

Total Factor Productivity Growth in Iran: Presenting a Model with Desirable and Undesirable Outputs

Abstract

The aim of this research is to present a model based on data envelopment analysis with consideration of desirable and undesirable outputs, and calculation of total factor productivity in Iran and the selected countries. To achieve this goal, a method based on data envelopment analysis (DEA) was used with consideration of desirable and undesirable outputs for 42 developing and developed countries in the period from 2012 to 2022. The data analysis was performed in GAMS software. The results of this study showed that the growth of total factor productivity until 2017 was upward in Iran, and shortly after a fluctuated trend was reported. Total factor productivity increased from 0.865 to 1.043 in 2017; that is, in has faced a decrease of 13.5 percent in 2013, and has reached a growth of 4.3 percent in total factor productivity in 2017. On the other hand, the results show that after 2017, the growth of total factor productivity in Iran has been fluctuating. In a way that it has even experienced a decrease of 10 percent and an increase of 14.7 percent in 2022.

Keywords: Efficiency, Total Factor Productivity, Desired Output, Undesirable Output, Data Envelopment Analysis (DEA)

1. Introduction

Economic growth is one of the variables important for examining and comparing countries in terms of development. The evidence show that different countries have experienced different situations either in economic growth or in sustainability of economic growth. The World Bank believes that differences between nations in income levels and growth rates are largely due to differences in productivity; in other words, productivity is considered as the “engine of growth in the economy” (Haider et al., 2020). The importance of productivity in theories of economics was mentioned by Adam Smith and David Ricardo in the 18th century. They assumed the benefits of specialization and trade to be the basis of the wealth of nations (Kim and Louisa, 2019). Hicks (1939) and Schumpeter (1942) always emphasized the importance of improving productivity and considered that related to innovation and creativity in the company. According to Lewis (1954), Kuznets (1957), and Chenery (1960), economic development requires structural changes that would cause resources to shift from less productive sectors to more productive sectors of the economy (Kim and Louisa, 2019). The benefit resulting from total productivity growth is due to the more efficient use of inputs, which would result in differences in economic growth and the level of development of countries (Kim and Park, 2018).

Several studies have been conducted on identify the role of productivity in economic growth in order to explain the wide variation in economic growth across countries. In most of these studies productivity growth factor has been considered as one of the most important elements for economic growth. For example, Eichengreen et al. (2012) found that in the sample studied on average a decline in the growth rate of total factor productivity explained about 85 percent of the decline in economic growth. On the other hand, Bulman et al. (2014) and Gijssoukon (2012) have argued that countries that have been able to experience a growth of higher than average, have had relatively high growth in total factor productivity. Other studies have emphasized the importance of productivity growth. They believe that to catch up with developed countries, developing countries must reduce the gap between factor productivity. All of these cases show that measuring total factor productivity is important in assessing the past and potential economic performance of countries; however, differences in the methods and initial assumptions in calculating productivity will lead to different results in this area.

Since the early 2000s, due to the increasing demand for natural resources such as crude oil, timber and metals, concerns about the different approaches of companies and emerging economies, and focus on economic growth with consideration of sustainable development concepts became more important than before (Tang and Zhou, 2012; Zhou et al., 2018). The Malmquist index is one of the conventional methods for analyzing changes in total factor productivity and efficiency over time, which can be calculated based on data envelopment analysis (DEA) models. Given the importance of environmental issues in the recent literature on economic growth and development, measuring total factor productivity requires the use of methods that consider environmental issues. DEA models based on desirable and undesirable outputs are of the methods in which units are credited for producing desirable outputs and are penalized for producing undesirable outputs. Therefore, in this study, a model based on data envelopment analysis has been presented that has

taking into account desirable and undesirable outputs. The total factor productivity status in Iran and developing countries would be calculated according to that. In this regard, the present study is divided into five general parts. In the second part, after the introduction, the theoretical foundations and background of the research are presented. In the third part, the model and description of the variables will be presented. The fourth part of this study presents the results, and eventually in the fifth part the summary, conclusions, and research suggestions are presented.

1) Theoretical foundations and research background

The Malmquist index is used to analyze changes in efficiency and productivity over time. The Malmquist index allows the separation of productivity into its two main components, namely technological changes and changes in efficiency. The Malmquist analysis allows the researcher to separate changes in the frontier (technological changes) from improvements or changes relative to the frontier (technical efficiency changes) (Azimian et al., 2013). These two components being different analytically and fundamentally, require separate policymaking from a policy perspective. The result of technology change and change in technical efficiency is the change in total factor productivity, which is measured by the Malmquist index. The Malmquist index was first introduced in 1953 by a person named Malmquist as a quality indicator with the aim of analyzing the use of production resources. Cowes et al. (1982) introduced this index into the productivity literature (Chen, 2004). In 1989, Farr et al. used data envelopment analysis techniques to calculate the Malmquist index. Then, in 1992, they decomposed the index into two factors: change in efficiency and change in technology, which was presented by Farr et al. in 1994 (Pashaei et al., 2013).

The figure below shows the efficiency frontier for period t and s for a hypothetical decision-making unit (DMU). In period t , the inputs and outputs are $x^t = (x_1^t, x_2^t, \dots, x_n^t)$ and $y^t = (y_1^t, y_2^t, \dots, y_n^t)$, respectively. In period s , the inputs and outputs are $x^s = (x_1^s, x_2^s, \dots, x_n^s)$ and $y^s = (y_1^s, y_2^s, \dots, y_n^s)$, respectively. If the hypothetical firm has a combination of inputs and outputs (x^t, y^t) in period t and (x^s, y^s) in period s , then two changes have occurred during periods t and s ; first, due to technological progress, the firm has produced more output per input in period s than in period t ; In fact, the input-output combination in period s makes it unjustified to use the technology of period t . The second change was a change in the technical efficiency of the firm, because in period s the operating point was closer to the frontier than in period t .

