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RESEARCH PAPER

Total Factor Productivity Contributions and Its Drivers: Endogenous Growth Accounting Approach

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Abstract

This paper applies the endogenous growth accounting Approach to measure total factor productivity (TFP) and its Contributions in 121 four-digit ISIC code manufacturing industries between 2003 and 2019. The basic problem of most researchers is that they use the theory of exogenous growth to account for. This study uses the endogenous growth theory and the induced innovation theory to justify the utilization of varying coefficient production functions and decomposes total factor productivity into two parts: input-embedded and input-free productivities. Input-free productivity is divided into technical efficiency change and technological progress, while input-embedded productivity depends on the inputs used in the production function (labor and capital). Findings show that the average value-added growth is % 6.7%. The average ratio of input-embedded productivity in the industry's growth is about 21.8%. The contribution of capital-embedded productivity is -6.7% and the contribution of labor-embedded productivity is 28.5%. Therefore, technology is more manifest in labor. The IFP-free productivity ratio is 1.4%, which is due to two factors: technical efficiency change and technological progress.

Keywords: Endogenous Growth Theory, Growth Accounting, Iran's Manufacturing Industries, Total Factor Productivity.

JEL Classifications: D24, O14, O47.

1. Introduction

Solow's standard growth accounting approach (1956) considers two factors: the contribution of changes in classical production inputs (labor force and capital stock), and the residual. Solow's residual is the portion of an economy's output growth that cannot be attributed to the accumulation of capital and labor. It is not explained by changes in production inputs, and it is usually measured by the increase in total factor productivity (TFP), which also represents technological progress. Therefore, growth accounting seeks to answer the question of whether the production growth of an economy is due to changes in available production inputs and technology. Growth accounting is a popular tool to measure the contribution of different economic drivers to economic growth through their impact on TFP growth (Akcigit et al., 2021). However, there are two problems with the standard growth accounting method. First, the fixed coefficients assumption in the standard production function, along with the exogenous growth theory, fails to capture the changing input-output relation across countries and over time. This contradicts the endogenous growth theory of Romer (1986) and Lucas (1988) as well as the induced innovation theory proposed by Hicks (1963). Some studies use the time-varying contribution of input costs as the time-varying coefficients of inputs, which rely on the assumption of constant returns to scale that may not be valid at the macro-level in endogenous growth theory, as shown in Barro (1999) (Kumbhakar et al., 2000). Second, standard growth accounting can only estimate the overall effect of a growth driver on economic growth, but is incapable of identifying the pathways or channels through which the growth drivers affect economic growth because all the possible routes are mixed in TFP measured by a Solow residual (Hac et al., 2021).

Lack of identification and partition of the overall effects is sometimes problematic. For example, suppose a country has a constraint in its public R&D budget, a question that is raised: where should we invest and how much should we invest in each field to promote economic growth? This is an important issue in the real world and requires comparing the effects of R&D on economic growth through different channels, which are unable to be fulfilled by the standard growth accounting approach (Heyets et al., 2019). By using endogenous growth and induced innovation theory, a production function is defined by variable coefficients in this paper that allows a varying coefficient production function to reflect the quality change of inputs without the restriction of constant returns to scale. Then, Total factor productivity (TFP) is decomposed into input-embedded productivity and input-free productivity. Accordingly, the second source of economic growth in standard growth accounting (the growth in TFP) can be further separated into growth in various input-embedded productivities and input-free productivity. Therefore, new growth accounting can evaluate various channels through which the growth drivers affect economic growth, including their effects on input quantity, input quality, and input-free productivity, which is unidentified in standard growth accounting. A recurring question among economists is: What is the source of a country's economic growth? Researchers use a variety of methods to answer this question. One simple and useful method is growth accounting (Ghosh et al., 2021). The contribution of this article is threefold. First, this study uses the endogenous growth theory and the induced innovation theory to justify the utilization of varying coefficient production functions. Second, this study decomposes total factor productivity (TFP) into input-embedded and input-free productivities. Third, this paper tends to generalize the traditional neoclassical growth accounting methodology to investigate various channels through which growth drivers affect economic growth. To do so, this paper applies the new model to investigate economic growth in 121 four-digit ISIC code manufacturing industries from 2003 to 2019.

The remainder of the paper is structured as follows. The next Section addresses the review of the related literature. The third Section establishes the new growth accounting model. In the succeeding Section, a data description is provided. Next, the empirical results are presented, and in the final Section conclusion and discussion.

2. Literature Review

2.1 Theoretical Framework

Barro and Sala-i-Martin (2004) suggest that, despite the significant importance of the economic growth rate, its drivers remain one of the biggest mysteries in economics. Adam Smith believed that specialization and the division of labor were the engines of economic growth. Classical economists like Malthus and Ricardo thought that limited natural resources were the main constraint on growth opportunities. During the 20th century, economists shifted focus toward investment in physical capital and infrastructure. However, in the 1950s, economists like Solow (1956; 1957) examined economic growth more seriously. Solow proposed that technology, capital stock, and labor were the key drivers of a nation's economic growth, testing his theory with U.S. data. Researchers applied his theory in various countries. Generally, three approaches are used to evaluate economic growth: the theoretical approach, which uses economic growth theories to explain contributing factors; the steady-state approach, focusing on stable economic growth; and the growth accounting approach, which measures the contributions of various factors to economic growth. The first approach can't precisely quantify individual contributions; the second is mainly for developed countries. The third approach, however, can quantify the contributions of different factors to economic growth.

2.2 Difference from Previous Studies

Many studies have investigated the factors driving economic growth and total factor productivity (TFP). Haouas et al. (2024), using an accounting framework, found that Algeria's economic growth performance has been weak and modest for decades. This is largely due to labor growth, with weak capital accumulation and significant losses in TFP growth. Zhang et al. (2023) showed that a 1% decrease in external technology dependence could lead to a 1% increase in TFP in China. They also found that the impact of external technology dependence on TFP is stronger in technology-intensive industries compared to other sectors. Herzer (2022) found that increases in domestic R&D expenditure positively impact the level and growth rate of TFP, as predicted by semi-endogenous growth theory. However, this effect is more pronounced in middle-income countries than in low-income ones. Herzer also showed that domestic R&D has a significantly greater effect on TFP in developing countries compared to international R&D spillovers. Rawat and Sharma (2021) revealed that technical change and efficiency improvement are key drivers of TFP growth in India. Albanese et al. (2021) indicated that, on average, local TFP appears to be relatively unresponsive to EU programs.

