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Extracting the Workforce Learning Curve for Selected Iranian Manufacturing Industries

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Abstract

In industrial economics, the learning curve illustrates that production costs decrease continuously as the number of production units increases due to an improvement in the learning rate as production increases. The objective of this research is to explore the concept of the workforce learning curve in the Iranian manufacturing industry from 1996 to 2015. The study uses panel data econometric methods, specifically the Fixed Effects method, to extract the learning curve model for six industrial activities within Iran's economy to achieve this. According to the econometric model results, it has been confirmed that the learning curve for the selected industries follows a quadratic model that is inverted U-shaped. Therefore, focusing on increasing production and utilizing economies of scale in these sub-sectors is advisable.

Keywords: Learning curve, Workforce learning, Manufacturing industries, Panel data.

1 | Introduction

In industrial economics, a learning curve is a graph that illustrates the progress rate of learning and improvement in a specific industry or process. This curve displays how the performance and productivity of a process or industry change over time as experience and production increase. In industrial economics, this curve is mainly used to determine greater productivity, improve processes, predict future changes, and choose optimal strategies for market competition. This useful tool helps corporations and organizations make productive and strategic decisions based on empirical and scientific data and improve performance. Studies conducted in various industries suggest that costs decrease as production increases. Two important factors, namely "economies of scale" and "In-service learning," are behind the emergence of this phenomenon. In the empirical studies of in-service learning, it is also called the learning curve. It was first identified by Wright

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in 1936 while studying aircraft assembly. He found that the cost of assembly can be reduced by performing a repetitive process [1]. The learning process, which improves productivity and reduces production costs, is classified into workforce learning and organizational learning. Workforce learning is a process by which individuals acquire the necessary skills and abilities through experience. Workers gain more experience, their performance improves, and the time required to produce each product decreases.

Organizational learning is a dynamic process that refers to a company's production abilities and skills gained through experience compared to their competitors. According to Noorani Azad and Khodadad Kashi [2], it is essential to develop knowledge to achieve production innovation, improve the production process, and enhance production quality. Firms more capable of producing new knowledge than their competitors are likely to be more effective and efficient in their operations. The learning curve, or the experience curve, is a commonly used tool for predicting costs and planning production in the economic sector. As a result, industry planners and strategic consultants rely on the learning curve for their analyses [2]. The learning curve refers to the benefits resulting from accumulated experience and skills. These benefits appear in lower costs, higher quality, more effective pricing, and marketing.

Developed countries are the main technology suppliers in world markets while developing countries are primary importers and technology users to improve their technological capabilities. While transferring new technology to developing countries can greatly enhance their technology base, it is not the only means of learning. These countries require a continuous and cumulative process of technological learning over the long term. Therefore, measuring the level of learning in different industries will help to manage technological policies in line with the efficient development of industries. Improving and accelerating the learning process is essential for increasing workforce productivity, economic growth, and development in the long term. Therefore, paying attention to dynamic technological learning in the industrial structure is crucial. By studying non-linear models, all representing the elasticity dynamics and learning rate over time, this non-linear (or dynamic) approach to the learning curve has been neglected in domestic studies.

Today, Iran's manufacturing industries face significant challenges regarding their dimensions and conditions. The most pressing issues are the absence of a clear industrial development strategy, uncertainty surrounding heavy industries, outdated technologies in several sectors, and a lack of prominent world-class exporting industries. These problems have resulted in Iran's industrial industries being unable to utilize their full technological capacity. Since technological capacity is interpreted as a progressing learning process, the inability to utilize the maximum capacity in the Iranian industrial industries has decreased learning progress. Considering the limited studies that have been conducted in the field of learning among the Iranian manufacturing industries and considering the lack of attention of these studies to the dynamic of learning, the present research examines the learning curve shape in selected Iranian manufacturing industries at the International Standard Industrial Classification (ISIC) two-digit codes level from 1996 to 2015.

2 | Methodology

The current research is of an applied nature, with an analytical-research methodology. To estimate learning elasticity, the research uses a model adapted from the study models of [3], [4]. These researchers proposed a cubic shape as the basis for their models:

$$\ln(L/Q)_t = \phi 1 + B\ln Xt + C(\ln Xt)2 + D(\ln Xt)3 + \phi 2\ln Lt + ut, \quad (1)$$

where

L/Q: is the relationship between the amount of required labor and each unit of output (cost per unit of output; c_t).

X: represents the output of the product (actualized by the producer price index of 2013 separately for each activity).

X: indicates the level of cumulative production.