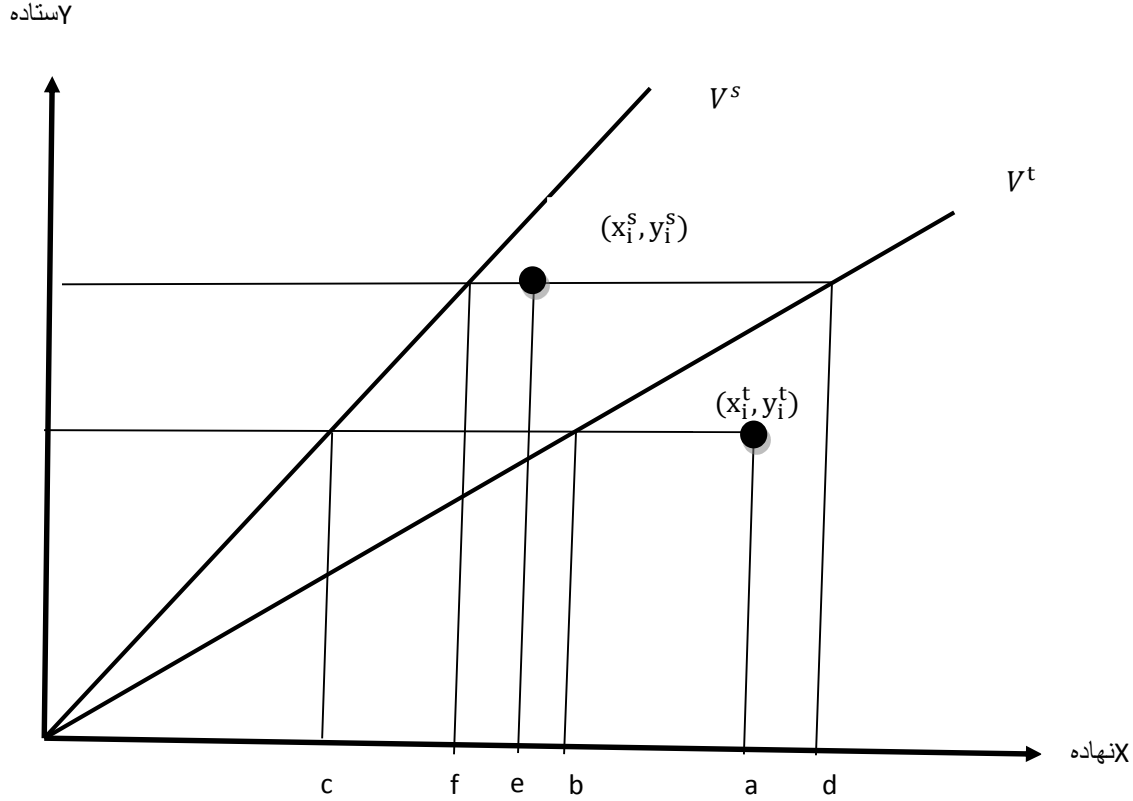


Figure (1): Fan changes and efficiency changes

According to the definition of the distance function and assuming the existence of n decision-making unit, and with the aim of calculating productivity growth from period t to period s , and decomposing that into the three factors mentioned, the Malmquist index is defined as follows:

$$M(x_s, x_t, y_s, y_t) = \left[\frac{d^t(x_s, y_s)}{d^t(x_t, y_t)} \times \frac{d^s(x_s, y_s)}{d^s(x_t, y_t)} \right]^{\frac{1}{2}} \quad (1)$$

In this relation $d^t(x_s, y_s)$ is the TFP value in period s using the technology of period t , $d^t(x_t, y_t)$ is the TFP value in period t using the technology of period t , $d^s(x_s, y_s)$ is the TFP value in period s using the technology of period s , and $d^s(x_t, y_t)$ is the TFP value in period t using the technology of period s .

With a few changes relation (1) can be transformed into relation (2):

$$M(x_s, x_t, y_s, y_t) = \frac{d^s(x_s, y_s)}{d^t(x_t, y_t)} \times \left[\frac{d^t(x_s, y_s)}{d^s(x_s, y_s)} \times \frac{d^t(x_t, y_t)}{d^s(x_t, y_t)} \right]^{\frac{1}{2}} \quad (2)$$

Farrell et al. stated that $M_0 > 1$ indicates progress or increase in productivity. $M_0 < 1$ it indicates a decrease in productivity and $M_0 = 1$ indicates no change in productivity. It should be noted that equation (3-4) is actually a geometric mean of two total factor productivity indices. In equation (3-4), the term outside the brackets, i.e. $\frac{d^s(x_s, y_s)}{d^t(x_t, y_t)}$ measures the change in technical efficiency between two periods t and s , which can be greater than, equal to, or less than one. Being greater than one means approaching the marginal production curve and improving efficiency; however, being smaller than one indicates moving away from the marginal curve and decreasing efficiency over time. The term within brackets also shows the technological change, which is equal to the geometric mean of the technological transfer between the two periods. This term can also be greater than, equal to, or less than one. Its value greater than one indicates an upward shift of the marginal production curve and technological progress, whereas its value less than one indicates a technological decline and a downward shift of the marginal production curve.