Jia et al. (2020) demonstrated that manufacturing TFP growth contributes directly to economic growth and indirectly through capital and labor input growth. In contrast, similar direct and indirect effects were not observed for non-manufacturing TFP growth. Bandyopadhyay et al. (2019) calibrated their model to the US economy and found that misallocation and its negative effects on TFP and GDP can be significant.

Most studies on economic growth accounting rely on exogenous models, but they fall short because they can't analyze total productivity growth, treating it as exogenous and using the Solow residual approximation. This article employs an endogenous approach to account for the economic growth of Iran's manufacturing industries, presenting two significant advantages over traditional methods. First, it rejects the assumption of constant returns to scale, allowing for the possibility of increasing returns. Second, it elucidates the nature of productivity growth and its driving factors, addressing a common flaw in earlier studies that often underestimated the share of productivity growth. Standard growth accounting only estimates the overall impact of a growth stimulus on economic growth without identifying the specific pathways or mechanisms through which these stimuli operate. This article's approach aims to fill that gap.

2.3 Standard Growth Accounting in the Form of Exogenous Growth Theory

Growth accounting is a common technique for measuring the contribution of factors of production to economic growth. It was first introduced in the form of the exogenous growth theory by Solow (1956; 1957) and Swan (1956). Subsequently, many researchers used this method in their studies (Jorgenson and Stiroh, 2000; Jones, 2002; Bai and Zhang, 2010). A classic production function with Cobb–Douglas formation is frequently used by many scholars in several growth-accounting studies (Gallup and Sachs, 2000; Miller, 2002; Deininger and Jin, 2005; Hammond and Thompson, 2008; Pope and LaFrance, 2013; Shee and Stefanou, 2015; Sheng et al., 2019). This production function is;

$$\mathrm{y_{it}} = \mathrm{a_{it}} + \beta \mathrm{k_{it}} + (1-\beta)\mathrm{l_{it}} \quad (1)$$

where $\mathrm{y_{it}}$ is the production, $\mathrm{a_{it}}$ is the TFP or technology level, $\mathrm{k_{it}}$ is the capital stock, and $\mathrm{l_{it}}$ is the labor. Therefore, production growth is as follows;

$$\dot{\mathrm{y}}_{\mathrm{it}} = \dot{\mathrm{a}}_{\mathrm{it}} + \beta \dot{\mathrm{k}}_{\mathrm{it}} + (1-\beta)\dot{\mathrm{l}}_{\mathrm{it}} \quad (2)$$

According to Equation (2), production growth is driven by the expansion of classical production factors and the improvement in productivity of all production factors. Therefore, the contribution of capital and labor to economic growth is equivalent to $\frac{\beta \dot{\mathrm{k}}_{\mathrm{it}}}{\dot{\mathrm{y}}_{\mathrm{it}}}$ and $\frac{(1-\beta)\dot{l}_{\mathrm{it}}}{\dot{\mathrm{y}}_{\mathrm{it}}}$, respectively. And, $\frac{\dot{\mathrm{a}}_{\mathrm{it}}}{\dot{\mathrm{y}}_{\mathrm{it}}}$ is a TFP contribution. TFP, in the long term, is often regarded as the major driving force of economic growth; however, it is a Solow residual that measures the portion of output not explained by the amount of inputs used in production (Sickles 2005; Jin et al. 2002; Deininger and Jin 2005).

2.4 New Standard Growth Accounting in the form of Exogenous Growth Theory

The framework of endogenous growth theory of input elasticity in time and specific to each company is affected by variables such as R&D investment, which is as follows;

$$y_{it} = a_{it} + \beta_{it} k_{it} + \theta_{it} l_{it} \quad (3)$$

where $\beta_{it} = f_1(W_{it})$ and $\theta_{it} = f_2(W_{it})$ and W_{it} are drivers of growth as R&D that affect input elasticity. Assuming that there is a linear relation between growth drivers and the input elasticity, Equation (3) is rewritten as follows;

$$y_{it} = \alpha_0 + \lambda W_{it} + (\beta_0 + \gamma W_{it})k_{it} + (\theta_0 + \rho W_{it})l_{it} \quad (4)$$

where α_0 , β_0 , and θ_0 are the level of TFP, capital elasticity, and labor elasticity when W = 0, respectively. Also, λ, γ, and ρ measure the effects of W on TFP, capital elasticity, and labor elasticity, respectively. In the production function, k_{it}

and l_{it} measure the quantity of the inputs, whereas the input elasticities to some extent can be regarded as the quality of the inputs. A greater input elasticity can increase output for a given amount of input.

The endogenous growth theory introduces spillovers on inputs, whereas the induced innovation theory introduces invention on inputs, but both can result in a better quality of the inputs, and therefore, more output is given fixed inputs. The theory of induced innovation emphasizes the differences in resource endowment and input prices across countries, and this can change the shape of the production function over time. As one of the growth drivers, International trade, though, can change resource allocation and input prices, and therefore affect input elasticity and productivity. Structural transformation, which refers to the reallocation of economic activity across agricultural sectors, industry, and services, is another growth driver (Herrendorf et al., 2014). In most cases, industry and services are more productive than agriculture. So, countries can improve their aggregated TFP by increasing their contribution to their non-agricultural sector. Above all, as each sector has its production technologies and therefore sector-specific input elasticity, structural transformation can also affect input elasticity. Accordingly, improving the contribution to a specific sector can make the total input elasticity of the economy closer to the input elasticity of that sector. Country-level input elasticities are not constant because the ratio of the three sectors varies across countries, and structural transformation happens all the time (Herrendorf et al., 2014). Supposing Equation (4) is the true data-generating process, we assume constant input elasticities. So, Equation (4) can be rewritten as:

$$\begin{aligned} y_{it} = \alpha_0 + \lambda W_{it} + \left[(\beta_0 - \hat{\beta}) + \gamma W_{it})\right] k_{it} + \\ \left[(\theta_0 - \hat{\theta}) + \rho W_{it})\right] l_{it} + \hat{\beta} k_{it} + \hat{\theta} l_{it} \end{aligned} \tag{5}$$

where $\hat{\beta}$ and $\hat{\theta}$ are estimates of capital and labor elasticities derived by the classic production function with Cobb–Douglas formation. Then, the measured TFP is:

$$\begin{aligned} T\hat{F}P_{it} &= \alpha_0 + \lambda W_{it} + \left[(\beta_0 - \hat{\beta}) + \gamma W_{it})\right] k_{it} \\ &\quad + \left[(\theta_0 - \hat{\theta}) + \rho W_{it})\right] l_{it} \\ &= \alpha_0 + \left(\beta_0 - \hat{\beta}\right) k_{it} + (\theta_0 - \hat{\theta}) l_{it} \\ &\quad + [\lambda + \gamma k_{it} + \rho l_{it})] W_{it} \end{aligned} \tag{6}$$

When the main purpose is to estimate the overall effects of Z on output, standard growth accounting is sufficient and appropriate, as the impacts of Z on productivity and input elasticities (i.e., λ, γ, and ρ), in the end, all contribute to the output. Furthermore, as TFP was defined earlier in this paper, it is reasonable to contribute all the residuals along with the quantity and quality of inputs into TFP. This new method measures the effects of growth drivers on the elasticity of inputs along with their effect on productivity. In general, the new growth accounting aims not only to decompose the economic growth into changes in input values and total factor productivity but also to decompose TFP growth into input-embedded productivities (labor-embedded and capital-embedded) independent of inputs or input-free. It is worth mentioning that the growth of additional input productivity refers to the increase in productivity due to the improvement of the quality of inputs. Therefore, new growth accounting can identify and measure the pathways or channels through which the growth drivers affect economic growth.

3. Methods and Materials

The weakness of standard growth accounting is the constant assumption of input elasticity. To overcome this shortcoming, the varying coefficient model is proposed by Hastie and Tibshirani (1993) in the form;

$$y = x_1 z_1(\phi_1) + \cdots + x_K z_K(\phi_K) + \varepsilon \tag{7}$$

where the coefficients of the non-parametric function are of threshold variables ϕ_K. On the other hand, the stochastic frontier model, which was proposed by Aigner et al. (1977) and Meeusen and Van den Broeck (1977) and has been widely used by many researchers (Jin et al., 2002; Wang et al., 2016; Yang et al., 2016), has the following form;

$$y_{it} = f(X_{it}; \beta) + \nu_{it} - u_{it} \tag{8}$$

where $f(X_{it}; \beta)$, in this stochastic frontier model, represents the maximum production with the available inputs in each period, and hence it measures the optimal relationship between inputs and production over time. Also, ν_{it} is the regression error term, and $-u_{it}$ is the technical inefficiency. In other words, technical efficiency is calculated as $TE_{it} = exp(-u_{it})$. Regarding the model with variable coefficients and the stochastic frontier model, the stochastic frontier model with variable coefficients is defined as follows;

$$y_{it} = \psi_0(\phi_{it}) + \sum_{k=1}^{p} \psi_k(\phi_{it}) x_{it}^k + \nu_{it} - u_{it} \tag{9}$$

where $\beta_{it}^k = \psi_k(\phi_{it})$ is a function to estimate the varying elasticity of the production input. The intercept, $\psi_0(\phi_{it})$ is also assumed to be a nonparametric function of the threshold variables to measure the effects of growth drivers on output through input-free productivity. Research and development (R&D) is the most important threshold variable as an economic growth driver, which also explains technological progress. The degree of openness of the economy or trade-to-GDP ratio can be the second growth driver considered as a threshold variable. On the other hand, the free exchange of outputs can improve input-free productivity growth, as comparative advantages can play a positive role in economic growth even with constraints in the input endowment. Thus, trade may affect economic growth through its effect on both input-embedded productivity (input elasticity) and input-free productivity. Structural transformation is the third economic driver. Even without technological progress, an economy can increase its economic growth by moving more resources from less productive to more productive sections. After estimating the coefficients, production growth can be decomposed by the following form;

$$\Delta y_{it} = \sum_{k=1}^{p} \left(\beta_{it}^{k}\, x_{it}^{k} - \beta_{i,t-1}^{k}\, x_{i,t-1}^{k} \right) + \Delta IFP_{it} + \Delta v_{it} \tag{10}$$

where $\Delta IFP_{it} = \psi_0(\phi_{it}) - u_{it}$ measures the input-free productivity growth for period *i* at time t. Also, to decompose productivity related to inputs, $\beta_{it}^{k}\, x_{it}^{k} - \beta_{i,t-1}^{k}\, x_{i,t-1}^{k}$, both sides of equation (10) are divided by Δy_{it}Thus, new growth accounting is achieved *as* follows;

$$1 = \underbrace{\sum_{k=1}^{p} \left[\frac{\Delta x_{it}^{k} (\beta_{it}^{k} + \beta_{i,t-1}^{k})}{2 \Delta y_{it}} \right]}_{input\ quantity} + \underbrace{\underbrace{\sum_{k=1}^{p} \left[\frac{\Delta \beta_{it}^{k} (x_{it}^{k} + x_{i,t-1}^{k})}{2 \Delta y_{it}} \right]}_{\text{input−embedded productivity}} + \underbrace{\frac{\Delta IFP_{it}}{\Delta y_{it}}}_{\text{input−free productivity}}}_{\text{total factor productivity}} + \underbrace{\frac{\Delta v_{it}}{\Delta y_{it}}}_{\text{residual}} \tag{11}$$

where the four parts on the right-hand side of Equation (11) are the contributions of changes in input quantities, input-embedded productivity, input-free productivity, and residuals, respectively. For comparison, the standard growth accounting model has the following form;

