industries with at least ten employees, based on the two-digit International Standard Industrial Classification of All Economic Activities (ISIC) codes (SCI, 2022b). The relevant data is obtained from the Statistical Center of Iran. Table 2 presents detailed information on the collected data and descriptive statistics.

[2] The titles of the industrial subsectors and their ISIC codes are provided in Appendix II.

**Table 2.** Description of Energy Efficiency Indicators and Their Descriptive Statistics

| Indicator | Definition | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Industrial sub-sectors output value | The actual output value of each industrial sub-sector is considered as the desirable output. To ensure the accuracy of the data, the nominal output value of the sub-sectors is adjusted for inflation by using the producer's price index and deflated into real output values with 2012 as the base period (million Rials) | 1223443 | 1889682 | 1999.76 | $1.03\times10^7$ |
| Industrial sub-sectors CO2 emissions | According to the available data and the carbon emissions reports of Iran's oil ministry (2018), equation 2 is employed in this study to compute the carbon emissions of the sub-industries in tons. $CO2 = \sum_{i=1}^{6} Q_i * LHV_i * CC_i$ (2) Where CO2 is the carbon emission of each industrial sub-sector, Q is the amount of consumption of various fuels like diesel fuel, fuel oil, kerosene, gasoline, natural gas, and liquid gas (gaseous fuels per $m^3$ and liquid fuels per liter), LHV, and CC indicate the heating value (per GJ/sm3 for gaseous fuels and GJ/liter for liquid fuels) and CO2 emission coefficient by fossil fuels (See Table IIIa in Appendix III for more information). | 3121349 | 6510279 | 10198.07 | $2.52\times10^7$ |
| Energy consumption | The sum of consumed energy by the industrial sub-sectors is used as a proxy for energy consumption (million barrels of crude oil). | $1.17\times10^7$ | $2.34\times10^7$ | 37070.95 | $9.22\times10^7$ |
| Industrial sub-sectors capital | The actual capital stock value of the industrial sub-sectors is utilized to represent physical capital. However, since data on capital stock is only available until 2012, we follow the approach of Wang and Zhao (2021) and use Equation 3 to calculate it in million Rials. $k_{i,t} = I_{i.t} + (1-\varphi)k_{i,t-1}$ (3) $k$ represents nominal industrial sub-sectors capital stock, $\varphi = 10\%$ is the rate of depreciation, and $I$ is the amount of fixed investment in the year $t$ (The values are converted into the constant price in 2012 by the producer price index) | 200094.7 | 265797.1 | 5804.681 | 1101312 |
| Labor | The total number of people employed by the investigated industrial sub-sectors. | 74139.93 | 75345.48 | 4412 | 304114 |

Note: source of all indicators is Statistical Center of Iran (SCI)'s annual survey of manufacturing firms with 10 or more workers (SCI, 2022b).

### 3.3.2. Explanatory Variable

Our core explanatory variable is the sanctions index. Given the extensive international sanctions imposed on Iran, it becomes clear that using certain variables such as the number of companies facing sanctions or the duration of sanctions may not be suitable indicators. These variables are often not easily scalable or lack sufficient explanatory power. Additionally, utilizing a binary dummy variable (0 or 1) may not provide accurate results, as it only indicates the presence or absence of sanctions and offers limited explanatory power compared to quantitative variables. Instead of directly collecting information on sanctions, a more precise approach involves examining the goals of sanctions. In other words, it is better to use variables influenced by sanctions as a proxy for sanctions variables instead of extracting sanctions-related information, because referring to variables influenced by sanctions provides more accurate and comprehensive information on sanctions. However, selecting a single target variable for sanctions is not very practical and will not have sufficient explanatory power, or incorporating multiple influenced variables as a proxy for sanctions may lead to limitations of the economic model due to independent variables adding in one economic model.

In the present study, we create an index that includes various factors and variables affected by sanctions, which can accurately capture the overall effects on industrial sub-sectors. A method to obtain such an index is through Principal Component Analysis (PCA), which consolidates multiple variables into a single index (Ezzati et al., 2020). Overall, the procedure for calculating the composite index of sanctions using the PCA method involves the following steps: 1) Collect data on the vulnerability of each selected industrial sub-sector to the impact of sanctions, informed by previous studies. We select variables that are highly impacted and sensitive to sanctions, including export volume, raw material import volume, machinery import volume, and currency rate (refer to Table 3). 2) Standardize the collected data. 3) Estimate the Principal Components (PC) and extract the principal components. 4) Select the desired principal components and determine the proportion of explained variance ratios. 5) Calculate weights based on the explained variance ratios and apply them to the data to compute the sanctions index. It is crucial to note that the sanctions index is computed based on the first one or two components of the PCA method.

**Table 3.** Description of Variables for Calculating Sanction Indicator

| Indicator | Definition | Mean | SD | Max | Min |
|---|---|---|---|---|---|
| Export | Export is defined as the direct export value of goods and services in the manufacturing industries with at least ten employees according to two-digit ISIC codes (million Rials). | $5.79 \times 10^7$ | $1.58 \times 10^8$ | $9.81 \times 10^8$ | 0 |
| Raw material import | The import value of raw materials, packaging materials, and low-durable foreign instruments and equipment in manufacturing industries with at least ten employees is implemented according to two-digit ISIC codes (million Rials). | $3.14 \times 10^7$ | $4.00 \times 10^7$ | $2.02 \times 10^8$ | 670002 |
| Equipment and machinery import | The purchase value of foreign capital assets in manufacturing industries with at least ten employees is implemented according to two-digit ISIC codes (million Rials). | 1325181 | 2013904 | 2437 | $1.37 \times 10^7$ |
| Currency rate | The currency rate is obtained by dividing the manufacturing industries export value per Rials by the corresponding value per U.S. dollar. | 55104.34 | 32408.2 | 27387.41 | 161792.7 |

Note: source of all indicators is SCI's annual survey of manufacturing firms with 10 or more workers (SCI, 2022b)

### 3.3.3. Control Variables

Furthermore, we incorporate the following various control variables into our analysis. Technological progress: Technological progress significantly impacts industrial energy efficiency (Chen and Lin, 2021). It optimizes production processes, improves methods, and enhances labor productivity, resulting in increased energy efficiency. Wang and Wang (2020) emphasize that new technologies in production can optimize fossil fuel consumption. Investigating this impact is crucial. In this study, technological progress is measured using the ratio of actual R&D expenditures in manufacturing industries with a minimum of 10 employees (based on two-digit ISIC codes) to the total number of employees in each sub-sector (measured per million Rials per individual).

Labor productivity: Improving energy efficiency relies on enhancing overall production factor productivity, including labor productivity, and substituting production factors (Lin et al., 2011).

Higher labor productivity reduces energy wastage during production, positively impacting industrial energy efficiency (Chen et al., 2022). Following He et al. (2018), the ratio of net actual output value to the total number of employees in industrial sub-sectors (per million Rials per employee) is used.