The Malmquist productivity index is constructed based on data envelopment analysis as the geometric mean of two Malmquist productivity indices. its represented by a discrete function D , assuming $D^k(y^k, x^k) = 1$ The Malmquist productivity index is decomposed into two components, one measuring the change in efficiency and the other measuring the change in frontier technology. The frontier technology is determined by the efficiency frontier, which is estimated using data envelopment analysis for a set of decision-making units.

In the Malmquist index, it is assumed that in period s there is a production function similar to that in period t . The calculation of the Malmquist index requires two separate mixed periodic scales. The two separate periodic scales can be determined by the efficiency frontier, and this efficiency frontier is estimated using data envelopment analysis. These two scales can be obtained using the CCR data envelopment analysis model, as shown in the model below.

$$\begin{aligned}
 D_0^i(x_0^i, y_0^i) &= \min \theta \\
 \text{st. } \sum_{i=1}^m \lambda_j x_{i0}^t &\leq x_{i0}^t, i = 1, 2, \dots, m \\
 \sum_{r=1}^s \lambda_j y_{r0}^t &\geq y_{r0}^t, r = 1, 2, \dots, s \\
 \lambda_j &\geq 0, j = 1, 2, \dots, n.
 \end{aligned} \tag{v}$$

In this model x_{ij}^t is the i^{th} input and y_{rj}^t is the r^{th} output for DMU_j in time period of t . The efficiency $D_0^i(x_0^i, y_0^i) = \theta$ is the amount by which the inputs can be reduced. By substituting s for t in the above model, we obtain $D_0^s(x_0^s, y_0^s)$:

$$\begin{aligned}
 \min \theta \\
 \text{st. } \sum_{i=1}^m \lambda_j x_{ij}^s &\leq \theta x_{i0}^s, i = 1, 2, \dots, m
 \end{aligned} \tag{xi}$$

$$\sum_{r=1}^s \lambda_j y_{t0}^r \leq y, r = 1, 2, \dots, s$$

$$\lambda_j \geq 0, j = 1, 2, \dots, n.$$

Similarly, another complex periodic index $D_0^s(x_0^s, y_0^s)$ is needed to estimate the input-oriented Malmquist productivity index and can be used for problems such as the issue of capability (3-7).

$$\begin{aligned} & \min \theta \\ & \text{st. } \sum_{i=1}^m \lambda_j x_{i0}^t \leq \theta x_{i0}^s, i = 1, 2, \dots, m \\ & \sum_{r=1}^s \lambda_j y_{rj}^s \geq y_{r0}^s, r = 1, 2, \dots, k \\ & \lambda_j \geq 0, j = 1, 2, \dots, n. \end{aligned} \quad (^\circ)$$

Early models in calculating performance in DEA method only valued desirable outputs and did not consider undesirable outputs. However, ignoring undesirable outputs is like saying that they have no value in the final evaluation, so this may lead to misleading results. Therefore, decision-making units shall be given credit for producing desirable outputs, and they shall be punished for producing undesirable outputs. The second problem is how to deal with imprecise data. Due to the problems of model construction and data availability, few papers have been published that have considered both issues together.

Farzipour Saen (2009) classified the options for dealing with undesirable outputs in DEA as follows. The first approach is to ignore the undesirable output. The second approach is to consider the undesirable output either as a nonlinear DEA model or change of the distance measure in a way that limits the propagation of undesirable outputs. The third approach is to consider undesirable outputs as inputs or to apply a uniform downward transformation to them (e.g. $y_b/1$, where y_b represents the undesirable output). Seaford and Zhou (2002) proposed an approach that examines undesirable outputs in the DEA framework. Undesirable factors since Farr et al. for the first time presented a nonlinear programming problem to evaluate efficiency in the presence of undesirable factors. Shell introduced some radial measures, so any change in the output level includes both desirable and undesirable outputs. Seaford and Zhou (2002) developed a radial model to improve efficiency by increasing desirable outcomes and reducing undesirable outcomes. Hadi-Winche et al. (2005) developed an efficiency assessment model that simultaneously considers undesirable inputs and undesirable outputs. Often, the situation is such that for factors such as the number of invoices received from a supplier without errors, only intermittent data from suppliers can be provided.

Kafaei and Bagherzadeh (2016) studied the effect of macroeconomic variables on total factor productivity in Iran. In this study, the Malmquist index and the auto-explanatory regression model (ARDL) were used with extended lags and data from the period 1979 to 2014. The results of this

study show that the real exchange rate variables, and foreign exchange earnings from oil exports have a positive effect in the long run. And the variables of economic instability, financial instability, and the share of government consumption expenditures have a negative effect on total factor productivity.

Dizji (2018) studied the prediction of total factor productivity in Iran. In this study, data from the period 1996 to 2016 and the feed-forward neural network model with the error back-propagation algorithm were used. The results of this study showed that the best model of the network was the number of model neurons with 18 neurons and the TANSIG input activation function and the TANSIG output function. In general, neural networks designed with the six variables studied will be able to predict the total factor productivity in the Iranian economy.

Fathi and Ghorbanian (2021) considering ecological footprint as an environmental assessment index and human development index as an output variable in a study investigated total factor productivity in Iran. In this study, the Malmquist method was used for calculating changes in sustainable total factor productivity in the MENA region countries and data from the period 1995 to 2016. The results of this study showed that countries in the very high and medium human development groups have higher sustainable technical efficiency than countries in the high and low human development groups.

