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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 shows that production costs decrease continuously as the number of units produced increases. This is 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. To achieve this, the study uses panel data econometric methods, specifically the Fixed Effects estimator, to estimate a learning curve model for six industrial activities in Iran's economy. According to the econometric results, the learning curves for the selected industries follow an inverted U-shaped quadratic model. Therefore, it is advisable to focus on increasing production levels and leveraging economies of scale in these sub-sectors.

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

1 | Introduction

In industrial economics, a learning curve is a graph that illustrates the 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 primarily used to increase productivity, improve processes, predict future changes, and choose optimal strategies for market competition. This helpful tool helps corporations and organizations make productive, strategic decisions based on empirical, scientific data and improve their performance. Studies conducted in a wide range of industries suggest that costs decrease as production increases. Two crucial 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. This was first identified by Wright in 1936 [1] while studying aircraft assembly. He found that the cost of assembly can be reduced by performing a repetitive process [2]. The learning process, which improves productivity and reduces production costs, is

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classified into two groups: workforce learning and organizational learning. Workforce learning is a process by which individuals acquire the necessary skills and abilities through experience. As 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 capabilities and skills gained through experience, compared to those of its competitors. According to Noorani Azad and Khodadad Kashi [3], to achieve production innovation, improve the production process, and enhance production quality, it is essential to develop knowledge. Firms that are more capable of producing new knowledge than their competitors are likely to be more effective and efficient in their operations. The learning curve, also known as the experience curve, is a commonly used tool in the economic sector for predicting costs and planning production. As a result, industry planners and strategic consultants rely on the learning curve for their analyses [4]. The learning curve refers to the benefits resulting from accumulated experience and skills. These benefits manifest as lower costs, higher quality, and more effective pricing and marketing.

Developed countries are the leading suppliers of technology in world markets, while developing countries are primary importers and users of technology to improve their technological capabilities. While the transfer of new technology to developing countries can significantly improve their technology base, it is not the only means of learning. These countries require a continuous, cumulative process of technological learning over the long term. Therefore, measuring learning levels across industries will help align technological policies with efficient industry development. Improving and accelerating the learning process is essential to increasing workforce productivity, economic growth, and long-term development. Therefore, paying attention to dynamic technological learning in the industrial structure is crucial. By studying non-linear models that represent elasticity dynamics and learning rate over time, this non-linear (or dynamic) approach to the learning curve has been neglected in domestic studies [5].

Today, Iran's manufacturing industries face significant challenges related to their dimensions and various conditions. The absence of a clear industrial development strategy, uncertainty about heavy industries, outdated technologies across several sectors, and a lack of prominent, world-class exporting industries are among the most pressing issues. These problems have prevented Iran's industrial sector from utilizing its full technological capacity. Since technological capacity is understood as a process of learning, the inability to fully utilize it in Iranian industrial sectors has led to a decline in learning progress. Given the limited studies on learning in Iranian manufacturing industries and the lack of attention to learning dynamics, the present research examines the learning curve shape in selected Iranian manufacturing industries at the ISIC two-digit code level from 1996 to 2015.

2 | Methodology

The current research is applied in nature, with an analytical research methodology. To estimate learning elasticity, the research uses a model adapted from the studies by Caravez and Albani [6], Badiru [7], and Carlson [8]. These researchers proposed a cubic shape as the basis for their models:

$$\ln{(L/Q)_t} = \phi 1 + \mathrm{BlnXt} + \mathrm{C(lnXt)2} + \mathrm{D(lnXt)3} + \phi 2\mathrm{lnLt} + \mathrm{ut}, \tag{1}$$

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 number of workers employed in each industrial activity.

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

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

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

$$d = 2^{-a}. \quad (3)$$

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 greater learning, while a value closer to one indicates lower learning. If d equals 1, no learning took place; if it's greater than 1, it indicates a decrease in learning or even forgetting [6].

3 | The Extraction of the research learning model

In the following section, a detailed explanation of the econometric model mentioned earlier will be provided. According to the traditional learning curve model, the cost per production unit in period 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:

$$c_t = c_1 X^{-\alpha}, \quad (4)$$

where (-α) represents the index or the elasticity of learning, and the progress rate is defined by *Eq. (3)*.