Energy consumption structure: Energy consumption structure is examined using various variables based on Li and Shi (2014). These variables include the ratio of consumed electricity to total energy consumption, the ratio of consumed natural gas to total energy consumption, the ratio of consumed diesel fuel to total energy consumption, and the ratio of consumed fuel oil to total energy consumption by manufacturing industries, all measured per barrels of crude oil. Different energy forms have diverse effects on industrial output (Li and Shi, 2014). Furthermore, these fuels vary in their pollution levels and emission of undesirable outputs, affecting energy efficiency differently. Chen et al., (2022) found that a 1% reduction in the coal consumption ratio to total energy consumption leads to a significant 34.5% increase in energy efficiency. The low heating value of coal not only inadequately supports the energy needs of the industrial sector but also generates substantial undesirable outputs, reducing energy efficiency.

Degree of trade openness: Trade openness positively affects industrial energy efficiency by enhancing environmental performance and providing resources for energy-saving measures (Chen et al., 2022). Increased market openness can lead to lower input prices through imports, reducing total expenditures for industrial units. The funds saved can then be invested in innovation, promoting energy efficiency within the industry. Imports also facilitate technology overflow, benefiting industries in terms of production and the environment, ultimately improving energy efficiency (He and Huang, 2023). In this study, trade openness is represented as the ratio of industrial imports to the total sales value of manufacturing industries (per million Rials), following Zhang and Fu (2022).

Enterprise scale: The scale of the enterprise significantly impacts energy efficiency. Larger industrial enterprises with higher production scales have the resources to invest in energy efficiency, such as advanced equipment and skilled labor (Zhang et al., 2022). It can acquire increasing return to scale and help to improve industrial efficiency (Wang et al., 2023). In this study, the enterprise scale is included as an independent variable, represented by the ratio of gross actual output values to the total number of production units in each industrial sub-sector (per million Rials per unit), following He et al., (2018). The data is adjusted using the producer price index of 2012. Studies, like Li and Shi (2014), suggest that the enterprise scale's effect on industrial energy efficiency follows an inverted U-shaped nonlinear pattern.

Capital-Labor structure: Increasing the ratio of physical capital to labor input is expected to reduce industrial energy efficiency as it is associated with increased energy consumption, according to Li and Shi (2014). However, they find that increasing the ratio of capital to labor increased energy efficiency. Thus, the variable is incorporated into the model in the present study, and, similar to Li and Shi (2014), it is defined as the ratio of the actual value of the capital stock of manufacturing industries with at least ten employees to the number of employees per million Rials for each individual.

Industrial concentration: According to Xiong et al., (2019) and Chen et al., (2022), industrial concentration can increase energy efficiency. According to Wang et al., (2017), this index calculates industrial competition, which may have positive effects on industrial energy efficiency. In the present study, following Setiawan et al., (2012), the Herfindahl-Hirschman concentration index is implemented to calculate industrial concentration using equation 4.

$$\mathrm{HHI} = \sum_{\mathrm{i}=1}^{\mathrm{N}} \left(\frac{\mathrm{xi}}{\mathrm{x}}\right)^2 \tag{4}$$

Where *xi* represents the sales value of manufacturing industries based on four-digit ISIC codes and *x* represents the sales value of these industries based on two-digit ISIC codes. A description of our model variables is presented in Table 4.

**Table 4.** Descriptive Statistics of the Dataset

| Variable | Definition | Obs. | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| $eff$ | Energy efficiency | 120 | 0.76 | 0.223 | 0.11 | 1 |
| $rlp$ | Labor productivity | 120 | 17.597 | 36.321 | 2.448 | 225.503 |
| $rltp$ | Technological progress | 120 | 0.010 | 0.017 | 0.0001 | 0.121 |
| $oc$ | The ratio of consumed fuel oil to total energy consumption | 120 | 0.006 | 0.020 | 0 | 0.112 |

| | | | | | | |
|---|---|---|---|---|---|---|
| $goc$ | The ratio of consumed diesel fuel to total energy consumption | 120 | 0.014 | 0.010 | 0.0004 | 0.047 |
| $gc$ | The ratio of consumed natural gas to total energy consumption | 120 | 0.649 | 0.135 | 0.212 | 0.939 |
| $ec$ | The ratio of consumed electricity to total energy consumption | 120 | 0.428 | 0.169 | 0.028 | 0.794 |
| $res$ | Enterprise scale | 120 | 1815.568 | 4465.661 | 76.324 | 31407.59 |
| $san$ | Sanction index | 120 | $2.59\times10^{-8}$ | 1.475 | -2.446 | 3.071 |
| $open$ | Degree of trade openness | 120 | 0.075 | 0.097 | 0 | 0.435 |
| $hhi$ | Industrial concentration | 120 | 0.538 | 0.289 | 0.103 | 1 |
| $cl$ | Capital-labor structure | 120 | 0.606 | 0.397 | 0.125 | 2.379 |
| $res2$ | Enterprise-scale square | 120 | $2.31\times10^{7}$ | $1.15\times10^{8}$ | 5825.388 | $9.86\times10^{7}$ |

Note: source of all variables is SCI’s annual survey of manufacturing firms with 10 or more workers (SCI, 2022b)

## 4. Empirical Results

### 4.1. Industrial Sub-Sectors' Energy Efficiency Calculation

In our analysis, each industrial sub-sector is considered a decision-making unit (DMU) and their energy inefficiency indices are computed using the DDF-DEA method. To convert the calculated values into energy efficiency, 1 is subtracted from the values and the outcomes are presented as the energy efficiency of the industrial sub-sectors. Table 5 displays the energy efficiency indices for 24 distinct industrial sub-sectors in Iran over the studied period. Simultaneously, Figure 2 depicts the mean values corresponding to each of these sub-sectors. The results presented in Table 5 highlight a significant variation in energy efficiency across the industrial sectors of Iran. On average, about 21% of the country's industrial segments exhibited efficient energy consumption from 2015 to 2019. Notably, five industrial sub-sectors—tobacco product manufacturing, wearing apparel production, coke and refined petroleum product manufacturing, computer and electronic product manufacturing, and machinery and equipment repair and installation—achieved the maximum index value of 1. This success can be attributed to the integration of advanced technologies and the use of modern production equipment in high-tech industries, along with increased investments in research and development. Conversely, a substantial portion of industrial sub-sectors, accounting for approximately 71% of the total, demonstrated energy efficiency indices ranging from 0.5 to 1 over the five-year period. This range indicates varying levels of energy consumption efficiency.