Khodabakhshi and Cheraghali (2022) studied different approaches of measuring partial and total factor productivity. In this study, different indicators were used to calculate productivity including the Malmquist index. The results of calculations for the Malmquist index of the industrial sector in 2011 showed that total factor productivity growth was favorable, but productivity in the mining sector experienced the highest decrease. The results also showed that the growth of total factor productivity of the economy in 2011 was almost uniform.

In their study, Olafsson et al. (2014) examined the effectiveness of environmental indicators and also their effect on the assessment of the environmental sustainability of different countries. Using Iceland as a case study, the effectiveness of four selected environmental indicators (Environmental Vulnerability Index, Environmental Performance Index, Environmental Footprint and Happy Planet Index) was investigated for governance institutions when formulating rational responses to challenges. The results of this study showed that economic activities in Iceland are not observed in accordance with the generally accepted concepts of sustainable development, which emphasize the interaction of economic, environmental and social goals along with the identification of current and future needs.

Li and Su (2022) studied total factor productivity and the impact of capital account liberalization on total factor productivity growth. The results of this study showed that an increase in the standard deviation of the capital account openness index was significantly associated with an increase in the TFP growth rate of firms. The study showed that the effects of productivity increases were higher and stronger for sectors with external financial dependence.

Lin et al. (2023) assessed the development sustainability of selected countries based on the DEA method and TOPSIS analysis. In this study, the performance of each OECD country was evaluated based on the weights obtained from data envelopment analysis (DEA), along with a modified technique for priority by the TOPSIS method. The results of this study show that member countries gradually adopt policies to reduce fossil fuel consumption. In addition, regional analysis showed that the overall performance of G7 countries was significantly different from that of non-G7 countries.

2. Model presentation and variable description

Here, models with desirable and undesirable outputs are presented, where outputs corresponding to indices $1, 2, \dots, k$ are desirable and outputs corresponding to indices $k+1, k+2, \dots, s$ are undesirable. It is preferable to produce as many desirable outputs as possible and not produce undesirable outputs. Suppose that $X \in R_+^{m \times n}$ and $Y \in R_+^{s \times n}$ are matrices consisting of non-negative elements containing the observed input and output measures for the decision-making units. The vector of inputs consumed by DMU_j is denoted by X_j . The quantity of input i consumed by DMU_i is denoted by X_{ij} . A similar notation is used for the outputs.

To take undesirable factors into account, Korenen and Loptych (2004) introduced a best-performance frontier data envelopment analysis model. Their model is based on the fact that all outputs are presented as a weighted sum, but negative weights are used for undesirable outputs, as shown in model (6):

$$\begin{aligned}
 \max \theta_o &= \sum_{r=1}^k u_r y_{ro} - \sum_{t=k+1}^s u_t y_{to} \\
 s.t \quad &\sum_{r=1}^k u_r y_{ro} - \sum_{t=k+1}^s u_t y_{tj} - \sum_{i=1}^m v_i x_{ij} \leq 0, \quad j \\
 &= 1, \dots, n. \\
 &\sum_{i=1}^m v_i x_{io} = 1, \\
 &u_r, v_i \geq \varepsilon, \quad r = 1, \dots, s, \quad i = 1, \dots, m
 \end{aligned} \tag{7}$$

Where u_r and u_t are the weights given to the desired and undesirable outputs, respectively. In general, data envelopment analysis models in which both the desired and undesirable outputs exist are presented as models (7) to (10):

$$\begin{aligned}
\max \theta_o^U &= \sum_{r=1}^k u_r y_{ro}^U - \sum_{t=k+1}^s u_t y_{to}^L \\
s.t. \quad &\sum_{r=1}^k u_r y_{rj}^U \\
&\quad - \sum_{t=k+1}^s u_t y_{tj}^L - \sum_{i=1}^m V_i X_{ij}^L \leq 0, \quad j = 1, \dots, n.
\end{aligned} \tag{V}$$

$$\begin{aligned}
\sum_{i=1}^m V_i X_{io}^L &= 1 \\
u_r, V_i &\geq \varepsilon, \quad r = 1, \dots, S, \quad i = 1, \dots, m. \\
\max \theta_o^L &= \sum_{r=1}^k u_r y_{ro}^U - \sum_{t=k+1}^s u_t y_{to}^L \\
s.t. \quad &\sum_{r=1}^k u_r y_{rj}^U - \sum_{t=k+1}^s u_t y_{tj}^L - \sum_{i=1}^m V_i X_{ij}^L \leq 0, \quad j = 1, \dots, n.
\end{aligned} \tag{A}$$

$$\begin{aligned}
\sum_{i=1}^m V_i X_{io}^L &= 1, \\
u_r, V_i &\geq \varepsilon, \quad r = 1, \dots, S, \quad i = 1, \dots, m. \\
\min \varphi_o^L &= \sum_{r=1}^k u_r y_{ro}^L - \sum_{t=k+1}^s u_t y_{to}^U \\
s.t. \quad &\sum_{r=1}^k u_r y_{rj}^L - \sum_{t=k+1}^s u_t y_{tj}^U - \sum_{i=1}^m V_i X_{ij}^U \geq 0, \quad j = 1, \dots, n \\
\sum_{i=1}^m V_i X_{io}^U &= 1,
\end{aligned} \tag{9}$$

$$\begin{aligned}
u_r, V_i &\geq \varepsilon, \quad r = 1, \dots, S, \quad i = 1, \dots, m \\
\min \varphi_o^U &= \sum_{r=1}^k u_r y_{ro}^U - \sum_{t=k+1}^s u_t y_{to}^L \\
s.t. \quad &\sum_{r=1}^k u_r y_{rj}^L - \sum_{t=k+1}^s u_t y_{tj}^U - \sum_{i=1}^m V_i X_{ij}^U \geq 0, \quad j = 1, \dots, n \\
\sum_{i=1}^m V_i X_{io}^U &= 1,
\end{aligned} \tag{10}$$

