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The Impact of Optimizing Industrial Energy Efficiency on Agricultural Development in OECD Countries

Haiyang Shang [1], Ying Feng [1], Ching-Cheng Lu [2,*] and Chih-Yu Yang [2]

[1] Business College, Northwest University of Political Science and Law, No. 558 West Chang An Road, Chang An District, Xi'an 710122, China
[2] Department of Economics, Soochow University, 56, Kueiyang St., Sec. 1, Taipei 100, Taiwan
* Correspondence: join1965@gmail.com

Abstract: This study evaluates the impact of industrial energy efficiency on agricultural development in the 31 member countries of the Organization for Economic Cooperation and Development (OECD) from 2015 to 2019. Using dynamic network slack-based measures (DN-SBM) and dynamic network total factor productivity (DN-TFP) indicators, dynamic cross-period information is used to assess the changes in efficiency and productivity of the industrial and agricultural sectors. The empirical results show that the industrial sector of the OECD is more efficient than the agricultural sector, and while some countries have low efficiency, productivity tends to improve. The study has three contributions: 1. Using the concept of the water–energy–food (WEF) nexus as a framework and combining its elements with variables to evaluate the efficiency performance of OECD countries; 2. using a dynamic two-stage DN-SBM model to objectively assess the overall efficiency value and provide improvement suggestions for different stages; 3. a comprehensive analysis of efficiency and productivity; the results can serve as a reference for OECD countries when formulating policies

Keywords: OECD; WEF nexus; industrial and agricultural sectors; DN-SBM; DN-TFP

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1. Introduction

The interconnection between water, energy, and food systems is called the WEF nexus, which has gained increasing attention in the global academic, policy, and social spheres, including relationships with ecosystems, livelihoods, and economies. This article aims to critically review the WEF integrated concept, research issues, and methods from three perspectives and identify future research directions and challenges. With rapid population growth, urbanization, and climate change, the global demand for water, energy, and food is expected to increase by over 50% from 2015 to 2050. [1]. This will create enormous pressure on the existing water, energy, and food systems, and in many parts of the world, the competitive demand for limited resources has already restricted the access of many people. Additionally, water, energy, and food are interconnected, and therefore, extreme drought caused by climate change could lead to significant food and energy security issues due to the increased pressure on the water supply. In this context, the WEF nexus has an integrative concept to comprehensively study and manage the global resource system. Further discussions on water, energy, and food will be provided below:

Water is a critical resource for life and essential for food and energy production. However, the increasing demand for water resources is putting pressure on the availability of freshwater, especially in arid and semi-arid regions. In developing countries and emerging economies, water resources are often insufficient to meet the basic needs of their populations. According to the United Nations World Water Development Report 2021 estimates (the United Nations World Water Development Report 2021: valuing water; executive summary. https://unesdoc.unesco.org/ark:/48223/pf0000375750, accessed on 1 March 2023), in global freshwater resource usage, the majority is used for agricultural irrigation (accounting for 69%). However, the increasing competition for water usage between different sectors and the exacerbation of water scarcity are challenging the amount of water needed for food production. Additionally, in many regions of the world, the water efficiency of food production is relatively low, which is also one of the main causes of environmental degradation, including excessive groundwater extraction, reduced river flow, and environmental pollution. Water scarcity can affect the availability of energy and food, while the production of energy and food requires water resources. Therefore, it is crucial to develop a comprehensive understanding of the interactions between water, energy, and food systems to ensure their sustainable use and management.

Energy is another important resource in the WEF nexus. It is used for pumping, treatment, and distribution of water, as well as food production and processing. However, the production and consumption of energy also have significant environmental impacts, such as greenhouse gas emissions, air pollution, and water depletion. (IEA, 2022) IEA World Energy Outlook 2022: https://www.iea.org/reports/world-energy-outlook-2022, accessed on 1 March 2023. Natural gas and coal prices have hit historic highs, causing a 90% increase in global electricity costs, exacerbating inflation and food insecurity, especially for poorer families. Almost 100 million people worldwide may be forced to use wood for cooking. The number of people without access to electricity is beginning to rise, causing serious difficulties in people's lives. The WEF nexus approach can help identify and address the balance and synergies between energy, water, and food systems. Renewable energy sources, such as solar and wind power, can provide sustainable solutions to meet the energy needs of water and food production.

Food production heavily relies on water and energy resources, according to the 2021 State of Food Security and Nutrition in the World (FAO, 2021) FAO report: The state of food security and nutrition in the world https://www.fao.org/publications/sofi/2021/en/, accessed on 1 March 2023. In 2020, the COVID-19 pandemic ravaged the world, and the issue of hunger reemerged. After five years of stable food insecurity rates, the rate increased from 8.4% to 9.9% in just one year, making the achievement of the Zero Hunger Goal by 2030 more challenging. It is estimated that between 720 million and 811 million people worldwide faced hunger in 2020. The WEF nexus approach can help identify the balance and synergies between food production, energy, and water use, reduce food waste, and promote sustainable food production and consumption.

The WEF nexus provides an integrated framework for the sustainable management of water, energy, and food resources. It is important to recognize the long-standing interdependence between these systems, not just short-term, to ensure their sustainable use and management (Figure 1). Due to population growth, economic development, urbanization, and changes in consumption patterns, developing countries and emerging economies are particularly vulnerable to the challenges faced by the WEF nexus. Therefore, a comprehensive approach is needed to consider the interdependence between these systems and identify sustainable solutions to address the challenges of the WEF nexus.

Previous studies have primarily focused on the internal efficiency of the industrial sector and the static efficiency analysis of economic development, but there is little in the literature that simultaneously discusses related issues such as industrial development, energy use, greenhouse gas emissions, agricultural production, and forest area protection. Therefore, this study aims to explore the impact of harmful outputs such as greenhouse gases and changes in water resources and forest area (as shown in Figure 2) by evaluating the efficiency of the industrial and agricultural sectors of OECD member countries. To achieve this goal, we used the DN-SBM method to evaluate the efficiency of the industrial and agricultural sectors of OECD member countries. In addition, we evaluated the impact of cross-period variables on overall efficiency and productivity over time based on dynamic cross-period data on DN-TFP productivity index. These assessment results provide useful information for evaluating the environmental efficiency of OECD member countries and serve as a reference for exploring more sustainable development paths. Therefore, we believe that these research findings will have substantive implications for policy makers and relevant stakeholders.

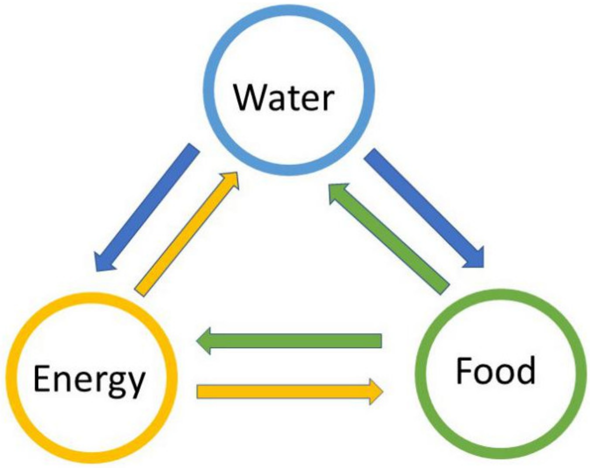

Figure 1. WEF nexus circular relation diagram.