**Table 5.** Industrial Sub-sectors Energy Efficiency Index

| Year / *DMU* | Description | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|
| P10 | Manufacture of food products | 0.76 | 0.73 | 0.78 | 0.57 | 0.56 |
| P11 | Manufacture of beverages | 0.74 | 0.74 | 0.85 | 0.56 | 0.67 |
| P12 | Manufacture of tobacco products | 1 | 1 | 1 | 1 | 1 |
| P13 | Manufacture of textiles | 0.44 | 0.42 | 0.45 | 0.47 | 0.49 |
| P14 | Manufacture of wearing apparel | 1 | 1 | 1 | 1 | 1 |
| P15 | Manufacture of leather and related product | 1 | 1 | 1 | 1 | 0.97 |
| P16 | Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials | 0.64 | 0.67 | 0.65 | 0.52 | 0.54 |
| P17 | Manufacture of paper and paper products | 0.57 | 0.57 | 0.72 | 0.5 | 0.52 |
| P18 | Printing and reproduction of recorded media | 0.72 | 0.67 | 0.61 | 0.67 | 0.71 |
| P19 | Manufacture of coke and refined petroleum products | 1 | 1 | 1 | 1 | 1 |
| P20 | Manufacture of chemicals and chemical products | 0.42 | 0.46 | 1 | 0.33 | 0.53 |
| P21 | Manufacture of pharmaceuticals, medicinal chemicals ,and botanical products | 1 | 0.97 | 0.85 | 0.83 | 0.8 |
| P22 | Manufacture of rubber and plastics products | 0.66 | 0.62 | 0.58 | 0.76 | 0.79 |
| P23 | Manufacture of other non-metallic mineral products | 0.16 | 0.18 | 0.25 | 0.11 | 0.2 |
| P24 | Manufacture of basic metals | 0.47 | 0.49 | 0.9 | 0.39 | 0.55 |
| P25 | Manufacture of fabricated metal products, except machinery and equipment | 0.7 | 0.65 | 0.64 | 0.67 | 0.73 |
| P26 | Manufacture of computer, electronic and optical products | 1 | 1 | 1 | 1 | 1 |
| P27 | Manufacture of electrical equipment | 0.83 | 0.85 | 0.73 | 0.84 | 0.96 |

| | | | | | | |
|---|---|---|---|---|---|---|
| P28 | Manufacture of machinery and equipment N.E.C. | 0.8 | 0.73 | 0.7 | 0.71 | 0.75 |
| P29 | Manufacture of motor vehicles, trailers, and semi-trailers | 1 | 1 | 1 | 0.91 | 0.91 |
| P30 | Manufacture of other transport equipment | 0.85 | 0.89 | 0.9 | 0.78 | 0.89 |
| P31 | Manufacture of furniture | 0.8 | 0.87 | 0.88 | 0.75 | 0.8 |
| P32 | Other manufacturing | 0.76 | 0.73 | 1 | 0.74 | 0.87 |
| P33 | Repair and installation of machinery and equipment | 1 | 1 | 1 | 1 | 1 |

Source: Own calculations.

However, the production of textiles and manufacture of other non-metallic mineral products exhibited inefficiency during these years, with an average energy efficiency index of less than 0.5. This can be attributed to the use of outdated technologies, obsolete equipment, and limited access to modern technologies in these industries. Factors such as accelerated inflation, high costs of capital and equipment procurement, and the absence of economies of scale have also contributed to the energy inefficiency of Iranian industries. Consequently, the sub-optimal adoption of technology and limited use of production factors, especially energy, have hindered these industries from fully realizing their potential. These findings align with the research conducted by Yousefi et al. (2020), emphasizing the significance of technology, access to modern equipment, and economies of scale in improving energy efficiency within the Iranian industrial sector.

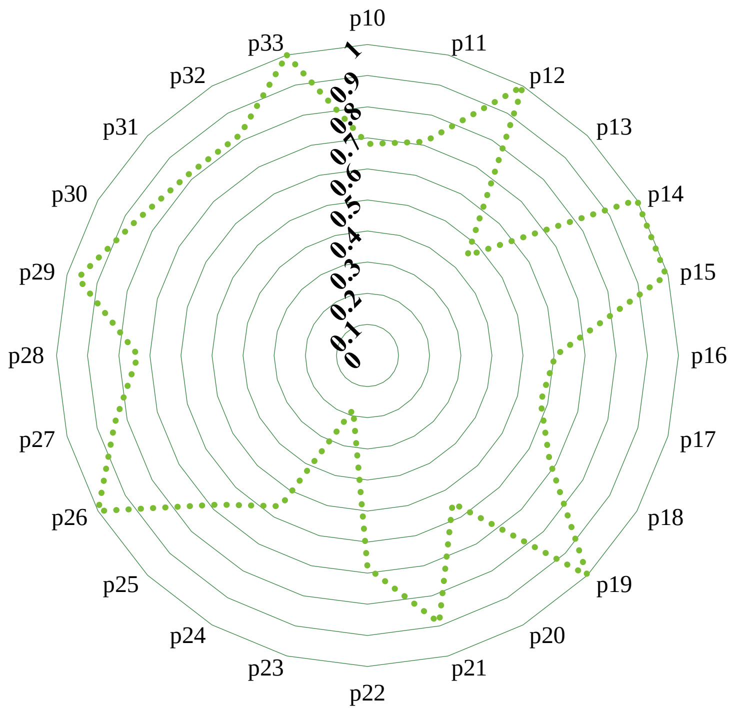



**Figure 2.** The Average of Industrial Sub-sectors' Energy Efficiency

Source: Own calculations.

### 4.2. Sanctions Index Calculation[3]

Figure 3 provides an overview of the average sanctions index for the 24 industrial sub-sectors in Iran over the investigated five-year period. The index is relatively low in the early years of the study, specifically in 2015, 2016 and 2017, compared to the subsequent years. This trend can be attributed to the implementation of the Iran Nuclear Deal, also known as the Joint Comprehensive Plan of Action (JCPOA). The JCPOA era, spanning from 2015 to the early months of 2018, refers to the agreement signed between Iran, the European Union (EU), and the P5+1 in Vienna. Under this agreement, Iran committed to various measures, including the reduction of its enriched uranium stockpile, limitations on uranium enrichment levels, and a decrease in its centrifuges. In return, the UN Security Council, the EU, and the U.S. agreed to gradually lift nuclear-related sanctions on Iran (Farzanegan and Fischer, 2021).

During 2015-2017, Iran fulfilled its commitments under the JCPOA, resulting in some relief from sanctions and a lower sanctions index. Consequently, Iranian industries experienced reduced

[3] The required information concerning U.S. sanctions imposed on Iran during 2015-2019 was obtained from the U.S. Department of the Treasury (2019) and Katzman (2022) to analyze the trend of the sanctions index.

impact from sanctions. However, in November 2018, U.S. President Donald Trump's decision to withdraw from the JCPOA led to the reinstatement of previous sanctions and the imposition of even harsher ones. These renewed sanctions were the most severe ever imposed by the U.S. on Iran, targeting key sectors of its economy. Entities like the Persian Gulf Petrochemical Industries Company and its subsidiaries faced sanctions for supporting Khatam al-Anbiya Construction Headquarters. European countries like Germany and France also imposed new sanctions, further worsening Iran's economic conditions.