Based on the above relations, the models of the Malmquist index for calculating $d_{t+1}^t(x_0, y_0)$, $d_t^t(x_0, y_0)$, $d_{t+1}^{t+1}(x_0, y_0)$ and $d_t^{t+1}(x_0, y_0)$ are as follows:

$$\begin{aligned}
d_{t+1}^t(x_0, y_0) &= \min \left(1 - \frac{1}{m_2} \sum_{i=1}^{m_2} \frac{S_i^-}{x_{io}^t} \right) / \left(1 + \frac{1}{S_2} \sum_{r=1}^{S_2} \frac{S_r^+}{y_{ro}^t} \right) \\
\sum \lambda_j x_{ij}^{t+1} + S_i^- &= x_{io}^t \quad i = 1, \dots, m_1 \\
\sum \lambda_j x_{ij}^{t+1} - S_i^- &= x_{io}^t \quad i = m_1 + 1, \dots, m_2 \\
\sum \lambda_j x_{ij}^{t+1} + S_i^- &= x_{io}^t \quad i = m_2 + 1, \dots, m \\
\sum \lambda_j y_{rj}^{t+1} - S_r^+ &= y_{ro}^t \quad r = 1, \dots, S_1 \\
\sum \lambda_j y_{rj}^{t+1} + S_r^+ &= y_{ro}^t \quad r = S_1 + 1, \dots, S_2 \\
\sum \lambda_j y_{rj}^{t+1} - S_r^+ &= y_{ro}^t \quad r = S_2 + 1, \dots, S
\end{aligned} \tag{11}$$

$$d^{t+1}_{t+1}(x_0, y_0) = \min \left(1 - \frac{1}{m_2} \sum_{i=1}^{m_2} \frac{s_i^-}{x_{io}^{t+1}} \right) / \left(1 + \frac{1}{S_2} \sum_{r=1}^{S_2} \frac{s_r^+}{y_{ro}^{t+1}} \right)$$

$$\begin{aligned} \sum \lambda_j x_{ij}^{t+1} + S_i^- &= x_{io}^{t+1} & i = 1, \dots, m_1 \\ \sum \lambda_j x_{ij}^{t+1} - S_i^- &= x_{io}^{t+1} & i = m_1 + 1, \dots, m_2 \\ \sum \lambda_j x_{ij}^{t+1} + S_i^- &= x_{io}^{t+1} & i = m_2 + 1, \dots, m \\ \sum \lambda_j y_{rj}^{t+1} - S_r^+ &= y_{ro}^{t+1} & r = 1, \dots, S_1 \\ \sum \lambda_j y_{rj}^{t+1} + S_r^+ &= y_{ro}^{t+1} & r = S_1 + 1, \dots, S_2 \\ \sum \lambda_j y_{rj}^{t+1} - S_r^+ &= y_{ro}^{t+1} & r = S_2 + 1, \dots, S \end{aligned} \tag{Y-3}$$

$$d^{t+1}_t(x_0, y_0) = \min \left(1 - \frac{1}{m_2} \sum_{i=1}^{m_2} \frac{s_i^-}{x_{io}^{t+1}} \right) / \left(1 + \frac{1}{S_2} \sum_{r=1}^{S_2} \frac{s_r^+}{y_{ro}^{t+1}} \right)$$

$$\begin{aligned} \sum \lambda_j x_{ij}^t + S_i^- &= x_{io}^{t+1} & i = 1, \dots, m_1 \\ \sum \lambda_j x_{ij}^t - S_i^- &= x_{io}^{t+1} & i = m_1 + 1, \dots, m_2 \\ \sum \lambda_j x_{ij}^t + S_i^- &= x_{io}^{t+1} & i = m_2 + 1, \dots, m \\ \sum \lambda_j y_{rj}^t - S_r^+ &= y_{ro}^{t+1} & r = 1, \dots, S_1 \\ \sum \lambda_j y_{rj}^t + S_r^+ &= y_{ro}^{t+1} & r = S_1 + 1, \dots, S_2 \\ \sum \lambda_j y_{rj}^t - S_r^+ &= y_{ro}^{t+1} & r = S_2 + 1, \dots, S \end{aligned} \tag{3-3}$$

$$d^t_t(x_0, y_0) = \min \left(1 - \frac{1}{m_2} \sum_{i=1}^{m_2} \frac{s_i^-}{x_{io}^t} \right) / \left(1 + \frac{1}{S_2} \sum_{r=1}^{S_2} \frac{s_r^+}{y_{ro}^t} \right) \tag{4-3}$$

$$\begin{aligned}
\sum \lambda_j x_{ij}^t + S_i^- &= x_{io}^t & i = 1, \dots, m_1 \\
\sum \lambda_j x_{ij}^t - S_i^- &= x_{io}^t & i = m_1 + 1, \dots, m_2 \\
\sum \lambda_j x_{ij}^t + S_i^- &= x_{io}^t & i = m_2 + 1, \dots, m \\
\sum \lambda_j y_{rj}^t - S_r^+ &= y_{ro}^t & r = 1, \dots, S_1 \\
\sum \lambda_j y_{rj}^t + S_r^+ &= y_{ro}^t & r = S_1 + 1, \dots, S_2 \\
\sum \lambda_j y_{rj}^t - S_r^+ &= y_{ro}^t & r = S_2 + 1, \dots, S
\end{aligned}$$