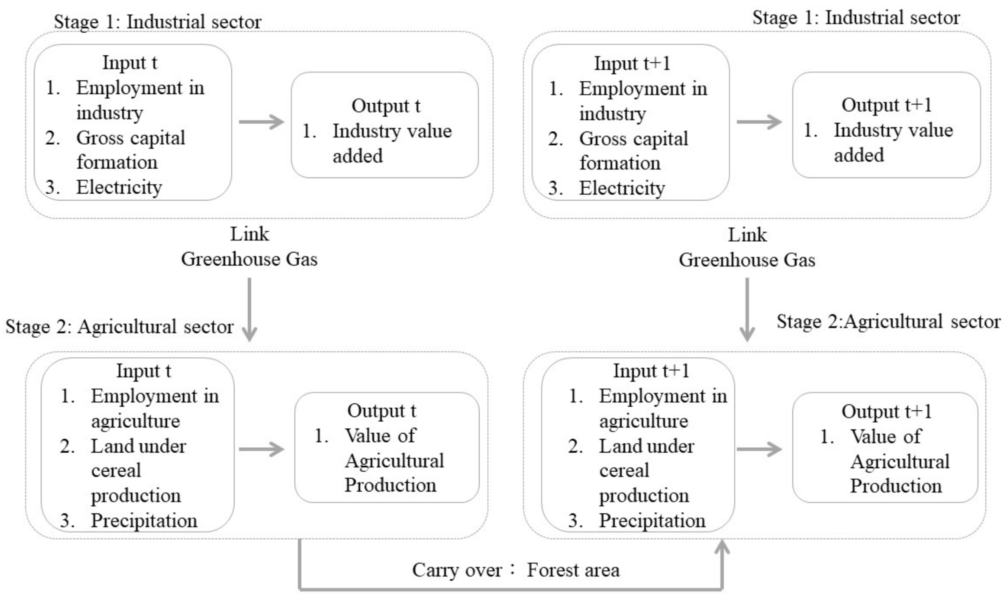

Figure 2. Schematic Diagram of Variables and Model Process in this Study.

2. Literature Review

The previous research has mainly focused on static efficiency analysis of the industrial and agricultural sectors, as well as economic development. However, there has been little in the literature exploring related issues such as industrial development, energy use, greenhouse gas emissions, agricultural production, and forest conservation simultaneously. To comprehensively examine these issues, this paper reviews the previous literature research, particularly in relation to the WEF nexus, energy efficiency, agricultural efficiency, and other relevant studies. Through this literature review, we can understand the findings and limitations of the previous research, as well as the research methodology and contributions of this study.

Research on the WEF nexus has been increasing in recent years. Some studies have investigated the interlinkages between resources such as water, energy, and food and how their scarcity or misuse can have negative impacts on the economy, society, and the environment, such as [2]. An evaluation of the efficiency of the food–energy–water (FEW) nexus system in China from 2005 to 2017 found that the efficiency was higher in provinces located in the eastern and central regions, while it was lower in provinces located in the western region. Improvement suggestions for sustainable resource utilization were also proposed. Lu et al. [3] evaluated the efficiency of the water–energy–land–food (WELF) nexus among Organization for Economic Cooperation and Development (OECD) countries, revealing differences in efficiency performance among member countries and assessing the impact of drought on WELF efficiency. In addition, some studies have explored the linkages between the WEF nexus and sustainable development, emphasizing the importance of considering the integrated use of resources across different domains. Sun et al. [4] investigated the relationship between water, food, and energy (W-E-F) in different regions of China and found that the overall regional and inter-provincial W-E-F nexus efficiency was low, with the food subsystem being the main reason for inefficiency in the entire system and the main reason for regional differences.

Research on energy efficiency in the industrial sector mainly focuses on energy production and consumption. Some studies have looked at the impact of improving energy efficiency on the environment and economy, while also exploring related issues in energy policy, such as [5], who evaluated the energy efficiency of each province in China from 2003 to 2012 using the data envelopment analysis (DEA) method with labor, capital, and energy as inputs and industrial output value and pollutant emissions as outputs. They found significant differences in energy efficiency in China due to differences between the eastern and western regions. Bian et al. [6] evaluated the energy efficiency of China's economic system using the DEA method with inputs of labor, capital, and energy and output of GDP. They found that low industrial efficiency would lower the overall economic efficiency. Guo et al. [7] used dynamic DEA to evaluate the energy efficiency of OECD countries and China. They found that China and Canada had lower energy use efficiency and CO_2 emission efficiency than other countries, while most countries showed progress in energy efficiency. Chen and Jia, [8] used DEA to evaluate the regional industrial environmental efficiency in China with inputs of industrial employment, energy consumption, and fixed assets and outputs of GDP, exhaust gas, and industrial solid waste. They found that China's environmental efficiency varied significantly by region and had problems with low environmental efficiency and imbalanced industrial development. Ziolo et al., [9] evaluated the relationship between energy efficiency and sustainable economic and financial development in OECD countries using DEA and regression analysis from 2000 to 2018. The results showed that the total factor energy efficiency (TFEE) of OECD countries slightly increased during the analysis period, but the TFEE level varied among countries. Developed OECD countries had higher TFEE levels than developing countries. Liddle and Sadorsky, [10] evaluated the energy efficiency of 81 OECD and non-OECD countries from 2000 to 2013. They found that non-OECD countries' energy efficiency was increasing, while the energy efficiency of OECD countries was declining. In addition, some studies have also explored the relationship between energy efficiency and innovation, evaluating the potential benefits of technological innovation in improving energy efficiency, such as [11], who used DEA and TFEE methods to assess the impact of environmental variables on technology and energy efficiency in the European region and found that most EU regions have not adopted the most efficient production technologies, which is the main reason for the differences. In addition, improving human capital and innovation will improve regional efficiency or ecological performance. Paramati et al. [12] evaluated the role of environmental-related technologies in energy demand and energy efficiency in 28 OECD economies and found that environmental technologies help OECD economies to reduce their overall energy consumption and improve their overall energy efficiency.