$$1 = \underbrace{\sum_{k=1}^{p} \left[\frac{\beta_{it}^{k}\, \Delta x_{it}^{k}}{\Delta y_{it}} \right]}_{\text{input quantity}} + \underbrace{\frac{\Delta TFP_{it}}{\Delta y_{it}}}_{TFP} + \underbrace{\frac{\Delta v_{it}}{\Delta y_{it}}}_{residual} \tag{12}$$

where β_{it}^{k} in Equation (12) is the conventional coefficient of the input that is fixed across sections and over time. The growth drivers may affect the level of output through the first three parts on the right-hand side of the above equation. These drivers may affect (input elasticity) β_{it}^{k} and ΔIFP_{it}, the input-free productivity of Equations (13) and (14):

$$\Delta IFP_{it} = \alpha + \delta_1 \mathrm{R\&D}_{\mathrm{it}} + \delta_2 \mathrm{trade}_{\mathrm{it}} + \delta_3 \mathrm{structure}_{\mathrm{it}} + \epsilon \tag{13}$$

$$\beta_{it}^{k} = \alpha^{k} + \eta_1^{k} R\&D_{it} + \eta_2^{k} trade_{it} + \eta_3^{k} structure_{it} + \upsilon^{k} \tag{14}$$

Equations (13) and (14) are for section *i* at time *t* and are derived from Equation (9). The estimation results of the parameters δ and η can measure the effects of the growth drivers.

Table 1. Descriptive Statistics

Variable	Indicator	Unit of measurement	Mean		St. deviation		Maximum		Minimum	
			Growth	Level	Growth	Level	Growth	Level	Growth	Level
Production	Value added (y)	Billion rials (Constant in 2011)	0.79	67	36.7	148.2	238.6	1232.8	-276.4	0.07
Inputs	Capital stock (k)	Billion rials (Constant in 2011)	-0.41	147.2	36.5	325.8	232.7	2947.2	-271.3	0.15
	Employment (L)	Thousands of people	2.1	12.88	22.4	17.2	175.2	111.4	-225.2	0.078
Growth drivers	Research and development (R&D)	R&D-to-output ratio	-0.04	0.002	0.96	0.006	10.92	0.15	-8.83	0.00
	Trade openness	Trade-to-production ratio	0.002	0.17	0.94	0.32	8.22	4.34	-5.73	0.00
	Structural changes	Capital stock to employment ratio	-2.5	9.3	28.7	9.9	221.2	135.2	-215.3	0.88

Source: Iran Statistical Center & Research finding.

This paper uses the data of 121 ISIC four-digit code manufacturing industries (with 10 employees or more) in Iran from 2003 to 2019. The variables used include the number of employees, capital stock, and added value. The capital stock data is estimated by the "perpetual inventory method (PIM)".

Added value and capital stock have been adjusted with the producer price index of the industrial sector. In this paper, to measure research and development, the R&D ratio to industrial-added value is used. The ratio of trade to industrial-added value is used to measure the economy's openness, and the capital stock ratio to employment is used as an approximation for structural changes.

4. Results and Discussion

In the first step, the varying coefficient stochastic frontier employed is used. To do this, the technical inefficiency term $-u_{it}$ is ignored, and, then, the model is estimated using the parametric estimation method proposed by Hsiao (2014). In this method, the coefficients of explanatory variables change both in time and between sections as follows:

$$y_{it} = \sum_{k=1}^{K}(\bar{\beta}_k + \alpha_{ki} + \lambda_{kt})x_{kit} + \nu_{it}; \quad i = 1, \dots, N; \;\; t = 1, \dots, T \qquad (15)$$

To estimate with the fixed effects method in this model, the parameters α_k and λ_k are considered constant as $\bar{\beta}$. After estimating Equation (15), the coefficients of explanatory variables are calculated. The estimation of this step is done using the Stata software version 17.

In the second step, the contribution of production inputs (labor and capital) and input-embedded productivity to economic growth is calculated using the estimation results of the variable coefficients in the first step. The estimations are derived using Excel software. In the third step, the goal is to estimate the technical efficiency (TE) which is one of the components of input-free productivity (IFP). Input-free productivity consists of technical inefficiency ($-u_{it}$) and technological progress $\psi_0(\phi_{it})$. As a result, after estimating Equation (15), the residuals ν_{it} are extracted. Then, the technical inefficiency term $-u_{it}$ is isolated from the residual using the "Error Components Frontier" (ECF) method proposed by Battese and Coelli (1992).

The fourth step is the estimation of technological progress $\psi_0(\phi_{it})$ which is another component of input-free productivity (IFP). To estimate technological progress, the panel data model with non-parametric time-varying coefficients of Li et al. (2011) is used. So, Equation (9) is estimated ignoring the technical inefficiency term $-u_{it}$ and then the trend function $\psi_0(\phi_{it})$ and the coefficients function are estimated using the "Non-parametric local linear method". Results of the trend function show technological progress in the factory industry. In the fifth step, the role of input-free productivity (IFP), the contribution of total productivity of production factors (TFP), and the contribution of residuals from the economic growth of manufacturing industries are calculated. To calculate the contribution of IFP, first, using the results of the third and fourth steps, technical efficiency and technological progress are collected, input-free productivity is obtained and by dividing it by production growth, the contribution of IFP is obtained. Then, by adding the contribution of IFP and the contribution of input-embedded productivity to economic growth, the TFP contribution to economic growth is obtained. Finally, by calculating other contributions, the contribution of the residue is measured.

4.1 Manufacturing Industries' Value-added Growth Accounting

Estimating the stochastic frontier model with varying coefficients (Equation10) Variable elasticities in time and among industries were obtained for capital stock and labor force (Figure1). The figure shows that the elasticity of the labor decreased from 2003 to 2013, and subsequently increased. The figure on the left also shows the capital stock elasticity. It can be seen that the capital stock elasticity has been increasing until 2011 and after that, it has remained almost steady.