L: represents the amount of workforce employed in each industrial activity.

According to the above equation, the learning elasticity (-a) is obtained from its first-order derivative as follows:

$$-\alpha = \frac{\partial \ln c_t}{\partial \ln X_t} = B + 2C\ln X_t + 3D(\ln X_t)^2. \tag{2}$$

After estimating the learning curve, the progress rate in each industry is calculated through the *Eq. (3)*:

$$d = 2^{-a}. \tag{3}$$

According to Relation 3, the progress ratio (d) is determined by learning elasticity. This ratio divides learning into four categories: high learning, low learning, no learning (zero learning), and forgetting. The value of parameter d is always between zero and one. A value closer to zero indicates an increase in learning, while a value closer to one suggests a lower level of learning. If d equals one, then no learning took place; if it's greater than one, it indicates a decrease in learning or even forgetting.

3 | The Extraction of the Research Learning Model

The following section provides a detailed explanation of the econometric model. According to the traditional learning curve model, the cost per production unit in guarantor t is determined by the cumulative production level (X_t) and the cost of each primary production unit (c_1). The relationship between these variables can be expressed as follows:

$$c_t = c_1 X^{-\alpha}. \tag{4}$$

where (-α) represents the index or the elasticity of learning, the progress rate is defined by *Eq. (3)*. *Eq. (4)* can be rewritten as *Eq. (5)*:

$$\ln c_t = \ln c_1 - \alpha \ln X. \tag{5}$$

Recently, Pramongkit et al. [5], [6] used the neoclassical production function and the traditional learning curve to estimate the rate of technological learning for the Thai manufacturing industry in the first half of the 1990s. They fitted the learning curve to the neoclassical production function to achieve this. To clarify, the concept of learning was incorporated into calculating multi-factor productivity. It means that productivity is assumed to include the process of learning. However, the model used a linear approach to the learning curve, which resulted in only one training rate being provided for each specific period. Such analytical approaches ignore any annual changes that may occur in different years. A special model that uses a dynamic empirical curve model was developed to solve this problem. This model is shown in *Eq (1)*. The major advantage of this model is its ability to estimate every annual movement and trend related to education over time. According to the neoclassical production function, in year (t), the production level (Q_t), the labor force function (L_t), and the physical capital (K_t) are represented as Q_t, L_t, & K_t, respectively. This function is displayed as follows:

$$Q_t = A_t K_t^{\alpha} L_t^{\beta}. \tag{6}$$

which in logarithmic dimensions can be written as follows:

$$\ln Q_t = \ln A_t + \alpha \ln K_t + \beta \ln L_t. \tag{7}$$

In this equation, α represents the elasticity of capital, and β represents the elasticity of labor. A_t stands for multi-factor productivity, which indicates the level of technology in a given year. The model also assumes that the relationship between the level of technology, A_t, and the cumulative level of production at time t (represented by X_t) is derived from the following equation:

$$A_t = H X_t^{a}. \tag{8}$$

This equation assumes that education is part of multifactorial productivity and is treated as a separate case.

$$X^a = \frac{c_1}{c_t}. \tag{9}$$

H is a constant value, and X^a is the inverse of X^{-a} obtained from the change in *Eq. (4)*.

By fitting the above equation in *Eq. (8)*, it can be rewritten as follows:

$$A_t = H\frac{c_1}{c_t}. \tag{10}$$

Its logarithmic form is as follows:

$$\ln A_t = \ln H + \ln\left(\frac{c_1}{c_t}\right). \tag{11}$$

This relationship indicates that the level of technology at time t is determined by the ratio of c_1 and c_t. Moreover, *Eq. (1)* shows that $\ln\left(\frac{c_1}{c_t}\right)$ takes on the following value:

$$\ln\left(\frac{c_1}{c_t}\right) = -[B\ln X_t + C(\ln X_t)^2 + D(\ln X_t)^3]. \tag{12}$$

If the value of $\ln\left(\frac{c_1}{c_t}\right)$ in *Eq. (11)* is replaced by *Eq. (12)*, the following equation will appear:

$$\ln A_t = \ln H - B\ln X_t - C(\ln X_t)^2 - D(\ln X_t)^3. \tag{13}$$

In the next step, *Eq. (13)* is fitted into *Eq. (7)* to yield the following one:

$$\ln Q_t = \ln H - B\ln X_t - C(\ln X_t)^2 - D(\ln X_t)^3 + \alpha\ln K_t + \beta\ln L_t. \tag{14}$$