The research on agricultural efficiency mainly concerns the issue of agricultural production efficiency. Some studies focus on the impact of productivity and efficiency improvements in agricultural production on food production while also evaluating the benefits of agricultural policies and inputs. For example, Diao et al., [13] evaluated the total factor productivity (TFP) and input redundancy of agriculture in different regions of China and found that between 1995 and 2014, China's agricultural TFP grew at an annual rate of

4.3%, mainly due to technological progress. Adetutu and Ajayi, [14] conducted an investigation using a stochastic frontier analysis (SFA) model on the impact of domestic and foreign research and development on agricultural productivity in 30 Sub-Saharan African (SSA) countries from 1981 to 2011. The study found that total factor productivity was strongly influenced by domestic and foreign agricultural sector research and development expenditures, highlighting the critical role of knowledge stock in promoting agricultural productivity in the SSA region. Chen et al., [15] used the DEA method to evaluate agricultural total factor productivity (AGTFP) in 30 provinces of China from 2000 to 2017. The study found that AGTFP was lower when considering carbon emissions and agricultural non-point source pollution (ANSP). Wan and Zhou [16] used the Malmquist-DEA model to evaluate the total factor productivity (TFP) of agricultural management in 12 cities in China, as well as technological change (TC) and technical efficiency change (EC). The study found that the growth rate of agricultural TFP varied significantly in different regions and had a positive and significant impact on agricultural output. In addition, some studies also explore the link between agricultural efficiency and environmental issues such as soil pollution, water resource management, and climate change. Toma et al. [17] used a bootstrap DEA method to evaluate the agricultural efficiency of EU countries from 1993 to 2013, focusing on the relationship between agricultural productivity and ecological protection. The study has been used to support planners and managers. The research found that most EU countries improve production efficiency by changing the use of inputs. In policy planning and decision-making, not only maximizing agricultural production should be considered but also excessive development of environmental resources. Rybaczewska-Błażejowska and Gierulski [18] used the combined application of life cycle assessment (LCA) and data envelopment analysis (DEA) to evaluate the agricultural ecological efficiency of 28 EU member states. The analysis showed that the agricultural sector's ecological efficiency is low in 18 of the 28 EU countries, which means that some countries' agricultural sectors have consumed too many natural resources (especially energy).

Meanwhile, many studies have explored the impact of industrial production on agricultural efficiency. For example, some studies have found that the industrialization process can reduce agricultural production efficiency because it may cause natural resource degradation and changes in land use during agricultural production. Pollutants emitted during industrial production may also have a negative impact on agricultural production efficiency, such as in [19]. India's air pollution problem has attracted special attention, and different rural areas may experience varying degrees of yield loss due to factors such as pollution level, exposure time, climate, soil, plant varieties, and cultivation practices, which can also have adverse effects on seed quality.

According to Wang et al. [20], the impact of industrial air pollution on agricultural production technology efficiency has had a significant impact, so the use of air pollution as an input production function was analyzed to assess its impact on rice production. This will help with understanding and reasonably estimating the agricultural losses caused by industrial air pollution. Wang and Wei [21] used survey data from southwestern China, to estimate the concentration of atmospheric pollutants and agricultural losses. It was found that modifying the layout of industrial plants can effectively reduce agricultural losses caused by air pollution. Dong and Wang, [22] evaluated the degree and scope of the impact of air pollution on agricultural total factor productivity (TFP) in 146 countries worldwide from 2010 to 2019, and it was found that for every 1% increase in the concentration of fine particulate matter (PM2.5) and tropospheric ozone (O3), agricultural TFP decreases by 0.104% and 0.207%, respectively. González-Abraham et al. [23] stated that in order to achieve climate, conservation, and production goals, the Mexican government used an integrated land use model to predict policy aspirations for policy changes and productivity improvements. This study predicts land use and greenhouse gas emissions under various policy and productivity changes. It was found that through policy reform, Mexico can achieve its goal of providing adequate nutrition by 2050 while reducing greenhouse gas emissions and expanding forest land.

Forests are one of the most important resources in human society and ecosystems, therefore, many studies focus on the impact of forest area on economic development and environmental protection. For example, L.-C. Lu et al. [24] found that forest area is an important factor in controlling CO_2 emissions. By studying data from 28 EU countries between 2009 and 2016, they found that increasing forest area can improve a country's energy efficiency and help reduce CO_2 emissions. L. C. Lu et al. [25] used a modified dynamic data envelopment analysis (DEA) model that takes into account the role of forest carbon sinks to evaluate the CO_2 emissions and productivity efficiency of European countries. The study results showed that the fixed amount of forest carbon sink significantly affected efficiency rankings. Denmark, Luxembourg, Norway, Sweden, and the UK were the best-performing countries in the overall factor efficiency analysis due to their long-term efforts to address the impact of forest carbon sinks and CO_2 emissions on efficiency. Teng et al., [26] used forest carbon absorption as a new expected output variable to evaluate China's energy efficiency from 2010 to 2019. The study found that as forest carbon absorption improved, the technology gap ratios between the central and western regions and the eastern region decreased from an average of 0.4 to 0.23 and from 0.36 to 0.2 from 2015 to 2019. In addition, dynamic DEA includes the carryover effect, which reflects the impact of past resource utilization on current production efficiency. Therefore, using dynamic data, DEA methods can comprehensively evaluate the efficiency of an economic system. Previous studies have used dynamic DEA methods and forest area as a carryover variable to evaluate the effects of environmental efficiency and sustainable development. For example, Lu et al., [3] used the DEA model to evaluate the energy, health efficiency, and productivity changes of OECD member countries between 2011 and 2015, with forest area as an indicator.

Based on the literature above, it can be seen that previous studies have mostly explored the relationships between various elements in the WEF system and have primarily focused on single-industry or agriculture efficiency, lacking dynamic assessments of the cross-period efficiency performance at the national or regional level. Therefore, this study adopts the DN-SBM dynamic two-stage method to objectively evaluate the impact of the industrial stage on the agricultural stage under the WEF nexus framework, where factors such as the economic development level and policy measures of each country have important influences. At the same time, the study analyzes the impact of forest area on the total efficiency of the OECD and further evaluates the changes in total productivity. The characteristic of the above research is our contribution and breakthrough in the academic field.

3. Research Method

3.1. Dynamic Network SBM, DN-SBM

The network DEA model improves the performance part of each department that the traditional DEA failed to analyze. Tone and Tsutsui [27] further put forward the weighted slack-based measures (SBM) dynamic network data envelopment analysis (DEA) model. They evaluated the efficiency of each department and found the optimal solution by taking the linkage between different departments of decision-making units as the analysis basis of the network DEA model, each department as the sub-DMU and carry-over activities as the linkage. The basic model and solution of DN-SBM are described as follows:

The basic mode has n (j = 1,...,n), each has k sectors (k = 1,...,K), and the time periods are T (t = 1,...,T); each DMU has input and output in period t through Carry over (link) to the next period t + 1.

Let and represent K input and H output of each department, while represent K to H of each department; represents the set of K and H departments, input–output, connection and existence period, defined as follows:

(1) Inputs and outputs

$X^t_{ijk} \in R_+(i = 1, \ldots, m_k;\ j = 1, \ldots, n;\ K = 1 \ldots, K;\ t = 1, \ldots, T)$: Represents the input item i of k sector in period t.

$y^t_{rjk} \in R_+(r = 1, \ldots, r_k;\ j = 1, \ldots, n;\ K = 1 \ldots, K;\ t = 1, \ldots, T)$: Represents the output term r of sector in phase t; if part of the output is not ideal, it is regarded as the input of sector k.