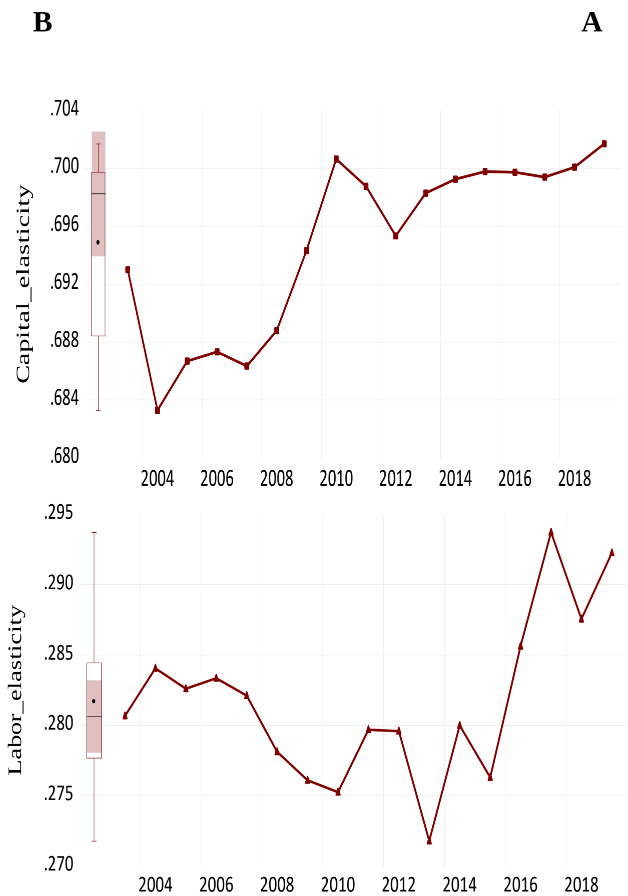

Figure 1. Labor Force and Capital Stock Trends in Iran's Manufacturing Industries, 2003-2019

Source: Research finding.

The return to scale has changed slightly until 2013. It seems that the return to scale has decreased until 2012 and then increased and reached a constant return to scale (Figure 2).

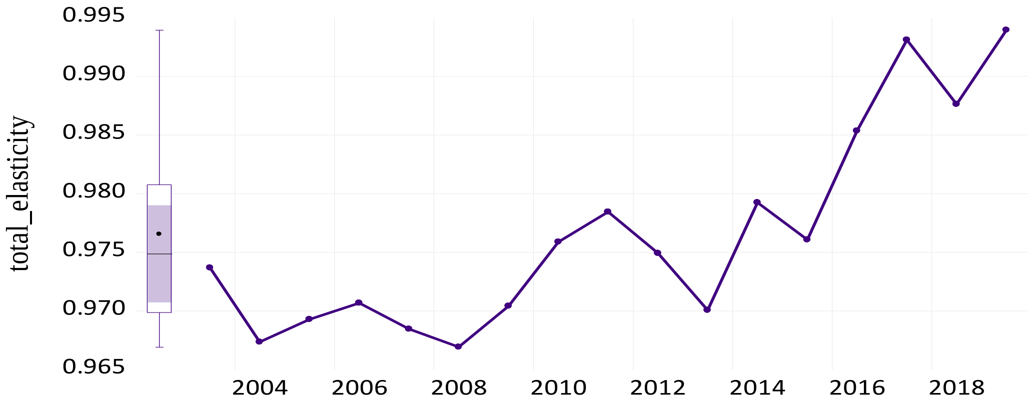

Figure 2. The Return To Scale Trend In Iran's Manufacturing Industries, 2003-2019
Source: Research finding.

By combining the estimation results of the stochastic frontier model with varying coefficients and the estimation of technical efficiency with the Boundary Element Method (BEM), classic TFP growth is decomposed into input-free productivity growth and input-embedded productivity growth. Input-free productivity growth includes two components: technical efficiency changes and technological progress. IFP growth was negative from 2003 to 2006, and it improved from 2007-2016 and growing by about 3% in 2016, and then started to decline again.

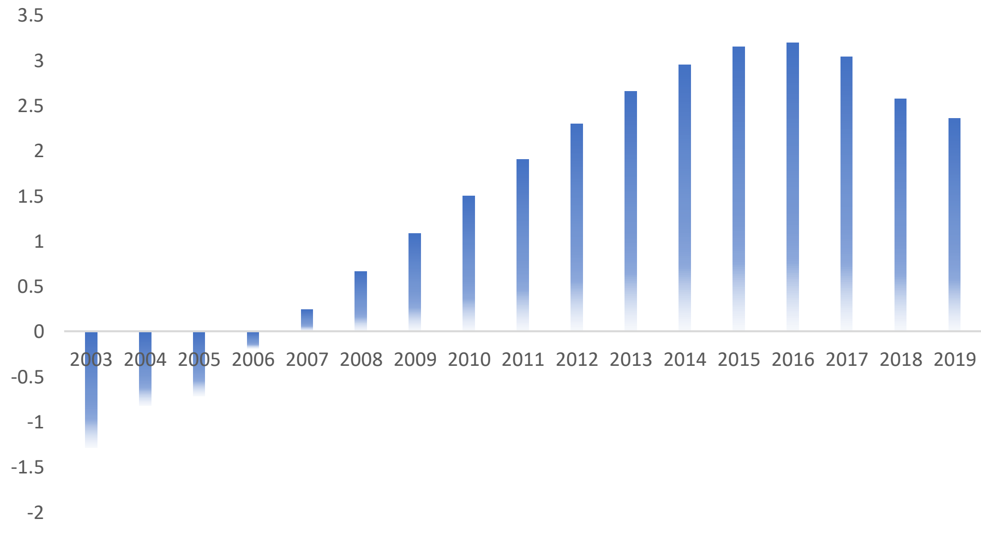

Figure 3. Input-Free Productivity Trend in Iran's Manufacturing Industries, 2003-2019
Source: Research finding.

Figure 3 shows the growth of labor, capital, and production elasticity along with the growth of technical efficiency and technological progress of Iran's manufacturing industries from 2003 to 2019. The average capital stock growth in this period is 5.4%; which is the highest growth in 2016 (%32.7) and the lowest in 2011 (%-19.1). The growth of labor has been stable and has grown by 3.7% annually on average. The labor has experienced negative growth in just 4 years. The elasticities of capital and labor stock experience fluctuating trends.