As a result, the Iranian economy, including the critical industrial sector, was increasingly harmed by the sanctions. The escalation of the sanctions index can be attributed primarily to the re-imposition of sanctions and the abandonment of the JCPOA, significantly impacting the Iranian industrial sector. This analysis highlights the detrimental effects of sanctions on Iran's economy, particularly on the industrial sector, and how the sanctions index fluctuated during the investigated period due to changes in the geopolitical landscape and policy decisions of key international players.

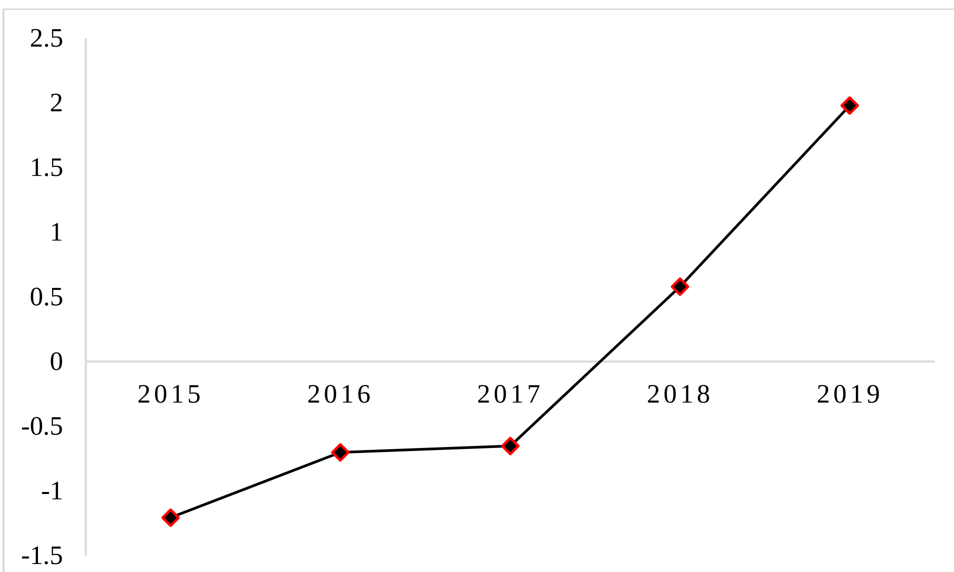



**Figure 3.** The Average of the Sanctions Index
Source: Own calculations.

### 4.3. Factors Affecting Industrial Energy Efficiency

In this section, we present the estimates regarding the effects of sanctions index on energy efficiency. To address the observed heteroscedasticity in the data, we employ the Generalized Least Squares (*GLS*) method for estimation. In this context, the *GLS* method is equivalent to the Feasible Generalized Least Squares (*FGLS*) method. Therefore, we proceed to estimate Equation 1 using the *FGLS* approach and present the obtained results in Table 6.

The findings highlight a significant negative impact of sanctions on energy efficiency in Iranian sub-industries. Specifically, for each one-unit increase in the sanctions index, energy efficiency decreases by approximately 0.02 units in Iranian industrial sub-sectors. This aligns with the findings of Chen et al., (2019), who also observed declines in energy efficiency due to sanctions in their study on various target countries.

The results indicate that technological progress has a significantly positive impact on energy efficiency in Iranian industrial sub-sectors, with coefficients ranging from 1.692 to 2.258 and a significance level of 1%. These findings align with previous studies conducted by Wang and Wang (2020), Chen et al., (2019), and Zhang and Fu (2022), which also highlight the positive relationship between technological progress and energy efficiency.

**Table 6.** FGLS Estimation to Investigate the Effect of Sanctions on Industrial Energy Efficiency

| Variables | Definition | *FGLS* Estimations | | | | |
|---|---|---|---|---|---|---|
| | | **Dependent variable:** Energy efficiency (eff) | | | | |
| | | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** |
| $san$ | Sanction | -0.020*** | -0.010*** | -0.022*** | -0.022*** | -0.011* |
| $rltp$ | Technological progress | 2.016*** | 1.82*** | 1.692*** | 1.761*** | 1.77*** |
| $rlp$ | Labor productivity | -0.0001 | 0.0015 | -0.0017 | -0.0019 | -0.0013 |
| $res$ | Enterprise scale | 0.00002* | 8.73e-06 | 0.00006*** | 0.00006*** | 0.00001 |
| $open$ | Degree of trade openness | 0.381** | 0.478** | | 0.275* | 0.471** |
| $cl$ | Capital-labor structure | 0.1408*** | 0.107*** | 0.170*** | 0.167*** | 0.108*** |
| $goc$ | The ratio of consumed diesel fuel to total energy consumption | 10.984*** | 11.658 *** | 7.631*** | 8.262*** | 11.581*** |
| $oc$ | The ratio of consumed fuel oil to total energy consumption | -4.026*** | -3.954*** | -3.801*** | -3.955*** | -3.931*** |
| $gc$ | The ratio of consumed natural gas to total energy consumption | -0.024 | -0.056 | -0.067 | -0.067 | -.0.059 |
| $hhi$ | Industrial concentration | | 0.042 | | | 0.046 |
| $res2$ | Enterprise scale squared | | | -1.02e-09*** | -1.01e-09*** | |
| $ec$ | The ratio of consumed electricity to total energy consumption | | | | | 0.004 |
| $Obs.$ | | 120 | 120 | 120 | 120 | 120 |
| $Wald\ Chi2$ | | 1006.51*** | 1097.42*** | 1304.49*** | 1271.35*** | 959.57*** |

Note: *** p<0.01, ** p<0.05.

In Section 3.2., the study uses four indicators ($oc, ec, gc,$ and $goc$) to represent energy consumption structure. The impact of these variables is analyzed separately. The findings show that the ratio of diesel fuel consumption to total energy consumption had a positive and significant effect on energy efficiency in Iranian industrial sub-sectors, based on the FGLS estimations. In contrast, the ratio of fuel oil consumption to total energy consumption had a significant negative impact on the energy efficiency of Iranian sub-industries. The remaining two variables, the ratio of electricity and natural gas consumption to total energy consumption, have positive and negative impacts on energy efficiency, respectively, but these effects are not statistically significant. Moreover, the study finds that neither labor productivity nor the industrial concentration index has a significant influence on the energy efficiency of Iranian industries.