(2) Links

$Z^t_{j(kh)t} \in R_+(j = 1; \ldots; n; l = 1; \ldots, L_{hk}; t = 1; \ldots, T)0$: Represents the links from the k sector to the h sector in the DMU_j of the link t period, where L_{hk} is the number of items linked from k to h.

$$Z^t_{j(kh)t} \in R_+(j = 1; \ldots; n; l = 1; \ldots, L_{kh}; t = 1; \ldots; T)$$

(3) Carry-overs

$Z^{(t,t+1)}_{jkl} \in R_+(j = 1, \ldots, n;\ l = 1, \ldots, L_k;\ k = 1, \ldots k, t = 1, \ldots, T-1)$: Represents the carry-overs from k sector to h sector in the DMU_j from t to t + 1 period, where L_k is the number of items in the carry-overs of k sector. The following is the mathematical formula of the basic model. First, production possible is defined as follows:

$$x^t_k \geq \sum_{j=1}^{n} x^t_{jk}\lambda^t_{jk}(\forall k, \forall t)$$

$$y^t_k \leq \sum_{j=1}^{n} y^t_{jk}\lambda^t_{jk}(\forall k, \forall t)$$

$z^t_{(kh)l} \geq, =, \leq \sum_{j=1}^{n} z^t_{j(kh)l}\lambda^t_{jk}(\forall l, \forall (kh)_l, \forall t)$ (output of k division in t period)
$z^t_{(kh)l} \geq, =, \leq \sum_{j=1}^{n} z^t_{j(kh)l}\lambda^t_{jh}(\forall l, \forall (kh)_l, \forall t)$ (input of h division in t period)
$z^{(t,t+1)}_{kl} \geq, =, \leq \sum_{j=1}^{n} z^{(t,t+1)}_{jkl}\lambda^t_{jk}(\forall k_l, \forall k, t = 1, \ldots, T-1)$ (carry-overs of t period)
$z^{(t,t+1)}_{kl} \geq, =, \leq \sum_{j=1}^{n} z^{(t,t+1)}_{jkl}\lambda^{t+1}_{jk}(\forall k_l, \forall k, t = 1, \ldots, T-1)$ (carry-overs of t + 1 period)

$$\lambda^t_{jk} \geq 0(\forall j, \forall k, \forall t).\sum_{j=1}^{n}\lambda^t_{jk} = 1(\forall k, \forall t), \tag{1}$$

Equation (1) represents return-to-scale.
Definition of DMU_o is as follows:
$DMU_o(o = 1 \ldots n) \in \rho$, is expressed as follows and the input and output limit formula are as follows

$$x^t_{ok} = X^t_k\lambda^t_k s^{t-}_{ko}\ (\forall k, \forall t)$$

$$y^t_{ok} = Y^t_k\lambda^t_k s^{t+}_{ko}\ (\forall k, \forall t)$$

$$e\lambda^t_k = 1\ (\forall k, \forall t)$$

$$\lambda^t_k \geq 0, s^{t-1}_{ko} \geq 0, s^{t+}_{ko} \geq 0, (\forall k, \forall t) \tag{2}$$

Period and Sector Efficiencies

Period and sector efficiencies are as follows:

(1) Period efficiency, as is shown in Formula (3):

$$\tau^{t^*}_o = \frac{\sum_{k=1}^{k} W^k\left[1 - \frac{1}{m_k + linkin_k + nbad_k}\left(\sum_{i=1}^{m_k}\frac{S^{t-}_{iok}}{x^t_{iok}} + \sum_{(kh)_l=1}^{linkin_k}\frac{s^t_{o(kh)_l in}}{z^t_{o(kh)_l in}}\right]\right.}{\sum_{k=1}^{k} W^k\left[1 + \frac{1}{r_k + linkout_k + ngood_k}\left(\sum_{r=1}^{r_k}\frac{S^{t+}_{rok}}{y^t_{rok}} + \sum_{(kh)_l=1}^{linkout_k}\frac{s^t_{o(kh)_l out}}{z^t_{o(kh)_l out}} + \sum_{k_l=1}^{ngood_k}\frac{s^{(t,(t+1))}_{ok_l good}}{z^{(t,(t+1))}_{ok_l good}}\right]\right.} \tag{3}$$

(2) sector efficiency, as is shown in Formula (4):

$$\delta^{*}_{ok} = \frac{\sum_{t=1}^{T} W^{t}\left[1 - \frac{1}{m_k + linkin_k + nbad_k}\left(\sum_{i=1}^{m_k} \frac{S^{t-}_{iok}}{x^{t}_{iok}} + \sum_{(kh)_l=1}^{linkin_k} \frac{s^{t}_{o(kh)_l in}}{z^{t}_{o(kh)_l in}}\right]\right.}{\sum_{t=1}^{T} W^{t}\left[1 + \frac{1}{r_k + linkout_k + ngood_k}\left(\sum_{r=1}^{r_k} \frac{S^{t+}_{rok}}{y^{t}_{rok}} + \sum_{(kh)_l=1}^{linkout_k} \frac{s^{t}_{o(kh)_l out}}{z^{t}_{o(kh)_l out}} + \sum_{k_l=1}^{ngood_k} \frac{s^{(t,(t+1))}_{ok_l good}}{z^{(t,(t+1))}_{ok_l good}}\right]\right.} (\forall k) \tag{4}$$

(3) Sector period efficiency is defined as follows, as is shown in Formula (5):

$$p^{t*}_{ok} = \frac{1 - \frac{1}{m_k + linkin_k + nbad_k}\left(\sum_{i=1}^{m_k} \frac{S^{t-}_{iok}}{x^{t}_{iok}} + \sum_{(kh)_l=1}^{linkin_k} \frac{s^{t}_{o(kh)_l in}}{z^{t}_{o(kh)_l in}}\right)}{1 + \frac{1}{r_k + linkout_k + ngood_k}\left(\sum_{r=1}^{r_k} \frac{S^{t+}_{rok}}{y^{t}_{rok}} + \sum_{(kh)_l=1}^{linkout_k} \frac{s^{t}_{o(kh)_l out}}{z^{t}_{o(kh)_l out}} + \sum_{k_l=1}^{ngood_k} \frac{s^{(t,(t+1))}_{ok_l good}}{z^{(t,(t+1))}_{ok_l good}}\right.} (\forall k; \forall t)$$

$$Z^{(0,1)}_{ol_k} = \sum_{j=1}^{n} Z^{(0,1)}_{jlk} \lambda^{l}_{jk} (\forall l_k) \tag{5}$$

From the above results, the overall efficiency, period efficiency, sector efficiency, and sector period efficiency can be obtained. From the above research method, it can be seen that if the research case is a performance comparison among multi-sector in multi-period, DN-SBM is more suitable for carry-overs across multiple sectors and periods compared with traditional DEA.

3.2. Dynamic Network Malmquist Total Factor Productivity, DN-TFP

Dynamic network Malmquist total factor productivity (DN-TFP) is used to measure changes in total factor productivity during different periods. On the one hand, it can be used to judge the stability of the efficiency of each DMU, and on the other hand, it can also be used to observe the changing trend in the efficiency value of each DMU. The Malmquist total factor productivity change index is decomposed into technical efficiency change, also known as the catch-up effect. Technical efficiency change is used to calculate the degree of support for each DMU to improve efficiency during different periods. Technological change is calculated to reflect changes in the efficiency frontier of the DMU during different periods.