In *Eq. (14)*, it is assumed that the relationship between capital and labor is as follows:

$$K_t = \mu L_t^{\lambda}. \tag{15}$$

The values of μ and λ are constant in this equation, and its logarithmic form can be added to *Eq. (14)*.

$$\ln Q_t = \ln H - B\ln X_t - C(\ln X_t)^2 - D(\ln X_t)^3 + \alpha(\ln\mu + \lambda\ln L_t) + \beta\ln L_t. \tag{16}$$

After adding lnL_t to both sides of the equation, the final relation is obtained:

$$\ln(L/Q)_t = -\ln H - \alpha\ln\mu + B\ln X_t + C(\ln X_t)^2 + D(\ln X_t)^3 + (1 - \alpha\lambda - \beta)\ln L_t. \tag{17}$$

For a more concise representation, it is assumed that $\phi_1 = -(\ln H + \alpha ln\mu)$, $\phi_2 = (1 - \beta - \alpha\lambda)lnL_t$ and $lnc_t = ln(L/Q)_t$, then we have:

$$\ln c_t = \phi_1 + B\ln X_t + C(\ln X_t)^2 + D(\ln X_t)^3 + \phi_2. \tag{18}$$

Eq. (18) is the final equation fitted by the Ordinary Least Squares (OLS) method for each industry sub-sector.

This study utilizes the OLS method within the panel data framework to determine the coefficients. For this method to be effective, the disturbance distribution must be a part of the normal distribution, and multiple assumptions of the Gauss-Markov theorem must also be valid. Estimating the classical linear model requires the estimation of unknown parameters $\beta_1,\ldots,\beta_k$ and σ^2. The OLS method selects the $\beta_1,\beta_2,\ldots,\beta_k$ values in such a way that the sum of squared errors is minimized, that is:

$$S(\hat{\beta}) = \sum_{t=1}^{T}\left(Y_t - \beta_1 X_{t1} - \ldots - \beta_k X_{tk}\right)^2. \tag{19}$$

The Gauss-Markov theorem affirms that the OLS estimator is the best linear unbiased estimator among all the linear unbiased estimators, abbreviated as BLUE. In simple terms, this theorem states that in a linear model, if the errors have a zero mathematical expectation, are uncorrelated, and have equal variances, then the best unbiased linear estimator for the coefficients of the system is equal to the least squares estimator [7], [8]. In OLS regression, the dependent variable is assumed to be linear to the coefficients and has the same variance. However, after regression and estimation, the above assumptions may not hold, and their accuracy should be checked. Several diagnostic tests need to be checked to ensure accurate results, including 1) the homogeneity of variance test, 2) the serial autocorrelation test, and 3) the normality test of disturbance sentences [9]. In this research, the research model will be examined within the panel data framework. Applying this model offers various benefits, such as increasing estimation results' efficiency by utilizing more and more diverse information.

Additionally, the model's ability to work with cross-sectional and time series data leads to comprehensive analysis results. The analysis results are more complete and comprehensive when using panel data compared to cross-sectional data or time series alone. Time series data can lead to collinearity issues when there is an increase in data. Similarly, cross-sectional data only provides a static view of the variables and doesn't allow for examining variable trends. Panel data solves both problems by comprehensively viewing the variables over time.

Panel data analysis involves two important approaches: fixed effects and random effects. Fixed and random effects are two approaches used in panel data analysis to assess the impact of changes in observations on the dependent variable. Fixed effects deal with fixed changes in observations, such as individuals, firms, or countries, and measure the effect of these changes on the dependent variable. In contrast, random effects deal with random changes in observations and account for the random variation between observations. The choice between these two approaches depends on the assumptions and purpose of the research. Fixed effects help us to manage the fixed changes in observations and evaluate the influence of changes in time and temporal variables. In contrast, random effects focus on the random variation between observations and use more temporal information. The selection between these two approaches depends on the research transactions and assumptions raised in the research [8].

It is important to note that this research utilized Eviews and Stata version 12 software to estimate the learning elasticity. The study's statistical population consisted of six industrial activities selected based on ISIC industrial codes. ISIC codes[1] are four digits long, where the first two digits indicate the industry in which the institution operates, the third digit indicates the industrial group, and the fourth digit indicates the specific title of the field in which the activity is carried out. The study innovates by utilizing a longer time series and focusing on industries where the Iranian economy has a comparative advantage (*Table 1*).

Table 1. Selected industrial activities based on industrial codes ISIC.