The capital-labor structure significantly and positively impacts energy efficiency in Iranian industrial sub-sectors (coefficients: 0.170 to 0.136 at a 1% significance level). This is in line with the findings of Li and Shi (2014). While an increase in capital-labor structure can raise energy consumption due to machinery use, it enhances energy efficiency by increasing desirable output compared to consumed energy. Trade openness also positively influences energy efficiency in Iranian industrial sub-sectors (coefficients: 0.275 to 0.388). Increased trade openness enables access to modern energy-saving technologies from international markets, enhancing energy efficiency with low CO2 emissions. Similar positive effects were found by Chen et al., (2019) and He and Huang (2023) in their studies on the impact of trade openness in China. Regarding enterprise scale, there is a negative nonlinear impact on energy efficiency. Initially, increasing scale boosts energy efficiency, but starts to decrease after a certain threshold. Beyond this point, the energy required for additional output outweighs scale benefits.

To compare the size of association of sanctions and energy efficiency with other explanatory variables, we use standardized coefficients ($\beta_j^*$). The following method used to calculate the standardized coefficients. To obtain these coefficients, first, the standard deviation of $Xj$ (independent and control variables) is divided by standard deviation of the energy efficiency and the obtained ratio is multiplied by the coefficients of the variables ($\beta_j$)[4].

$$\beta_j^* = \beta_j \times \frac{S_{X_j}}{S_{eff}} \tag{5}$$

For sanctions, the value -0.127 suggests that an increase in sanctions of one of its standard deviations (1.475) results in a decrease in Iran’s sub-industrial energy efficiency of 0.127 of its

[4] For more information, refer to Siegel and Wagner(2022)

standard deviation (0.233). That is, a sanctions index increase of 1.475 (one standard deviation) results in a sub-industrial energy efficiency decrease about of 2.9%, computed as (-0.127 × 0.233) × 100. Now, we can compare these Standardized Regression Coefficients (see Tables 7 and 8). The results show that the absolute value is -0.127 for sanctions. Its impact is less than some other variables such as energy consumption structure, degree of trade openness, enterprise scale, and capital-labor structure.

**Table 7.** Sanctions Standardized Regression Coefficient

| Model | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Standard deviations of *eff* | 0.233 | 0.233 | 0.233 | 0.233 | 0.233 |
| Standard deviations of *san* | 1.475 | 1.475 | 1.475 | 1.475 | 1.475 |
| *san* coefficient | $-0.020^{***}$ | $-0.010^{***}$ | $-0.022^{***}$ | $-0.022^{***}$ | $-0.011^{*}$ |
| Standardized *san* Coefficient | $-0.127^{***}$ | $-0.063^{***}$ | $-0.139^{***}$ | $-0.139^{***}$ | $-0.070^{*}$ |
| *san* coefficient of one of standard deviation | -2.96% | -1.47% | -3.24% | -3.24% | -1.63% |

**Table 8.** Control Variables Standardized Regression Coefficient in Model (1)

| Variables | Standard deviation | Regression coefficient in model (1) | Standardized regression coefficient in model (1) | Regression coefficient of one of standard deviation in model (1) |
|---|---|---|---|---|
| $rlp$ | 36.321 | -0.0001 | -0.016 | -0.37% |
| $rltp$ | 0.017 | $2.016^{***}$ | 0.147 | 3.43% |
| $oc$ | 0.020 | $-4.026^{***}$ | -0.346 | -8.06% |
| $goc$ | 0.010 | $10.984^{***}$ | 0.471 | 10.97% |
| $gc$ | 0.135 | -0.024 | -0.014 | -0.33% |
| $res$ | 4465.661 | $0.00002^{*}$ | 0.383 | 8.92% |
| $open$ | 0.097 | $0.381^{**}$ | 0.159 | 8.88% |
| $cl$ | 0.397 | $0.1408^{***}$ | 0.24 | 5.59% |

## 5. Conclusion

Industrialization has played a pivotal role in driving economic transformations globally, contributing to enhanced economic development, elevated living standards, market expansion, and increased employment opportunities. In recent decades, Iran has also witnessed substantial industrial growth. However, this progress has brought about environmental challenges, primarily stemming from energy-intensive industries and a heavy reliance on fossil fuels. To ensure sustainable development alongside continued industrial expansion, it is imperative for Iran to prioritize initiatives that bolster energy efficiency and environmental protection.

This study investigates the impact of sanctions on the energy efficiency of industrial sub-sectors in Iran spanning from 2015 to 2019. It identifies key factors influencing energy efficiency through a comprehensive analytical framework. The findings reveal that sanctions have negative impacts on Iran’s industrial sub-sectors energy efficiency. The study demonstrates that various factors positively affect the energy efficiency of Iranian industrial sub-sectors. These include technological progress, capital-labor structure, trade openness, the ratio of diesel fuel consumption to total energy consumption (as an indicator of energy consumption structure), and industrial concentration. On the other hand, the ratio of fuel oil consumption to total energy consumption (another indicator of energy consumption structure) has a negative impact on the country's industrial energy efficiency. The scale of enterprises exhibits a negative nonlinear effect, with an inverted U-shaped relationship on the energy efficiency of Iranian industrial sub-sectors.

## Resources

Apeaning, R. W., & Thollander, P., 2013. Barriers to and driving forces for industrial energy efficiency improvements in African industries–a case study of Ghana's largest industrial area. Journal of Cleaner Production, 53, 204-213.

Ashena, M., & Hossein Abadi, S., 2020. Factors influencing CO2 emission changes in Iran with emphasis on the role of urbanization; a decomposition analysis. Journal of Geography and Environmental Hazards, 9(2), 145-163.

Balali, H., Farzanegan, M. R., Zamani, O., & Baniasadi, M., 2023. Air pollution and economic sanctions in Iran. MAGKS Papers on Economics, 202303, Marburg.

Biglaiser, G., & Lektzian, D., 2011. The effect of sanctions on US foreign direct investment. International Organization, 65(3), 531-551.

CBI, 2022. Central Bank of Iran: Economic Time Series Database, National account based on the base year of 2017. (Accessed on October, 2023). Available from: tsd.cbi.ir/Display/Content.aspx.

Chen, H., Qi, S., & Tan, X., 2022. The improvement pathway for industrial energy efficiency under sustainability perspective. Sustainable Energy Technologies and Assessments, 51, 101949.

Chen, Y. E., Fu, Q., Zhao, X., Yuan, X., & Chang, C.-P., 2019. International sanctions' impact on energy efficiency in target states. Economic Modelling, 82, 21-34.

Chen, Y., & Lin, B., 2021. Understanding the green total factor energy efficiency gap between regional manufacturing—insights from infrastructure development. Energy, 237, 121553.

Cheratian, I., Goltabar, S., & Farzanegan, M.R., 2023. Firms persistence under sanctions: Micro-level evidence from Iran. The World Economy, 46(6).2408-2431.

Dizaji, S. F., & Farzanegan, M. R., 2021. Do sanctions constrain military spending of Iran? Defence and Peace Economics, 32(2), 125-150.