As is shown in Figure 3, the input and output of a DMU in the two different periods of p and q are P(x_p,y_p) and Q(x_q,y_q). The technical efficiency change is calculated as:

$$\mathrm{Catch-up} = \frac{\text{inQof efficency frontier in periodQ}\left(\mathrm{x_q, y_q}\right)\text{the efficiency}}{\text{inPof efficency frontier in periodQ}\left(\mathrm{x_p, y_p}\right)\text{the efficiency}} \tag{6}$$

In accordance with Figure 3, Equation (6) can be converted into

$$\mathrm{Catch-up} = \frac{\frac{BQ'}{BQ}}{\frac{AP'}{AP}} \tag{7}$$

This represents the relative progress efficiency from period p to time q. A value greater than 1 indicates a trend of progress, a value equal to 1 indicates the status quo is maintained, and a value less than 1 indicates a trend of regression.

From Figure 3, the technique change in the frontier-shift effect from point p′ to point C in period $P\left(x_p, y_p\right)$ is φ_p, which is represented by Formula (8):

$$\varphi_\mathrm{p} = \frac{\text{inpof efficency frontier in periodP}\left(\mathrm{x_p, y_p}\right)\text{the efficiency}}{\text{inqof efficency frontier in periodP}\left(\mathrm{x_p, y_p}\right)\text{the efficiency}} = \frac{\frac{\mathrm{AP'}}{\mathrm{AP}}}{\frac{\mathrm{AC}}{\mathrm{AP}}} = \frac{\mathrm{AP'}}{\mathrm{AC}} \tag{8}$$

In the same way, the frontier-shift in q period is ϕ_p. Therefore, the frontier-shift is the geometric average of ϕ,$\phi_p$and ϕ_q. As is shown in (9):

$$\text{Frontier} - \text{shift} = \phi = \sqrt{\phi_p \phi_q} \tag{9}$$

The Malmquist production index (represented by MPI) is the product of catch-up (represented by C) and frontier-shift (represented by F). Its mathematical symbols are represented as (10), (11) and (12), and the symbol δ represents efficiency.

$$C = \frac{\delta^q\left((x_q, y_q)^q\right)}{\delta^p\left((x_p, y_p)^p\right)} \tag{10}$$

$$F = \left[\frac{\delta^p\left((x_p, y_p)^p\right)}{\delta^q\left((x_p, y_p)^p\right)} \times \frac{\delta^p\left((x_q, y_q)^q\right)}{\delta^q\left((x_q, y_q)^q\right)}\right]^{1/2} \tag{11}$$

$$MPI = \left[\frac{\delta^p\left((x_q, y_q)^q\right)}{\delta^p\left((x_p, y_p)^p\right)} \times \frac{\delta^q\left((x_q, y_q)^q\right)}{\delta^q\left((x_p, y_p)^p\right)}\right]^{1/2} \tag{12}$$

In addition to the sectoral concept mentioned above, MPI also includes dynamic changes over time. Its MPI value represents the growth and changes of DMU's total factor productivity (TFP). It mainly discusses the progress or regression of the frontier technology effect from period 1 to period 2, which are as follows:

Overall DN-TFP

The overall DN-TFP is the weighted geometric average of the sectoral MPI, expressed as (13):

$$\text{DN} - \text{TFP} = \mu_o = \prod\nolimits_{k=1}^{K} (\mu_{ok})^{wk} (o = 1, \ldots n) \tag{13}$$

where μ_{ok} is the weighted geometric average of ${\mu_{ok}}^{t \to t+1} (t = 1, \ldots, T-1)$, $w_k \geq 0$, and $\sum w_k = 1$.

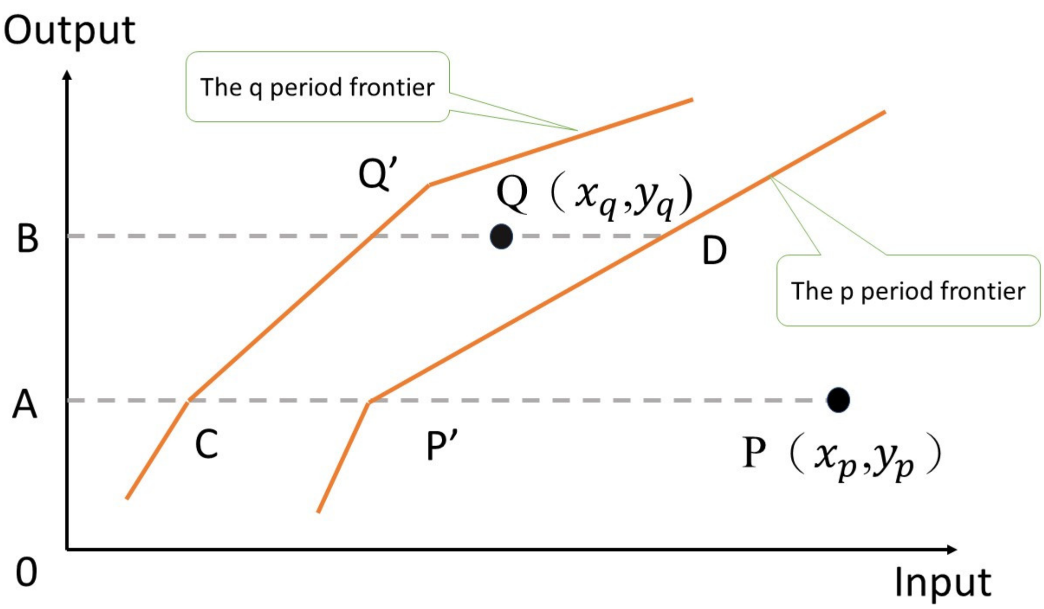

Figure 3. Input-oriented technical efficiency changes and technical changes.

4. Empirical Analysis

Using the framework of the WEF nexus concept, this study evaluates the efficiency of the industrial and agricultural sectors in OECD countries using the DN-SBM model and measures their DN-SBM and DN-TFP changes using the industrial and agricultural sectors' data from 2015 to 2019.

4.1. Data Source

This study focuses on 31 OECD countries, covering a 5-year period from 2015 to 2019. The data sources mainly include the United Nations Data Retrieval System and the World Bank Open Data. The data are annual.

4.1.1. Variable Description

The variables used in this study are described in Table 1.

Table 1. Unit description of each variable.

	Variable	**Unit**
Industrial Sector Input	Employment in industry Gross capital formation Electricity	Person Current Millions of US dollars Gigawatt hours
Output	Industry value added	Current Millions of US dollars
Link	Greenhouse Gas	Thousand tons CO_2-eq
Agricultural sector Input	Employment in agriculture Land under cereal production Precipitation	Person Hectares mm/year
Output	Value of Agricultural Production	Current Millions of US dollars
Carry over	Forest area	sq. km

4.1.2. Descriptive Statistical Analysis

In the section describing the maximum values of descriptive statistics (Table 2), employment in industry, gross capital formation, electricity, and industry value added show a slight increase in trend, while the other variables remain relatively unchanged. In the section for minimum values, gross capital formation shows an increasing trend, electricity shows a slight decrease in trend, and the other variables remain relatively unchanged. In the section for mean values, gross capital formation, industry value added, and value of agricultural production show a slight increase in trend, while the other variables remain relatively unchanged.