Industry Code	Title
23	Coal production industries-oil refineries
24	Chemical products industries
25	Rubber and plastic manufacturing industries
26	Other non-metallic mineral manufacturing industries
27	Basic metal production industries
28	Fabricated metal products, except machinery and equipment, manufacturing industries

*Source: Statistical Center of Iran

4 | Finding

Correlation coefficients

Table 2 displays the reciprocal correlation coefficients of model variables. It can be observed that the sign of the correlation coefficients is consistent with the theoretical foundations and is statistically significant. Furthermore, a substantial and negative relationship exists between the amount of labor required to produce a unit of output or product (as a dependent variable) and the cumulative production variables. Correlation coefficients provide a simple understanding of how two variables, X and Y, change. The closer they are to +1 or -1, the more accurate predictions can be made. In this research, panel data is utilized to analyze the effect of explanatory variables on the dependent variable and extract learning elasticity simultaneously.

[1]The ISIC system is a method of classification that categorizes economic activities, rather than goods and services. The classification of an economic enterprise is determined based on the type of production operations it engages in, and then grouped with other enterprises that share similar operations. It doesn't matter whether these operations are manual or mechanized.

Table 2. Reciprocal correlation coefficients of the dependent variable and explanatory variables.

	Lnlq	Lnx	Lnx2	Inx3	Lnl
Lnlq	1.000				
Lnx	-0.8718	1.0000			
	0.000				
Lnx2	-0.8821	0.9981	1.0000		
	0.000	0.0000			
Inx3	-0.8892	0.9928	0.9983	1.0000	
	0.0000				
lnl	0.1467	0.3169	0.3067	0.2952	1.0000
	0.1098	0.0004	0.0007	0.0011	

*Source: Research findings.

Research model estimation

The results of the research's econometric model estimation are displayed in *Table 3*. The fixed effects[1] of the six selected industries show that the learning curve is of the second degree and is in the early stages of production. Thus, the concept of labor learning is not applicable at this stage. However, as time passes and the level of production increases, the required workforce for each production unit decreases. Therefore, increasing production levels and taking advantage of economies of scale in selected industries is advisable.

Table 3. Econometric model estimation results for selected industries in terms of fixed effects (dependent variable of workforce required for each production unit).

Variables	Coefficients	Standard Deviation	t Statics	Probability Value
Lnx	0.6496378	0.1685961	3.85	0.000***
Lnx2	-0.0373732	0.0045863	-8.15	0.000***
Lnl	0.5052408	0.1643746	3.07	0.003***
_Cons (fixed sentence)	-10.92147	2.406664	-4.54	0.000***
Model diagnostic tests	R-sq: Within = 0.9754 , Between = 0.9616 , Overall = 0.9315 F(3,111) = 1465.32, Prob > F= 0.0000			

*Source: research findings. ***: Significance at the one percent level. **: Significance at the five percent level. *: Significance at the 10% level.

Based on the findings presented in *Table 3*, it can be concluded that the coefficients of determination (R-sq) are high, and the regression is statistically significant. The coefficient of determination indicates that the explanatory variables can account for 93% of the changes in the dependent variable.

5 | Discussion and Conclusion

The findings of this research have a direct impact on industrial management and administrative decision-making. The study examined the learning curve of six different industries, including oil refineries, chemical products, rubber and plastic manufacturing, non-metallic mineral manufacturing, basic metal production, and fabricated metal product manufacturing. The results showed that the learning curve of these industries is of the second degree. Therefore, it is recommended that the production level be increased and economies of scale used to improve efficiency. Workforce learning is a valuable investment for factories as it can help to reduce costs. This is because employees can perform their tasks more efficiently and effectively when they learn new skills or improve their existing ones. As a result, production time is reduced, waste and errors are minimized, product quality is improved, and maintenance needs are reduced. Ultimately, this leads to increased productivity and better overall performance. Skilled workers can suggest improvements in processes and activities, significantly enhancing overall plant costs and productivity. Moreover, skilled workers tend to

[1] The article omits the results of the Hausman test which confirmed the superiority of fixed effects over random effects.

make fewer mistakes, which can reduce rework and raw material repurchase costs. In short, workforce learning can improve performance and reduce costs in the factory.

Author Contribution

All authors have equally contributed to the research, execution, and writing of this article. Each author participated in the conception and design of the study, data collection and analysis, interpretation of results, and drafting and revising the manuscript. The collaborative effort ensured a comprehensive and cohesive final paper, with each author sharing responsibility for all aspects of the work.

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Data Availability

All the data are available in this paper.

Conflicts of Interest

The authors declare no conflict of interest.

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