Ebrahimi, S., 2022. Financial constraint and output pricing: the case of international sanctions against Iran. Journal of Applied Economics, 25(1), 1219-1238.

Eyre, N., 1997. Barriers to energy efficiency: more than just market failure. Energy & Environment, 8(1), 25-43.

Ezzati, M., Heydari, H., & Moridi, P., 2020. The effect of economic sanctions on production and employment of industry in Iran. Quarterly Journal of the Macro and Strategic Policies, 8(1), 38-65.

Farzanegan, M. R., & Batmanghelidj, E., 2023. Understanding economic sanctions on Iran: A survey. The Economists' Voice, 20, 197-226.

Farzanegan, M. R., & Fischer, S., 2021. Lifting of international sanctions and the shadow economy in Iran—a view from outer space. Remote Sensing, 13(22), 4620.

Fu, Q., Chen, Y. E., Jang, C.-L., & Chang, C.-P., 2020. The impact of international sanctions on environmental performance. Science of the total environment, 745, 141007.

Ghasseminejad, S., & Jahan-Parvar, M. R., 2021. The impact of financial sanctions: The case of Iran. Journal of Policy Modeling, 43(3), 601-621.

Gholami, N., Sadeghi, Z., & Jalaei, S., 2019. Energy efficiency and the abatement cost of marginal carbon dioxide emission in Iranian cities. Journal of Applied Economics Studies in Iran, 8(30), 107-125.

Gómez-Calvet, R., Conesa, D., Gómez-Calvet, A. R., & Tortosa-Ausina, E., 2014. Energy efficiency in the European Union: What can be learned from the joint application of directional distance functions and slacks-based measures? Applied Energy, 132, 137-154.

Gurvich, E., & Prilepskiy, I., 2015. The impact of financial sanctions on the Russian economy. Russian Journal of Economics, 1(4), 359-385.

Hansen, C. B. 2007. Generalized least squares inference in panel and multilevel models with serial correlation and fixed effects. Journal of Econometrics, 140(2), 670-694.

He, L.-Y., & Huang, G., 2023. Can importing improve the energy efficiency? Theory and evidence from Chinese industrial firms. International Review of Economics & Finance, 83, 451-469.

He, Y., Liao, N., & Zhou, Y., 2018. Analysis on provincial industrial energy efficiency and its influencing factors in China based on DEA-RS-FANN. Energy, 142, 79-89.

Howarth, R. B., & Andersson, B., 1993. Market barriers to energy efficiency. Energy Economics, 15(4), 262-272.

IEA, 2023. International Energy Agency: Multiple benefits of energy efficiency (accessed on February, 2023). Available from:https://www.iea.org/reports/multiple-benefits-of-energy-efficiency/energy-security.

Iran's oil ministry, 2018. Iran's oil ministry: Guidance on measuring and reporting Greenhouse Gas emissions (Iran's oil ministry) Available from: https://t1p.de/boo5j.

Jalo, N., Johansson, I., Kanchiralla, F. M., & Thollander, P., 2021. Do energy efficiency networks help reduce barriers to energy efficiency?-A case study of a regional Swedish policy program for industrial SMEs. Renewable and Sustainable Energy Reviews, 151, 111579.

Katzman, K., 2022. Iran sanctions: Diane Publishing. Available from:https://sgp.fas.org/crs/mideast/RS20871.pdf.

Kazemi, M., & Kazemi, A., 2022. Financial barriers to residential buildings' energy efficiency in Iran. Energy Efficiency, 15(5), 30.

Kmenta, J., 1986. Elements of Econometrics, second ed., Macmillan, NY.

Langlois-Bertrand, S., Benhaddadi, M., Jegen, M., & Pineau, P.-O., 2015. Political-institutional barriers to energy efficiency. Energy Strategy Reviews, 8, 30-38.

Laudati, D., & Pesaran, M. H., 2023. Identifying the effects of sanctions on the Iranian economy using newspaper coverage. Journal of Applied Econometrics, 38(3), 271-294.

Le, H. T., & Hoang, D. P., 2021. Economic sanctions and environmental performance: the moderating roles of financial market development and institutional quality. Environmental Science and Pollution Research, 1-22.

Li, H., & Shi, J.-f., 2014. Energy efficiency analysis on Chinese industrial sectors: an improved Super-SBM model with undesirable outputs. Journal of Cleaner Production, 65, 97-107.

Liao, N., & He, Y., 2018. Exploring the effects of influencing factors on energy efficiency in industrial sector using cluster analysis and panel regression model. Energy, 158, 782-795.

Liao, Y. H., & Lee, H. S., 2023. Using a directional distance function to measure the environmental efficiency of international liner shipping companies and assess regulatory impact. Sustainability, 15(4), 3821.

Lin, B., & Chen, Y., 2020. Will land transport infrastructure affect the energy and carbon dioxide emissions performance of China's manufacturing industry? Applied Energy, 260, 114266.

Lin, B., Wu, Y., & Zhang, L., 2011. Estimates of the potential for energy conservation in the Chinese steel industry. Energy Policy, 39(6), 3680-3689.

Liu, X., Ji, X., Zhang, D., Yang, J., & Wang, Y., 2019. How public environmental concern affects the sustainable development of Chinese cities: An empirical study using extended DEA models. Journal of environmental management, 251, 109619.

Madani, K., 2021. Have international sanctions impacted Iran's environment? World, 2(2), 231-252.

Mirkina, I., 2018. FDI and sanctions: An empirical analysis of short-and long-run effects. European Journal of Political Economy, 54, 198-225.

Mohammadi, V., Tabar, A. M. M., & Dashti, N., 2022. Inter-fuel substitution and decomposition analysis of energy intensity: Empirical evidence from Iran. Energy Strategy Reviews, 39, 100773.

Moteng, G., Raghutla, C., Njangang, H., & Nembot, L. N., 2023. International sanctions and energy poverty in target developing countries. Energy Policy, 179, 113629.

Neuenkirch, M., & Neumeier, F., 2015. The impact of UN and US economic sanctions on GDP growth. European Journal of Political Economy, 40, 110-125.

Parks, R. (1967). Efficient estimation of a system of regression equations when disturbances are both serially and contemporaneously correlated. Journal of the American Statistical Association, 62(298), 500-509.

SCI, 2022a. Statistical Center of Iran: National accounts of Iran data. (Accessed on February, 2023). Available from: https://www.amar.org.ir/hesabmelli.

SCI, 2022b. Statistical Center of Iran: Annual survey of manufacturing firms with 10 or more workers (Accessed on September, 2022). Available from: https://www.amar.org.ir/sanat.

Setiawan, M., Emvalomatis, G., & Lansink, A. O., 2012. The relationship between technical efficiency and industrial concentration: Evidence from the Indonesian food and beverages industry. Journal of Asian Economics, 23(4), 466-475.