Table 2. Input–output of OECD variables to descriptive statistical analysis chart from 2015 to 2019.

		Employment in Industry	**Gross Capital Formation**	**Electricity**	**Industry Value Added**	**Greenhouse Gas**
Max	2015	37,445,319.59	3,859,763	4,109,219	33,839,77.115	6,689,006.13
	2016	37,818,786.61	3,844,982	4,119,445	3,373,013.267	6,537,871.03
	2017	39,437,363.87	4,558,260	4,236,927	3,908,533.954	6,689,006.13
	2018	39,437,363.87	4,558,260	4,236,927	3,908,533.954	6,689,006.13
	2019	39,437,363.87	4,558,260	4,236,927	3,908,533.954	6,689,006.13
Min	2015	39,921	3398.974485	2738	3537.62447	4746.024
	2016	38,716	4384.008718	2168	4064.186221	4692.48
	2017	35,956	5376.285015	2204.811	4846.374721	4776.967
	2018	40,384	5850.274779	2170.172	5161.739529	4847.088
	2019	38,377	5243.821439	1877.378	4918.171152	4713.009

Table 2. *Cont.*

		Employment in Industry	**Gross Capital Formation**	**Electricity**	**Industry Value Added**	**Greenhouse Gas**
Average	2015	4,280,958.438	299,316.6691	289,633.9	296,547.8839	434,829.016
	2016	4,322,013.254	303,525.6767	291,647.3	300,008.4507	430,037.309
	2017	4,382,999.656	321,048.2218	292,560.8	315,344.2028	429,735.341
	2018	4,447,133.462	345,313.9125	297,112.1	335,314.2987	431,342.955
	2019	4,451,693.684	352,894.9669	294,085.8	334,365.6366	632,357.843
St Dev.	2015	7,464,689.608	704,040.3221	741,776.6	636,356.3478	1,197,366.58
	2016	7,528,023.506	706,333.5941	743,027.9	644,511.2976	1,170,671.86
	2017	7,604,771.65	742,329.5852	737,329.2	679,785.36	1,163,663.02
	2018	7,726,565.533	796,135.8071	763,085.2	721,168.3267	1,194,822.81
	2019	7,789,510.195	831,098.8412	754,459.9	734,050.0275	1,623,890.78
		Employment in agriculture	Land under cereal production	Precipitation	Value of Agricultural Production	Forest area
Max	2015	7,476,523.112	58,124,740	1940	2,790,602.87	3,100,950
	2016	7,319,259.506	58,445,763	1940	2,722,427	3,100,950
	2017	7,489,642.452	58,445,763	1940	2,846,178.41	3,100,950
	2018	7,489,642.452	58,445,763	1940	2,846,178.41	3,100,950
	2019	7,489,642.452	58,445,763	1940	2,846,178.41	3,100,950
Min	2015	3348	1455	435	2373.82	481.6
	2016	3309	2300	435	2297.58	486.6
	2017	4645	2100	435	2763.93	493.8
	2018	3608	1500	435	2838.07	500.4
	2019	2414	2200	435	2637.91	506.9
Average	2015	753,733.9634	4,489,500.71	934.8065	253,562.5184	217,360.311
	2016	745,114	4,424,700.419	934.8065	251,158.6084	217,753.913
	2017	747,157	4,271,956.129	934.8065	263,145.9048	217,794.477
	2018	731,794.0176	4,193,802.097	934.8065	267,690.7819	217,940.652
	2019	713,782.3127	4,176,708.194	934.8065	262,925.7271	218,092.742
St Dev.	2015	1,448,894.294	10,797,194.8	403.6056	509,858.478	586,418.715
	2016	1,418,468.485	10,787,376.53	403.6056	499,627.1191	587,007.838
	2017	1,444,949.138	9,988,974.662	403.6056	518,714.6516	586,488.961
	2018	1,402,110.18	9,968,133.91	403.6056	515,326.6791	586,468.461
	2019	1,348,335.55	9,790,477.275	403.6056	515,053.9373	586,455.652

4.2. DN-SBM Empirical Result

4.2.1. The Industrial Sector Efficiency

This study evaluates the efficiency of the OECD industrial sector from 2015 to 2019, and Table 3 shows the efficiency value results for this period. The average efficiency value of the industrial sector is 0.8719, with a maximum value of 1 and a minimum value of 0.5835 and a standard deviation of 0.1288. Among them, Germany, Iceland, Israel, Luxembourg, Netherlands, Switzerland, Australia, Ireland, Italy, Norway, Poland, and Slovenia are the best countries with an efficiency value of 1 during these five years. In addition, 14 countries have an efficiency value above the average, and 17 countries have an efficiency value below the average. The countries with the lowest efficiency values are Portugal (0.7147), France (0.6002), and Sweden (0.5835).

4.2.2. Agricultural Sector Efficiency

This study evaluates the efficiency of the OECD agricultural sector between 2011 and 2015, and Table 3 shows the efficiency and ranking of the agricultural sector. The average efficiency value of the agricultural sector is 0.7666, with a maximum value of 1 and a minimum value of 0.2708 and a standard deviation of 0.2730. Among them, Germany, Iceland, Israel, Luxembourg, Netherlands, Switzerland, United States, New Zealand, Japan, and Denmark are the most efficient countries in the agricultural sector with an efficiency value of 1 during these five years. In addition, 17 countries have an efficiency value below the average. The countries with the lowest efficiency values are Estonia (0.3134), Slovenia (0.2890), and Slovak Republic (0.2708).

Table 3. OECD ranking analysis of industrial, agricultural sector, and overall efficiency from 2015 to 2019.

DMU	Industrial Sector	Agricultural Sector	Overall	DMU	Industrial Sector	Agricultural Sector	Overall
Germany	1	1	1	Chile	0.7874	0.8271	0.7038
Iceland	1	1	1	Turkey	0.8353	0.8134	0.6880
Israel	1	1	1	France	0.6002	0.9945	0.6505
Luxembourg	1	1	1	Portugal	0.7147	0.5909	0.5447
Netherlands	1	1	1	Austria	0.7453	0.5248	0.5257
Switzerland	1	1	1	Hungary	0.7510	0.5587	0.5166
Australia	1	0.9564	0.9714	Poland	1	0.3286	0.5020
United States	0.9519	1	0.9637	Slovenia	1	0.2890	0.4575
Ireland	1	0.9126	0.9418	Sweden	0.5835	0.4729	0.4520
Greece	0.9921	0.9339	0.9302	Czech Republic	0.8533	0.3447	0.4515
Italy	1	0.9512	0.8912	Finland	0.7619	0.3608	0.4367
Japan	0.8504	1	0.8839	Slovak Republic	0.7898	0.2708	0.3649
Denmark	0.8305	1	0.8484	Estonia	0.7325	0.3134	0.3607
New Zealand	0.8675	1	0.8322	Max	1	1	1
Spain	0.8062	0.9813	0.8081	Min	0.5835	0.2708	0.3607
Norway	1	0.6366	0.7632	Average	0.8719	0.7666	0.7411
Belgium	0.7802	0.8921	0.7458	StDev.	0.1288	0.2730	0.2221
United Kingdom	0.7951	0.8113	0.7406				

4.2.3. DN-SBM Overall Efficiency

Regarding the overall section (Table 3), the overall average is 0.7411, with a maximum value of 1 and a minimum value of 0.3607 and a standard deviation of 0.2221. Among them, Germany, Iceland, Israel, Luxembourg, Netherlands, and Switzerland are the best countries with an efficiency value of 1 during these five years. In addition, there are 14 countries below the average. The countries with the lowest efficiency values are Finland (0.4367), Slovak Republic (0.3649), and Estonia (0.3607).