In 2004 and 2005, the elasticity of capital stock declined most sharply to -1.4%, while the elasticity of labor showed a positive growth of 1.2% in the same year. This happened again in 2016 and 2017, but the opposite was observed in other years as well. It seems that labor and capital have replaced each other in the process of production. Of course, these two inputs have changed in the same direction over the years. The average annual growth rates of elasticity of capital and labor are -0.03% and 0.27%, respectively. Technical efficiency (TE) is an important measure to evaluate the firm's performance. When maximum production efficiency is achieved, the unit uses almost all the available input, and production efficiency will be at 100 while the minimum will be 0. The average technical efficiency of Iran's manufacturing industries is 78.7%, which is 21.3% away from the efficient frontier. At the leading edge, the level of efficiency has gradually increased and reached 93.8% in 2019. Technological progress has also increased slowly annually and has grown by an average of 0.3%.

Table 2. The Growth of the Number of Inputs, the Elasticity of Labor and Capital, the Growth of Technical Efficiency and the Technological Progress in Iran's Manufacturing Industries, 2003-2019

Year	Capital stock		Labor		Technical efficiency		Technological progress growth
	Elasticity growth	Quantity growth	Elasticity growth	Quantity growth	Growth	Quantity	
2003	0.2	32.7	-1.5	12.4	-1.3	73.1	-0.04
2004	-1.4	17.4	1.2	1.4	-0.8	72.3	-0.03
2005	-1.4	4.1	1.2	0.1	0.0	72.3	0.0
2006	0.1	11.3	0.3	2.1	-0.9	71.4	0.0
2007	-0.1	20.7	-0.4	13.9	0.1	71.5	0.15
2008	0.4	1.2	-1.4	6.7	0.4	71.9	0.25
2009	0.8	2.0	-0.7	4.0	0.7	72.7	0.34
2010	0.9	-1.9	-0.3	4.3	1.1	73.8	0.41
2011	-0.3	-19.1	0.6	2.9	1.4	75.2	0.47
2012	-0.5	-1.9	-0.04	-4.6	1.8	77	0.52
2013	0.4	-0.5	-2.8	9.3	2.1	79.1	0.56
2014	0.1	1.9	3.1	2.2	2.4	81.4	0.58
2015	0.1	22.8	-1.3	11.8	2.6	84.0	0.58
2016	-0.01	10.2	3.4	-0.2	2.6	86.7	0.55
2017	-0.05	3.1	2.9	-0.7	2.6	89.2	0.44
2018	0.1	-11.5	-2.1	-6.0	2.4	91.7	0.16
2019	0.2	-1.0	1.7	4.0	2.1	93.8	0.24
Average	-0.03	5.4	0.27	3.7	1.1	78.7	0.3

Source: Research finding.

Note: It should be noted that this study was conducted for 121 manufacturing industries in Iran during the period from 2003 to 2019, and the numbers presented in the table are the average of these 121 industries for each year; the average for all these years is also provided in the last row of the table. Additionally, summaries of this data are displayed in Figures 1 to 3.

Table 3. Economic Growth Accounting of 121 Manufacturing Industries in Iran, 2003-2019; %

Year (1)	Production growth (2)	New growth accounting						Standard growth accounting		
		Input quantity contribution		Total factor productivity contribution			Residual	Factors contribution		
		Capital	Labor	Capital-embedded productivity	Labor-embedded productivity	Input-free productivity		Capital	Labor	TFP
2003	33.9	84.2	8.9	-1.1	3.6	-0.6	5.0	66.9	10.3	22.8
2004	8.7	138.1	4.5	-9.5	44.9	-60.7	-17.3	137.1	4.5	41.6
2005	6.8	41.7	0.6	-10.6	57.8	-78.6	89.1	41.6	0.6	57.8
2006	12.8	60.5	4.6	-1.5	6.8	2.7	26.9	60.5	4.6	34.9
2007	18	62.5	-6.0	-1.2	4.2	1.9	38.6	79.0	21.8	0.7
2008	0.3	65.2	-4.0	-4.7	18.3	-5.5	30.7	258.5	583.2	741.7
2009	6.5	2.3	52.8	21.6	-49.7	48.3	24.7	20.9	17.0	62.1
2010	3.4	92.8	12.6	-9.8	3.4	-14.4	14.5	-30.2	27.1	103.1
2011	-17.7	75.5	-4.5	-10.7	-29.9	5.7	64.0	75.4	-4.5	29.2
2012	-5.5	108.5	-12.6	30.9	-1.1	-16.6	-9.1	24.3	23.2	52.5
2013	-4.2	41.5	-9.7	-29.5	79.0	-12.3	31.0	8.3	-59.6	151.3
2014	10.7	19.7	7.2	23.1	59.0	2.9	-12.0	12.2	5.9	81.9
2015	19.4	67.5	17.3	-6.8	6.6	-0.4	15.8	82.6	16.7	0.9
2016	19.9	35.7	-0.3	16.1	56.3	-0.1	-7.6	35.7	-0.3	64.6
2017	10.6	20.7	-1.8	28.6	88.1	-1.7	-33.9	20.7	-1.8	81.1
2018	-15.8	50.8	10.9	-10.8	29.9	-1.7	20.9	50.8	10.8	38.4
2019	5.1	-13.9	23.0	46.1	106.2	16.9	-78.2	-13.9	23.2	90.7
Average	6.7	56.1	6.1	4.1	28.5	-6.7	12.0	54.7	40.1	5.2

Source: Research finding.

Table 3 shows Iran's manufacturing Industries' value-added growth, which is estimated based on both standard growth accounting and new growth accounting approaches, which differ in TFP. Total factor productivity (TFP) in the new growth accounting approach is decomposed into input-embedded productivity (labor and capital) and input-free productivity. Input-free productivity is divided into technical efficiency change and technological progress, while input-embedded productivity depends on the inputs used in the production function (labor and capital). Findings obtained from applying a new growth accounting approach show that the average contribution of inputs to growth (ignoring technology) is %62.2. The contribution of capital and labor are 1.56% and 1.6%, respectively. The ratio of these inputs in standard growth accounting is 94.8%. The average value-added growth is %6.7.