Siegel, A. F., & Wagner, F. R., 2022. Chapter 12 - Multiple Regression: Predicting One Variable from Several Others, Practical Business Statistics, 371-431. doi.org/10.1016/B978-0-12-820025-4.00012-9.

Su, Q., & Chen, X. (2021). Efficiency analysis of metacoupling of water transfer based on the parallel data envelopment analysis model: A case of the South–North Water Transfer Project-Middle Route in China. Journal of Cleaner Production, 313, 127952.

Thanh, T. T., Van Song, N., Huyen, N. T. T., & Huong, T. T. L. 2024. An exploration of linkage between climate-related financial policies and natural rents: Evidence from the global database. Resources Policy, 88, 104450.

U.S. Department of the Treasury, 2019. Treasury Sanctions Iran's Largest Petrochemical Holding Group and Vast Network of Subsidiaries and Sales Agents. (Accessed on October, 2023). Retrieved from: https://home.treasury.gov/news/press-releases/sm703.

Vakili, S. V., Ballini, F., Dalaklis, D., & Ölçer, A. I., 2022. A conceptual transdisciplinary framework to overcome energy efficiency barriers in ship operation cycles to meet IMO's initial green house gas strategy goals: case study for an Iranian shipping company. Energies, 15(6), 2098.

Wang, F, Min, W., & Du, X., 2023. Dose industrial upgrading improve eco-efficiency? Evidence from China's industrial sector. Energy Economics, 106774.

Wang, H., & Wang, M., 2020. Effects of technological innovation on energy efficiency in China: Evidence from dynamic panel of 284 cities. Science of the Total Environment, 709, 136172.

Wang, J.-M., Shi, Y.-F., & Zhang, J., 2017. Energy efficiency and influencing factors analysis on Beijing industrial sectors. Journal of Cleaner Production, 167, 653-664.

Wang, N., Zhu, Y., & Yang, T., 2020. The impact of transportation infrastructure and industrial agglomeration on energy efficiency: Evidence from China's industrial sectors. Journal of Cleaner Production, 244, 118708.

Wang, Q., & Zhao, C., 2021. Dynamic evolution and influencing factors of industrial green total factor energy efficiency in China. Alexandria Engineering Journal, 60(1), 1929-1937.

Wei, Z., Han, B., Pan, X., Shahbaz, M., & Zafar, M. W. 2020. Effects of diversified openness channels on the total-factor energy efficiency in China's manufacturing sub-sectors: Evidence from trade and FDI spillovers. Energy Economics, 90, 104836.

Wen, J., Zhao, X., Wang, Q.-J., & Chang, C.-P., 2021. The impact of international sanctions on energy security. Energy & Environment, 32(3), 458-480.

Xiong, B., Zou, Y., An, Q., & Yan, X., 2022. Cross-direction environmental performance evaluation based on directional distance function in data envelopment analysis. Expert Systems with Applications, 203, 117327.

Xiong, S., Ma, X., & Ji, J., 2019. The impact of industrial structure efficiency on provincial industrial energy efficiency in China. Journal of Cleaner Production, 215, 952-962.

Xu, J. J., Wang, H. J., & Tang, K. 2022. The sustainability of industrial structure on green eco-efficiency in the Yellow River Basin. Economic Analysis and Policy, 74, 775-788.

Xu, T., You, J., Li, H., & Shao, L., 2020. Energy efficiency evaluation based on data envelopment analysis: A literature review. Energies, 13(14), 3548.

Yousefi, M. G., Amadeh, H., & Sangsari, S., 2020. Comparing Actual Efficiency and Productivity of Iranian Manufacturing Industries with an Ideal Index. Iranian Journal of Economic Research, 85(25), 167-213.

Yu, Y., Zheng, X., & Han, Y. 2014. On the demand for natural gas in urban China. Energy Policy, 70, 57-63.

Zakari, A., Khan, I., Tawiah, V., Alvarado, R., & Li, G. (2022). The production and consumption of oil in Africa: the environmental implications. Resources Policy, 78, 102795.

Zamani, O., Farzanegan, M. R., Loy, J.-P., & Einian, M., 2021. The impacts of energy sanctions on the black-market premium: evidence from Iran. Economics Bulletin, 41(2), 432-443.

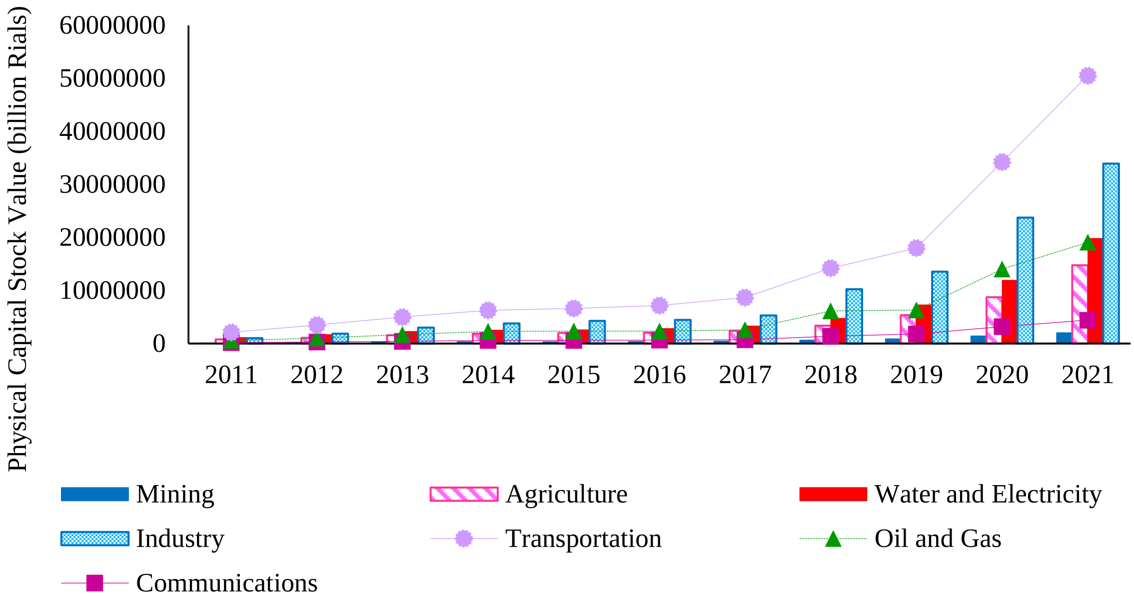
Zamanialaei, M., Brown, M. E., McCarty, J. L., & Fain, J. J., 2023. Weather or not? The role of international sanctions and climate on food prices in Iran. Frontiers in Sustainable Food Systems, 6, 998235.

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.

Zhang, X., Liu, P., & Zhu, H., 2022. The impact of industrial intelligence on energy intensity: evidence from Chaina. Sustainability, 14(12),7219.