In previous studies, efficiency was usually investigated for a single country or industry. However, in this study, we chose to use the WEF nexus framework to integrate three elements: water, energy, and food, and objectively evaluate the impact of OECD industrial production on agriculture. The study found that countries with higher industrial sector efficiency did not necessarily have better agricultural sector efficiency, such as Australia, Ireland, Italy, Norway, Poland, and Slovenia. Among them, Poland (1, 0.3286) and Slovenia (1, 0.289) were the most obvious, with an average industrial sector efficiency of 1, ranking first over a five-year period. However, their agricultural sector efficiency was low, resulting in an overall decline to 0.502 for Poland and 0.4575 for Slovenia. Similarly, countries with higher agricultural sector efficiency did not necessarily have better industrial sector efficiency, such as the United States, Japan, Denmark, and New Zealand, with New Zealand being the most obvious, having an average agricultural sector efficiency of 1 but an industrial sector efficiency of only 0.8675, the main reason for its overall decline to 0.8322.

Therefore, this study is different from the traditional research, which only investigates efficiency for a single country or industry. The uniqueness of this study lies in its use of a dynamic and multi-stage approach, which provides a more objective evaluation of a country's overall efficiency and enables the identification of areas for improvement and recommendations based on efficiency performance at different stages. This has significant implications for national policy-making, providing policymakers with a more comprehensive and objective method of evaluating efficiency.

4.3. DN-TFP Empirical Results

From 2015 to 2019, the average DN-TFP value for OECD countries was 1.0776, as shown in Table 4, indicating a slight improvement trend. Among them, Japan (1.7059) had the best productivity performance, while Turkey (0.8489) had the lowest DN-TFP value with a standard deviation of 0.1681. DN-TFP values for 22 OECD countries were greater than 1, indicating a trend in progress. DN-TFP values for 9 countries were less than 1, indicating a trend of decline. Australia (0.9645), Slovenia (0.9126), and Turkey (0.8489) had the lowest DN-TFP values.

Table 4. OECD DN-TFP from 2015 to 2019.

DMU	2015–2016	2016–2017	2017–2018	2018–2019	Ave.	DMU	2015–2016	2016–2017	2017–2018	2018–2019	Ave.
Japan	1.2858	0.9401	1.0719	6.5367	1.7059	Luxembourg	1	0.9602	1.0961	1.0008	1.0131
Spain	1.2384	1.1153	1.1853	2.8674	1.4719	Italy	0.9305	1.0658	1.1274	0.937	1.0117
Ireland	0.8485	1.229	1.1257	2.9084	1.3593	France	0.8208	1.212	1.2907	0.8153	1.0115
Germany	0.9443	1.0192	0.8734	2.752	1.2333	Czech Republic	1.0138	1.0338	1.0032	0.9948	1.0113
Belgium	0.8983	1.3411	1.3443	1.0669	1.1465	Austria	0.9984	1.0388	1.0608	0.932	1.0063
Netherlands	1.267	1.1844	0.9733	1.1523	1.139	Norway	0.7691	1.3899	1.3443	0.6851	0.9961
United Kingdom	0.8842	1.0322	1.0795	1.6755	1.1335	United States	0.9333	1.081	0.9901	0.9627	0.9903
Chile	1.2176	1.1579	1.1958	0.9454	1.1236	Sweden	0.9759	1.0896	0.9927	0.8996	0.9872
Poland	1.4331	0.7494	0.666	1.8547	1.0732	Estonia	0.8287	1.186	0.9405	0.9958	0.9795
New Zealand	1.0633	1.2644	1.146	0.8495	1.0696	Hungary	1.0556	0.9924	0.9155	0.9402	0.9745
Israel	1.1053	1.1453	0.9629	1.0423	1.0617	Iceland	1.042	1.0124	0.9801	0.8697	0.9738
Slovak Republic	1.0776	0.9875	1.1845	0.9762	1.0532	Australia	0.9667	1.1301	0.9775	0.8102	0.9645
Denmark	1.1021	1.1714	0.8275	1.1281	1.0477	Slovenia	1.7484	0.6294	0.6305	0.9994	0.9126
Portugal	0.95	1.0522	1.0054	1.1419	1.035	Turkey	0.8543	0.8135	0.6649	1.1237	0.8489
Switzerland	0.9886	1.0177	1.1197	0.9975	1.0296	Max	1.7484	1.3899	1.3443	6.5367	1.7059
Greece	0.9762	1.0601	0.9992	1.0678	1.0251	Min	0.7691	0.6294	0.6305	0.6851	0.8489
Finland	0.9785	1.0715	1.014	1.0056	1.0168	Average	1.0386	1.0701	1.0254	1.3850	1.0776
						StDev.	0.1996	0.1563	0.1752	1.1220	0.1681

This study further compared the overall efficiency values of DN-SBM and DN-TFP (as shown in Table 4 and Figure 4). The study found that five countries, including Germany (1, 1.2333), Israel (1, 1.0617), Luxembourg (1, 1.0131), the Netherlands (1, 1.139), and Switzerland (1, 1.0296), had an overall efficiency value of 1 and showed progress in productivity. However, Iceland (1, 0.9738) showed a slight decline in productivity. Among the three countries with lower efficiency values, Finland (0.4367, 1.0168) and Slovakia (0.3649, 1.0532) showed progress in productivity, while Estonia (0.3607, 0.9795), which had the lowest efficiency value, not only had low efficiency but also showed a decline in productivity. Eight countries had declining productivity, but there was still room for improvement in efficiency, including Norway (0.7632, 0.9961), the United States (0.9637, 0.9903), Sweden (0.452, 0.9872), Estonia (0.3607, 0.9795), Hungary (0.5166, 0.9745), Australia (0.9714, 0.9645), Slovenia (0.4575, 0.9126), and Turkey (0.6880, 0.8489). The study found that although Japan had a relatively lower efficiency value (0.8504) in the industrial stage, its productivity showed a significant growth trend (1.7059). By adjusting the inputs and resource allocation in the industrial stage, it is expected to further improve overall efficiency performance. This finding shows that a single efficiency value is not the only standard for measuring a country's productivity, and multiple factors need to be considered. Moreover, it provides a reference for other countries to improve their efficiency performance, especially those with slow productivity growth.