As mentioned earlier, technology increases the quality of inputs. Therefore, part of the ratio of inputs to growth is due to the quality of inputs. The input quality change, which is also referred to as productivity, is one of the components of the productivity of all factors. The findings show that the average ratio of input-embedded productivity in the growth of industries is about 21.8%. The contribution of capital-embedded productivity is -6.7% and the contribution of labor-embedded productivity is 28.5%. Therefore, technology is more manifested in labor. The IFP-free productivity ratio is 1.4%, which is due to two factors; technical efficiency change and technological progress.

4.2 Input-free Productivity Growth and Input Elasticity Drivers

The new growth accounting can identify and quantify the pathways or channels through which the growth drivers affect production growth. In this section, the effect of growth drivers including research and development (R&D), trade, and structural transformation on input-free productivity growth and elasticity of inputs were estimated.

All three growth drivers have a statistically significant positive influence on labor force elasticity. In terms of the capital elasticity model, R & D and Structural transformation are both positive, whereas the impact of trade drivers is negative. Therefore, it can be said that the growth drivers have increased the return to scale efficiency in Iran's manufacturing industries. Figure 2 shows that the return to scale has improved relatively over time. The drivers cause an increase in the input quality (capital and labor), capital services, and production labor, which is manifested in the production process. The contribution of input crystallization productivity to production growth is about 22.8%, which also shows the positive impact of factors affecting input elasticity in manufacturing industries.

Table 4. The Estimation of the Effects of Growth Drivers on The Input Elasticity and Input-Free Productivity Growth

Variables	**Capital elasticity**	**Labor elasticity**	**Input-free productivity**
R & D	0.0003* (0.00014)	0.0003** (0.00016)	0.0001 (0.0003)
Trade	-0.0002* (0.00008)	0.0002* (0.00011)	-0.0004** (0.00018)
Structural transformation	0.006*** (0.0001)	0.003*** (0.0002)	0.017*** (0.0003)
intercept	0.66*** (0.001)	0.26*** (0.001)	-0.097*** (0.0002)
$\bar{R}^2$	0.97	0.96	0.72
F-statistic	353.8***	286.2***	10.02***
Hausman Test	27.8***	59.1***	811.5***
Estimation Method	F.E	F.E	F.E
Number of observations	1713	1713	1713

Source: Research finding.
Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are in parentheses.

In the input-free productivity model, research and development R&D has a significant negative impact on IFP. Trade has a statistically significant negative impact at the 10% level on IFP whereas structural transformation has a significant positive impact at the 1% level on IFP. The coefficient of this indicator shows that by increasing this ratio, input-free productivity increases. In fact, by increasing this ratio, the quantity of capital stock ratio to labor increases in the production process. That is, using new capital (such as machinery and equipment) in the production process. Input-free productivity components (technical efficiency and technological progress) provide the basis for improvement.

4.3 Robustness of the Estimations

In this section, we check the robustness of the results of the model in Equations (13) and (14). Ordinary least squares estimators are sensitive to the presence of observations that lie outside the norm for the regression model of interest. The sensitivity of conventional regression methods to these outlier observations can result in coefficient estimates that do not accurately reflect the underlying statistical relationship. We use the M-estimation method which was introduced by

Huber (1973). M-estimation addresses dependent variable outliers where the value of the dependent variable differs markedly from the regression model norm (large residuals).

Table 5. Robust Estimation of Growth Drivers' Effects on the Input Elasticity and Input-Free Productivity Growth

Variables	Capital elasticity	Labor elasticity	Input-free productivity
R & D	0.002***	0.003***	0.001***
	(0.0004)	(0.0005)	(0.0002)
Trade	0.003***	0.002***	-0.0005***
	(0.0002)	(0.0003)	(0.0001)
Structural transformation	0.009***	0.005***	0.01***
	(0.0005)	(0.0006)	(0.0003)
intercept	0.66***	0.28***	-0.07***
	(0.004)	(0.001)	(0.003)
R-squared	0.19	0.1	0.44
Rw-squared	0.28	0.14	0.51
Rn-squared	503.3***	213.3***	1454.4***
Estimation Method	M-estimation	M-estimation	M-estimation
Number of observations	1713	1713	1713

Source: Research finding.

Note: *** indicates significance at the 1% level; Standard errors are in parentheses.

Economic growth is not a natural occurrence; it's driven by market forces, various economic factors, and shifts in macroeconomic policies. One of the paper's findings is the negative contribution of capital stock productivity, likely due to the depreciation of capital stock in manufacturing industries and insufficient new investments to compensate for this depreciation. This scenario can lead to diminishing or even negative returns. Another key finding is the relatively high contribution of labor productivity to the economic growth of Iran's manufacturing industries. This could be linked to the accumulation of human capital. Human capital spillovers have been validated by Acemoglu and Angrist (2000). However, the observed lack of spillovers at the macro level contradicts micro-level data, where individual-level wage payments are seen as investments in human capital.

Another finding is the role of research and development (R&D) in total factor productivity (TFP) growth. The paper's results indicate that total factor productivity significantly impacts the economic growth of Iran's manufacturing industries. Empirical evidence suggests that R&D undeniably improves productivity and enhances economic growth at the industry or firm level. The evidence also shows that R&D spillovers can be considerable, indicating that the social return on R&D spending may exceed private returns. Other studies have found that the rate of return on R&D for some companies ranges between 20 and 30 percent. If this estimate is accurate, it suggests that Iran's manufacturing industries allocate far fewer resources to R&D than they should.

Technological advancement is another key driver of productivity and economic growth in Iran's manufacturing industries. Due to the law of diminishing returns, a country cannot maintain long-term growth solely by accumulating more capital or labor. Therefore, the primary driver for long-term growth must be technological progress. Evidence shows a positive relationship between past TFP and future economic growth in developed economies. This indicates that countries where growth was driven by TFP before a crisis tend to experience higher post-crisis growth. Meanwhile, the relationship between post-crisis economic growth and the share of capital stock or labor force in economic growth is negative. This suggests that countries whose growth is primarily driven by capital or labor accumulation may struggle, especially during economic downturns.