Based on the desired model, the variables of this study are as follows:

Table 1. Sample of countries under study

Variable Name	Type	Definition
Labor Force	Input	The population over 15 years of age authorized to work
Energy Consumption	Input	Energy consumption of oil, natural gas, coal, and electricity
Natural Resource Consumption	Input	Natural resources such as metals, minerals, and timber
GDP	Desired output	The market value of all goods and services produced in the economy at constant prices
Human Development Index	Desired output	The HDI measures a country's average achievement in three dimensions of human development: long and healthy life, knowledge, and standard of living. Long and healthy life is measured by life expectancy at birth, knowledge is measured by a combination of adult literacy rate and combined net enrollment ratio in primary, secondary, and tertiary education, and standard of living is measured by GDP per capita or income.
Carbon dioxide emissions	Undesirable output	Greenhouse gas emissions include carbon dioxide, methane, nitrous oxide, perfluorocarbons, hydrofluorocarbons, and sulfur hexafluoride. The amount of carbon dioxide equivalent determines the unit of emission.

The countries in question are presented in the table below.

Table 2. Sample of countries studied

Row	Country Name	Row	Country Name
1	Norway	22	Belgium
2	Switzerland	23	Finland
3	Australia	24	Austria
4	Singapore	25	Luxembourg
5	South Korea	26	France
6	Iceland	27	Slovenia
7	Hong Kong	28	Spain
8	Sweden	29	Czech Republic
9	Republic of Ireland	30	Italy
10	Netherlands	31	Turkey
11	Germany	32	Kazakhstan
12	Canada	33	Iran
13	United States	34	Brazil
14	United Kingdom	35	China
15	Japan	36	Thailand
16	New Zealand	37	Taiwan
17	Denmark	38	Saudi Arabia
18	Portugal	39	Romania
19	Oman	40	United Arab Emirates
20	Russia	41	Qatar
21	Malaysia	42	Greece

Data for the above countries were used in the period 2012 to 2022 and the results were analyzed using GAMS software.

3) Presentation of Results

Table (3) to Table (6) indicate the results of calculating the total factor productivity index extracted from the model presented in this study. If the Malmquist index is greater than one, it indicates an improvement in total factor productivity, and if its value is less than 1, it indicates that total factor productivity has decreased. The results of calculating the Malmquist index show that some countries have experienced an increase in total factor productivity in some years. As observed in the tables, among the countries studied and in the period under consideration, the highest increase in the growth rate of total factor productivity was in the Czech Republic in 2013 with a growth rate of 33 percent, and the lowest was in Brazil with a decrease of about 20 percent in the growth rate of total factor productivity. As seen in the tables, the growth of total factor productivity in Iran was on the rise until 2017 and then it was faced with a fluctuating trend. It reached from 0.865 to 1.043 in 2017; that is, in 2013 it faced a decrease of 13.5 percent in total factor productivity and reached 4.3 percent growth in 2017.

Table 3. Results of the Malmquist Index measurement in 2013-2014

Country	2013	2014	Country	2013	2014
Australia	1.012	0.891	Brazil	0.807	1.004
Singapore	1.201	0.982	France	0.979	0.935
South Korea	1.166	1.221	Luxembourg	1.042	0.904
Iceland	1.142	1.190	United Kingdom	0.970	1.153
Hong Kong	1.045	0.820	Germany	1.021	1.021
Switzerland	1.097	1.048	China	1.038	1.07
Republic of Ireland	1.024	0.801	Thailand	1.0183	0.907
Netherlands	1.406	0.989	Finland	0.926	0.962
New Zealand	1.123	1.071	Taiwan	1.148	0.927
Belgium	1.069	1.067	Saudi Arabia	1.035	0.901
Austria	1.166	0.893	Norway	0.883	1.056

Slovenia	0.936	1.024	Sweden	1.069	1.153
Spain	1.099	1.080	Portugal	1.619	1.020
Czech Republic	1.334	0.948	Oman	1.099	1.174
Italy	1.038	1.036	Russia	1.189	0.954
Turkey	0.840	1.053	Malaysia	1.192	0.907
Kazakhstan	1.037	1.038	Romania	0.865	0.868
Japan	068/1	1.026	United Arab Emirates	0.666	058
Denmark	1.256	0.906	Qatar	0.979	1.081
Iran	0.865	0.888	United States	1.044	1.044
			Canada	0.911	0.925