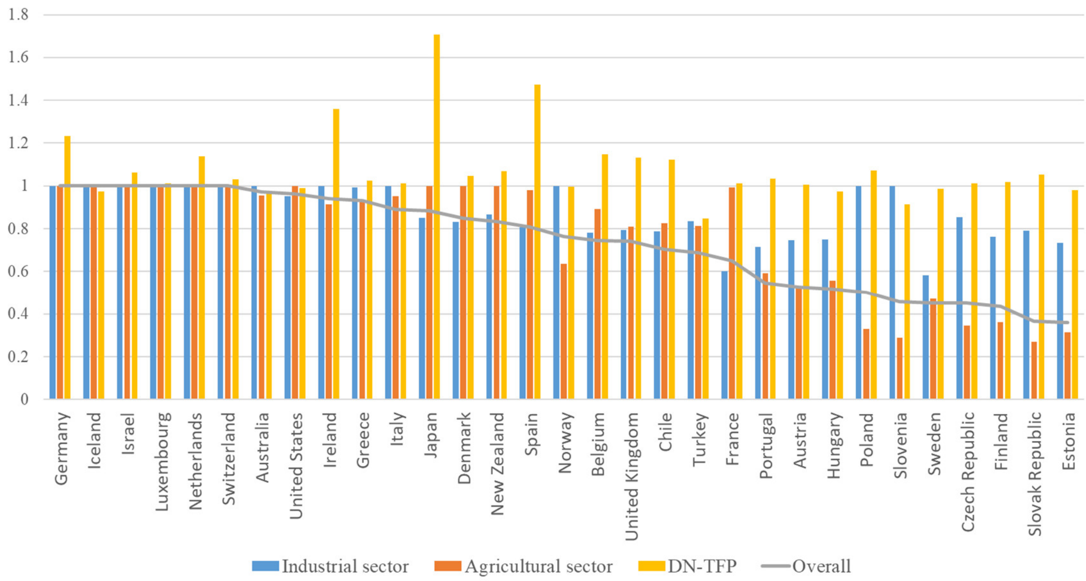

Figure 4. Comparison of DN-DDF and DN-TFP.

4.4. Policy Implications and Discussion

According to research findings, the overall efficiency performance of OECD countries is 0.7411, which still has room for improvement. Among them, the average efficiency of the industrial sector is 0.8719, which is better than the average efficiency of the agricultural sector at 0.7666. This indicates that the efficiency of the agricultural sector can be improved through resource allocation and other methods to enhance overall efficiency performance. Although the average productivity of OECD countries is 1.0766, showing a slight improvement trend, some OECD countries are already developed countries. If these countries cannot effectively develop industry, agriculture, protect water resources, and maintain forests, developing countries will undoubtedly face more difficulties in achieving the goals of the Paris Agreement. Therefore, this study uses the WEF nexus as a framework to re-examine and evaluate the performance of efficiency and productivity in OECD countries and strengthen the implementation of related policies to make more contributions to sustainable development and climate change issues. In addition, OECD countries should focus on promoting industrial innovation and technological progress to enhance overall efficiency, for example, by strengthening innovation investment, encouraging industrial and agricultural research and development of new technologies, and expanding the scope of new technology applications. Moreover, education and training can be used to improve the skills and knowledge of workers and increase the quality and efficiency of the labor force. At the same time, OECD countries should strengthen cross-border cooperation and jointly respond to global challenges such as climate change to promote sustainable development goals.

5. Conclusions

The main purpose of this study is to comprehensively assess the impact of industrial production on agricultural output and efficiency in 31 OECD countries from 2015 to 2019 in order to further understand the relationship between the two. To achieve this goal, we used the DN-SBM model to evaluate the efficiency of two stages and the DN-TFP model to measure the changes in total factor productivity. Through in depth analysis of these factors, we can better grasp the interaction between industry and agriculture and further develop more effective policies to promote economic and sustainable development. The empirical results of this study are summarized as follows:

(1) The average efficiency value of the OECD industrial sector during the study period is 0.8719, with a maximum value of 1 and a minimum value of 0.5835. The efficiency

values of 14 countries are higher than the average level, and the efficiency values of 17 countries are lower than the average level. The countries with the lowest efficiency values are Portugal (0.7147), France (0.6002), and Sweden (0.5835).

(2) The average efficiency value of the agricultural sector is 0.7666, with a maximum value of 1 and a minimum value of 0.2708 and a standard deviation of 0.2730. The efficiency values of 20 countries are higher than the average level, and the efficiency values of 11 countries are lower than the average level. The countries with the lowest efficiency values are Estonia (0.3134), Slovenia (0.2890), and the Slovak Republic (0.2708).

(3) The overall average value of DN-SBM is 0.7411, with a maximum value of 1 and a minimum value of 0.3607 and a standard deviation of 0.2221. The efficiency values of 17 countries are higher than the average level, and 14 countries are lower than the average level. The countries with the lowest efficiency values are Finland (0.4367), the Slovak Republic (0.3649), and Estonia (0.3607).

(4) The DN-TFP average value is 1.0776, indicating a slight improvement trend. Japan (1.7059) shows the best productivity performance, while Turkey (0.8489) has the lowest DN-TFP value with a standard deviation of 0.1681. DN-TFP values for 22 OECD countries are greater than 1, indicating a trend in progress. DN-TFP values for 9 countries are less than 1, indicating a declining trend. The DN-TFP values for Australia (0.9645), Slovenia (0.9126), and Turkey (0.8489) are the lowest.

(5) This study further compares DN-SBM and DN-TFP and finds that the overall efficiency values for five countries, including Germany (1.2333), Israel (1.0617), Luxembourg (1.0131), Netherlands (1.139), and Switzerland (1.0296), are 1, and productivity has improved. Among the three countries with lower efficiency values, Finland (0.4367, 1.0168) and Slovakia (0.3649, 1.0532) have improved productivity, while Estonia (0.3607, 0.9795), with the lowest efficiency value, not only has lower efficiency but also a decline in productivity. Eight countries have a decline in productivity, but there is still room for improvement in efficiency.

Efficiency was typically investigated for individual countries or industries in previous studies. However, in this study, we chose to use the WEF nexus framework to comprehensively assess the impact of industrial production in OECD countries on agriculture by combining the three elements of water, energy, and food and objectively evaluating their efficiency. The study found that countries with higher efficiency in the industrial sector did not necessarily have better efficiency in the agricultural sector. Similarly, countries with higher efficiency in the agricultural sector did not necessarily have better efficiency in the industrial sector. Therefore, this study is different from traditional research that only investigates the efficiency of individual countries or industries.

The uniqueness of this study lies in its use of dynamic and multi-stage methods to more objectively evaluate the overall efficiency of a country and determine the areas that need improvement and recommendations based on the efficiency performance at different stages. This has significant implications for national policy-making and provides policy makers with a more comprehensive and objective efficiency assessment method.

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