**Appendix I.**

**Figure I$_a$.** Physical Capital Stock Value in Iran's Economic Sectors (base year of 2017 and Billion IRR)




Source: Own presentation and CBI (2022).

**Appendix II.**

**Table IIa.** Iranian Industrial Sub-sectors (Based on 2-Digital ISIC Codes, Rev.4)

| Code | Description |
|---|---|
| | Manufacture of food products |
| | Manufacture of beverages |
| | Manufacture of tobacco products |
| | Manufacture of textiles |
| | Manufacture of wearing apparel |
| | Manufacture of leather and related product |
| | Manufacture of wood and of products of wood and cork, except furniture; manufacture articles of straw and plaiting materials |
| | Manufacture of paper and paper products |
| | Printing and reproduction of recorded media |
| | Manufacture of coke and refined petroleum products |
| | Manufacture of chemicals and chemical products |
| | Manufacture of pharmaceuticals, medicinal chemicals ,and botanical products |
| | Manufacture of rubber and plastics products |
| | Manufacture of other non-metallic mineral products |
| | Manufacture of basic metals |
| | Manufacture of fabricated metal products, except machinery and equipment |
| | Manufacture of computer, electronic and optical products |
| | Manufacture of electrical equipment |
| | Manufacture of machinery and equipment N.E.C. |
| | Manufacture of motor vehicles, trailers, and semi-trailers |
| | Manufacture of other transport equipment |
| | Manufacture of furniture |
| | Other manufacturing |
| | Repair and installation of machinery and equipment |

Source: SCI (2022b)

**Appendix III.**

**Table III$_a$.** Guide for Calculating $CO_2$ Emissions

| Type of fossil fuel | heating value | | $CO_2$ emission coefficient |
|---|---|---|---|
| | Net Calorific Value | Unit | |
| Natural gas | $34.2*10^{-3}$ | $GJ/sm^3$ | $56.1*10^{-3}$ |
| Liquid gas | $26.49*10^{-3}$ | GJ/liter | $63.1*10^{-3}$ |
| Gasoline | $33.1*10^{-3}$ | GJ/liter | $69.3*10^{-3}$ |
| Kerosene | $35.7*10^{-3}$ | GJ/liter | $71.9*10^{-3}$ |
| Diesel fuel | $36.7*10^{-3}$ | GJ/liter | $74.1*10^{-3}$ |
| fuel oil | $39.6*10^{-3}$ | GJ/liter | $77.4*10^{-3}$ |

Source: Carbon emission report of Iran's oil ministry (2018)

## Appendix IV: Directional Distance Function (DDF) Inefficiency Index

Data Envelopment Analysis (DEA) is a non-parametric method for calculating efficiency based on input and output levels in the production process (Wang and Zhao, 2021). Unlike Stochastic Frontier Analysis (SFA), DEA's flexibility allows it to be used with one or multiple outputs to measure energy efficiency (Su and Chen, 2021). Energy efficiency improves when decision-making units optimize resource utilization by reducing inputs and producing more desirable outputs while minimizing undesirable ones. To accurately measure energy efficiency, accounting for undesirable outputs becomes crucial. This need has led to improvements in DEA models, including various ones considering undesirable outputs, such as the Directional Distance Function (Gómez-Calvet et al., 2014; Lin and Chen, 2020; Xiong et al., 2019).

The DDF, a non-radial DEA approach introduced by Chamber et al., (1996), offers two key advantages over early models. Firstly, it accurately determines the size of invalid inputs and outputs, enabling precise calculations for efficiency improvement, thereby reducing costs. Secondly, it provides three categories: output-oriented, input-oriented, and input-output-oriented models, catering to different research objectives (minimizing inputs, maximizing desirable outputs, or both) (Wang & Zhao, 2021). The model is constructed based on the assumption that a production system comprises n decision-making units (DMU), each producing a constant output using a fixed amount of input. $X= (x_1, x_2,.. , x_n) \in R^{i*n}$ denotes the vector of I inputs, $Y=(y_1, y_2, \ldots , y_n) \in R^{r*n}$ is the vector of R desirable outputs, and $B=(b_1, b_2, \ldots , b_n) \in R^{d*n}$ is the vector of D undesirable outputs. Furthermore, the production possibility frontier set, denoted as T, can be expressed as $T = \{(X, Y, B; X \text{ can produce } (Y, B)\}$. According to the theory of production, T is both closed and convex, signifying that the limited output can be produced using the available input. Additionally, the model considers two important assumptions. The first assumption is the null-jointness assumption, illustrated as $(X, Y, B) \in T$, and when $B=0$, it follows that $Y=0$. The second assumption is the Weak Disposability Assumption, represented as $(X, Y, B) \in T$, and when $0<\theta \leq 1$, the combination $(X, \theta Y, \theta B) \in T$ is also valid. The first assumption is based on the fact that the production of undesirable outputs during the process of production is inevitable, and the only way to stop its production is the cessation of all economic activities. In contrast, the second assumption holds that reducing the production of undesirable outputs has a cost, and that cost is the reduction of desirable output. Nevertheless, since T lacks a functional form, it cannot be directly incorporated into empirical analyses and this can be resolved by using the DEA method (Liu et al., 2019). In general, the DEA-DDF method can be defined as Equation $IV_a$.

$$\vec{D}(Y,B,X\,;g^y,-g^b,-g^x)=SUP(\theta:(Y+\theta g^y,B-g^b,X-g^x)\,\epsilon\,T(X,Y,B) \qquad (IV_a)$$

The two assumptions mentioned above are derived from Equation $IV_a$, as they establish a link between desirable and undesirable outputs. By considering these assumptions, the DDF method can effectively compute relative inefficiency and provide an optimal solution that can be solved using linear planning methods. The DDF-DEA method for each investigated DMU can be expressed as Equation $IV_b$[5]:

$$\begin{aligned}
& max\,\theta_0 \\
s.t.\quad & \sum_{j=1}^{n}\lambda_j x_{ij} \le x_{i0}-\theta_0 g_{i0}^{x} && ,i=1,2,\dots,I \\
& \sum_{j=1}^{n}\lambda_j y_{rj} \ge y_{r0}+\theta_0 g_{r0}^{y} && ,r=1,2,\dots,R \\
& \sum_{j=1}^{n}\lambda_j b_{dj} \le b_{d0}-\theta_0 g_{d0}^{b} && ,d=1,2,\dots,D \qquad (IV_b) \\
& \sum_{j=1}^{n}\lambda_j = 1 && ,j=1,2,\dots,n \\
& \lambda_j \ge 0
\end{aligned}$$

Where *Θ* indicates the inefficiency of each DMU. Thus, *Θ=0* means that the intended DMU works efficiently, while *Θ>0* is an indication of the inefficient performance of the DMU (Xiong et al., 2022).

[5] The main idea in the DDF-DEA method is to maximize the desirable output and minimize the undesirable output while maintaining the input level.