Source: Research findings

Table 4. Results of the Malmquist Index measurement in 2015-2017

Country	2015	2016	2017	Country	2015	2016	2017
Australia	0.933	0.988	0.946	Brazil	1.069	1.035	1.044
Singapore	1.157	1.107	1.068	France	1.085	0.910	1.042
South Korea	0.890	1.047	1.074	Luxembourg	0.945	0.953	0.905
Iceland	1.038	0.967	0.988	United Kingdom	1.232	0.881	0.961
Hong Kong	1.031	1.023	0.995	Germany	1.243	1.062	0.950
Switzerland	0.820	1.177	0.841	China	1.127	1.096	0.931
Republic of Ireland	0.811	0.961	1.165	Thailand	0.957	1.108	0.932
Netherlands	0.860	1.187	1.113	Finland	0.957	0.898	1.073
New Zealand	0.884	1.024	1.011	Taiwan	1.007	1.032	0.944
Belgium	0.982	0.925	1.035	Saudi Arabia	1.102	0.979	1.041
Austria	0.963	0.903	1.011	Norway	0.981	1.099	1.088
Slovenia	0.874	1.069	0.929	Sweden	1.032	1.025	0.954
Spain	0.902	1.038	1.112	Portugal	0.953	0.933	0.997
Czech Republic	0.895	1.055	0.928	Oman	1.025	1.037	0.979
Italy	0.968	1.064	1.024	Russia	0.822	1.077	0.928
Turkey	0.800	1.011	1	Malaysia	1.001	0.964	0.949
Kazakhstan	0.899	1.074	0.994	Romania	0.936	1.570	0.891
Japan	1.003	0.914	1.168	United Arab Emirates	1.046	1.099	1.037

Denmark	1.025	1.101	1.092	Qatar	0.889	1.274	1.05
Iran	0.952	1.013	1.043	United States	1.065	1.004	0.938
				Canada	0.921	0.862	0.929

Source: Research findings

Table 5. Results of the Malmquist Index measurement in 2018-2020

Country	2018	2019	2020	Country	2018	2019	2020
Australia	1.078	0.944	0.996	Brazil	0.929	0.941	1.047
Singapore	1.053	1.052	1.075	France	1.024	0.895	1.143
South Korea	1.103	1.052	1.117	Luxembourg	0.982	1.042	1.065
Iceland	1	1.055	1.054	United Kingdom	1.034	1.191	1.024
Hong Kong	1.038	1.001	0.926	Germany	1.024	1.064	1.035
Switzerland	0.839	0.993	0.921	China	0.964	0.789	1.080
Republic of Ireland	0.961	0.927	0.875	Thailand	1.015	1.033	1.024
Netherlands	1.024	0.961	0.911	Finland	0.945	0.995	1.035
New Zealand	0.990	1.035	1.040	Taiwan	1.019	0.960	0.892
Belgium	1.012	0.988	1.027	Saudi Arabia	0.955	1.004	0.933
Austria	1.035	1.050	0.993	Norway	1.042	1.053	0.932
Slovenia	0.971	1.007	0.976	Sweden	1.899	0.922	1.012
Spain	1.038	0.974	0.947	Portugal	1.036	1.025	1.046
Czech Republic	1.123	0.954	0.997	Oman	1.091	0.968	1.016
Italy	1.006	0.973	1.027	Russia	1.147	0.978	1.042
Turkey	1.054	0.937	1.062	Malaysia	1.008	1.008	1.097
Kazakhstan	1.051	0.943	0.977	Romania	1.156	0.981	1.082
Japan	0.895	0.943	1.067	United Arab Emirates	1.008	0.945	0.985
Denmark	1.041	0.978/1	0.927	Qatar	1.124	1.051	1.087
Iran	0.900	1.058	1.057	United States	0.932	1.058	1.072
				Canada	0.946	1.014	0.989

Source: Research findings

Table 6. Results of the Malmquist Index measurement in 2021-2022

Country	2021	2022	Country	2021	2022
Australia	1.035	1.149	Brazil	1.067	1.210
Singapore	1.052	1.068	France	1.023	0.963
South Korea	1.090	1.192	Luxembourg	0.920	1.043
Iceland	1.046	1.233.	United Kingdom	1.131	0.906
Hong Kong	0.911	1.067.	Germany	0.942	1.066
Switzerland	1.082	1.038	China	1.161	1.031
Republic of Ireland	1.136	1.186	Thailand	1.101	1.148
Netherlands	1.046	1.024	Finland	1.050	0.948
New Zealand	1.166	0.996	Taiwan	1.056	1.132
Belgium	1.049	1.033	Saudi Arabia	0.861	0.943
Austria	1.052	1.138	Norway	1.055/	0.907
Slovenia	0.962	1.080	Sweden	0.971	1.015
Spain	0.896	1.134	Portugal	0.955	1.032
Czech Republic	1.042	1.118	Oman	0.985	1.112
Italy	0.912	1.035	Russia	1.050	1.173
Turkey	0.981	1.057	Malaysia	0.955	1.058
Kazakhstan	1.158	1.046	Romania	1.068	1.031
Japan	1.084	0.926	United Arab Emirates	1.026	1.157
Denmark	0.979	0.927.	Qatar	1.034	1.008
Iran Country	0.945	1.147	United States	0.938	1.065
			Canada	0.930	1.012

Source: Research findings

Another point is that after 2017, the growth of total factor productivity in Iran has been fluctuating. It has even experienced a decrease of 10 percent to an increase of 14.7 percent in 2022. The reasons for this can be sought in the effects of sanctions against Iran in these years. With the sanctions imposed on Iran, the country has faced various restrictions both financially and technologically. This matter has led to a decrease in total factor productivity in Iran. On the other hand, with the lifting of sanctions on Iran in some of these years, the country's situation has improved, and with the re-imposition of sanctions, the growth of total factor productivity in Iran has also decreased.