Based on the results, physical capital accumulation emerged as the most significant driver of value-added growth. On average, it contributes approximately 56% to the total value added, with a peak of over 80% in some years. This finding underscores the pivotal role that physical capital plays in generating value in industries. Technological advancements have also improved capital efficiency, leading to an additional 4.1% increase in the capital share. Consequently, the total share of capital rises to around 60%. In traditional calculations, the capital share is about 55%, which is not substantially different from the new method.

The average labor share is approximately 6%, which represents the net contribution of labor to value-added growth without the influence of technology on labor productivity. This indicates the basic contribution from labor, exclusive of any technological enhancements. Given this, we can infer that technology plays a significant role in boosting labor productivity. The combined effect of technology and labor is estimated to be around 28.5%, bringing the total share of labor and technology to 34.5%. In comparison, the labor share calculated through traditional growth accounting methods is about 40%. This difference suggests that conventional methods might overestimate the contribution of the labor force. By accounting for technology's impact on labor productivity, these newer calculations provide a more accurate depiction of the factors driving value-added growth.

In the traditional framework, the share of total productivity—often considered a proxy for technology—is about 5.2 percent. However, this approach leaves the source or nature of this growth unclear. By contrast, the new method provides a more detailed understanding of technology's role, demonstrating that it primarily improves labor productivity. In this approach, technology is seen as embedded within the labor force, aiding in their productivity. It also contributes to capital efficiency, though to a lesser extent. Notably, the neutral technology effect is negative. This distinction suggests that the new method better explains how technology contributes to value-added growth. It primarily does so by enhancing labor productivity, while also providing a slight boost to capital productivity through increased capital services. Therefore, the traditional method may undervalue the role of technology by focusing on a generalized estimate of total productivity without accounting for these nuanced impacts on labor and capital.

The impact of technology on the productivity of capital and labor is often uneven, with capital productivity facing greater fluctuations, especially in economies like Iran's, which have been subjected to international sanctions. These sanctions make it difficult to import advanced technology, leading to rapid obsolescence of capital equipment and diminishing capital returns. The inability to repair or replace outdated machinery reduces capital's production capacity, thus negatively impacting its productivity. Although this also affects labor productivity, the labor force tends to be more resilient. This resilience stems from the adaptability of human resources; workers can maintain or even improve productivity by enhancing their skills and utilizing medium- or low-cost technologies. In contrast, capital often relies on high-end technology, which is largely inaccessible due to sanctions. The labor force's broader range of skills and adaptability contribute to this resilience, even though specialized skills may face greater challenges. Ultimately, Iran's economy, in the face of sanctions, experiences a greater impact on capital productivity, while the labor force demonstrates a capacity to endure and adapt.

Research and development (R&D), structural changes, and trade are all significant drivers of labor-augmented technology, capital-augmented technology, and neutral technology. R&D provides the foundation for technological innovation, while trade enables the flow of technology and expertise across borders, giving industries the resources they need for modernization. Structural changes, including shifts in economic frameworks and capital deepening, can further contribute to improved productivity by fostering more efficient processes and systems. Capital per capita, a key factor in growth theories, can catalyze economic development by enabling a shift from labor-intensive to capital-intensive industries. This transition generally leads to higher productivity, as it provides the workforce with advanced tools and machinery, enhancing efficiency and output.

By increasing capital per capita, economies not only make better technology available to their workforce but also create a context in which labor can be used more effectively, supporting broader economic growth.

5. Conclusion

This paper aims to answer the question of how technology contributes and what role it plays in the production of manufacturing industries. There are two approaches to answering this question: Using standard growth accounting or new growth accounting. Using endogenous growth theory and the induced innovation theory with the benefit of the stochastic frontier model with varying coefficients allowed changing the quality of inputs in the growth accounting method. The growth accounting method outperforms standard growth accounting because it enables us to monitor the importance of technology through which the technology affects growth from two paths of impact on inputs (labor-embedded and capital-embedded) and input-free productivity. New growth accounting is adopted to study the economic growth of Iran's manufacturing industries using a balanced panel of 121 ISIC four-digit code manufacturing industries from 2003 to 2019. Results show that, on the one hand, labor is being replaced by capital in the production process, which is consistent with the induced innovation theory.

On the other hand, there is an increasing trend of returns to scale, which is consistent with the endogenous growth theory. The decomposition of the value-added growth showed that inputs (capital and labor) still play a dominant role. However, part of their contribution to the growth of added value is due to the presence of technology. The findings showed that technology has been manifested more in the productivity of manpower, and work-augmenting technology has made an important contribution to the growth of the added value of Iran's manufacturing industries. The contribution of capital-augmenting technology to the production process is trivial. Also, the results showed that the conventional growth accounting method has an estimation error in estimating TFP contribution. The new growth accounting method showed that technology impacts the input productivity (capital and labor) and it plays an important role in input-free productivity.

The average technical efficiency of Iran's manufacturing industries is 78.7%, which is 21.3% away from the efficient frontier. However, the level of efficiency has gradually increased, and technological progress has also grown by an average of 0.3%. In the second part, the effect of economic growth drivers on the input elasticity and input-free productivity was estimated using the fixed effects method. The results showed that growth drivers like research and development, trade, and structural transformation have a significant positive impact on labor elasticity. In terms of the capital elasticity model, research and development and structural transformation have a positive and significant impact on capital elasticity, whereas trade has a significant negative influence on capital elasticity. This means that growth drivers have increased the labor quality and capital in the production process.

Considering the results, it is recommended to establish and expand research and development (R&D) units within Iran's manufacturing industries to accelerate the process of attracting researchers, innovators, and technological advancements. Additionally, to maximize the spillover effects of R&D from technologically advanced countries and adapt them to local conditions, efforts should be made to harness these technologies, which could significantly boost production in the manufacturing industries. Furthermore, it is suggested to provide efficient support to companies in the manufacturing industry for productivity improvement or technological modernization.

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