2) Summary and Conclusions

To provide an explanation for the wide variation in economic growth among countries, several studies have been conducted to identify the role of productivity in economic growth. In most of these studies the growth of factor productivity has been considered as one of the most important elements for economic growth. The Malmquist index is one of the conventional methods for analyzing changes in efficiency and total factor productivity over time, which can be calculated based on data envelopment analysis (DEA) models. Given the importance of environmental issues in the recent literature related to economic growth and development, measuring total factor productivity requires the use of methods that consider environmental issues. And DEA models based on desirable and undesirable outputs are of the methods that give credit to units for desirable outputs and punish them for producing undesirable outputs. Therefore, in this study, a model based on data envelopment analysis has been presented with consideration of desirable and undesirable outputs, and based on that the total factor productivity status in Iran and developing countries is calculated. To achieve this goal, a method based on data envelopment analysis (DEA) was used, considering desirable and undesirable outputs for 42 developing and developed countries in the period from 2012 to 2022. Data analysis was also performed in GAMS software.

The results of this study showed that the growth of total factor productivity in Iran was increasing until 2017 and then it was faced with a fluctuating trend. It reached from 0.865 to 1.043 in 2017; That is, it faced a decrease in total factor productivity of 13.5 percent in 2013 and reached a growth of 4.3 percent in total factor productivity in 2017. On the other hand, the results show that after 2017, the growth of total factor productivity in Iran has been fluctuating, in a way that in even experienced a decrease of 10 percent and an increase of 14.7 percent in 2022. The reasons for this can be sought in the effects of sanctions against Iran in these years. With the sanctions imposed on Iran, the country has faced various limitations both financially and technologically. This has led to a decrease in the total factor productivity in Iran. On the other hand, with the lifting of sanctions on Iran in some of these years, the country's situation has improved, and with the re-imposition of sanctions, the growth of total factor productivity in Iran has decreased. What is clear is that dependence on oil revenues and sanctions on the country have affected the growth of total factor productivity in Iran; therefore, reducing dependence on foreign countries on one side, and resolving political conflicts on the other side can improve Iran's situation in this regard.

Conflict of Interest Statement

The authors declare that there is no conflict of interest regarding the publication of this manuscript.

References

- Khodabakhshi, M., & Chiragali, Z.** (2012). Measuring partial and total factor productivity of the country's economic sectors. *Decision Making and Operations Research*, 7(4), 580-569.
- Dizji, M.** (2018). Forecasting total factor productivity in the Iranian economy. *Economic Strategy*, 7(25), 45-70.
- Fathi, F., & Ghorban, E.** (2019). Sustainability of factor productivity in the MENA region with emphasis on ecological footprint. *Environmental Sciences*, 19(3), 192-177.
- Kafaei, S. M. A., & Bagherzadeh, M.** (2016). The effect of key macroeconomic variables on total factor productivity in Iran. *Economic Research and Policies*, 24(79), 215-243.
- Bodini, A., Bondavalli, C., & Allesina, S.** (2012). Cities as ecosystems: Growth, development and implications for sustainability. *Ecological Modelling*, 245, 185-198.
- Campbell, D. E., & Garmestani, A. S.** (2012). An energy systems view of sustainability: Emergy evaluation of the San Luis Basin, Colorado. *Journal of Environmental Management*, 95(1), 72-97.
- Cook, D., Saviolidis, N. M., Davíðsdóttir, B., Jóhannsdóttir, L., & Ólafsson, S.** (2017). Measuring countries' environmental sustainability performance—The development of a nation-specific indicator set. *Ecological Indicators*, 74, 463-478.
- Lemke, C., & Bastini, K.** (2020). Embracing multiple perspectives of sustainable development in a composite measure: The Multilevel Sustainable Development Index. *Journal of Cleaner Production*, 246, 118884.
- Lin, S. W., Lo, H. W., & Gul, M.** (2023). An assessment model for national sustainable development based on the hybrid DEA and modified TOPSIS techniques. *Complex & Intelligent Systems*, 1-18.
- Kim, Y. E., & Loayza, N.** (2019). Productivity growth: Patterns and determinants across the world. *World Bank Policy Research Working Paper*, (8852).
- Li, X., & Su, D.** (2022). Total factor productivity growth at the firm-level: The effects of capital account liberalization. *Journal of International Economics*, 139, 103676.
- Ou, C. H., & Liu, W. H.** (2010). Developing a sustainable indicator system based on the pressure–state–response framework for local fisheries: A case study of Gungliau, Taiwan. *Ocean & Coastal Management*, 53(5-6), 289-300.
- Ólafsson, S., Cook, D., Davíðsdóttir, B., & Jóhannsdóttir, L.** (2014). Measuring countries' environmental sustainability performance—A review and case study of Iceland. *Renewable and Sustainable Energy Reviews*, 39, 934-948.

Pope, J., Annandale, D., & Morrison-Saunders, A. (2004). Conceptualising sustainability assessment. *Environmental Impact Assessment Review*, 24(6), 595-616.

Tang, C. S., & Zhou, S. (2012). Research advances in environmentally and socially sustainable operations. *European Journal of Operational Research*, 223(3), 585-594.

Winfield, M., Gibson, R. B., Markvart, T., Gaudreau, K., & Taylor, J. (2010). Implications of sustainability assessment for electricity system design: The case of the Ontario Power Authority's integrated power system plan. *Energy Policy*, 38(8), 4115-4126.

Zhou, H., Yang, Y., Chen, Y., & Zhu, J. (2018). Data envelopment analysis application in sustainability: The origins, development and future directions. *European Journal of Operational Research*, 264(1), 1-16.