Eq. (4) can be rewritten as *Eq. (5)*:

$$\ln c_t = \ln c_1 - \alpha \ln X. \quad (5)$$

Recently, Pramongkit et al. [9] 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. To achieve this, they fitted the learning curve to the neoclassical production function. To clarify, the concept of learning was incorporated into the calculation of multi-factor productivity. This means that productivity is assumed to include the learning process. However, the model used a linear learning curve, resulting in a single training rate for each period. Such analytical approaches ignore annual changes that may occur from year to year. A special model based on a dynamic empirical curve was developed to solve this problem. This model is shown in *Eq. (1)*. Its primary advantage is its ability to estimate annual movements and trends in education. 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:

$$Q_t = A_t K_t^{\alpha} L_t^{\beta}. \quad (6)$$

which in logarithmic dimensions can be written as follows:

$$\ln Q_t = \ln A_t + \alpha \ln K_t + \beta \ln L_t. \quad (7)$$

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:

$$A_t = H X_t^{a}. \quad (8)$$

Eq. (8) assumes that education is a part of multifactorial productivity, and it is treated as a separate case. H is a constant value, and $\mathrm{X^a}$ is the inverse of $\mathrm{X^{-a}}$ obtained from the change in *Eq. (4)*.

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

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

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

Its logarithmic form is as follows:

$$\mathrm{lnA_t = lnH + ln\left(\frac{c_1}{c_t}\right)}. \tag{11}$$

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

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

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

$$\mathrm{lnA_t = lnH - BlnX_t - C(lnX_t)^2 - D(lnX_t)^3}. \tag{13}$$

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

$$\mathrm{lnQ_t = lnH - BlnX_t - C(lnX_t)^2 - D(lnX_t)^3 + \alpha lnK_t + \beta lnL_t}. \tag{14}$$

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

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

Eq. (15), the values of μ and λ are constant, and their logarithmic form can be added to *Eq. (14)*.

$$\mathrm{lnQ_t = lnH - BlnX_t - C(lnX_t)^2 - D(lnX_t)^3 + \alpha(ln\mu + \lambda lnL_t) + \beta lnL_t}. \tag{16}$$

After adding $\mathrm{lnL_t}$ to both sides of the equation, the final relation is obtained:

$$\mathrm{ln(L/Q)_t = -lnH - \alpha ln\mu + BlnX_t + C(lnX_t)^2 + D(lnX_t)^3 + (1 - \alpha\lambda - \beta)lnL_t}. \tag{17}$$

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

$$\mathrm{lnc_t = \phi_1 + BlnX_t + C(lnX_t)^2 + D(lnX_t)^3 + \phi_2}. \tag{18}$$

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

This study uses the OLS method within a panel data framework to estimate 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 thevalues in $\beta_1,\beta_2,\ldots,\beta_k$ 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 states that the OLS estimator is the best linear unbiased estimator (BLUE). In simple terms, this theorem states that in a linear model, if the errors have zero mean, are uncorrelated, and have equal variances, then the best unbiased linear estimator of the system's coefficients is the least-squares estimator [10], [11].

This means that in an OLS regression, the dependent variable is assumed to be linear in the coefficients and to have the same variance. However, after regression and estimation, the above assumptions may not hold, and their accuracy should be checked. To ensure accurate results, several diagnostic tests need to be checked, including: 1) the homogeneity of variance test, 2) the serial autocorrelation test, and 3) the normality test of disturbance terms [10]. In this research, the research model will be examined within the framework of panel data. Applying this model offers various benefits, such as improving the efficiency of estimation results by leveraging higher and more diverse information.

Additionally, the model's ability to handle both cross-sectional and time-series data yields comprehensive analysis results. The analysis results are more complete and comprehensive when using panel data than when using cross-sectional or time-series data alone. Time series data can lead to collinearity issues as data volumes increase. Similarly, cross-sectional data provides only a static view of the variables and doesn't allow for examining trends in the variables. Panel data solves both problems by providing a comprehensive view of the variables over time.

Panel data analysis involves two crucial approaches: fixed effects and random effects. Fixed effects 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 control for fixed differences across observations, such as individuals, firms, or countries, and measure the effect of these differences on the dependent variable. In contrast, the random effects model accounts for random variation in observations and allows for random changes in observations. The choice between these two approaches depends on the research's assumptions and purpose. Fixed effects help us control for fixed effects in the observations and evaluate the influence of changes over time and across temporal variables. In contrast, random effects focus on the random variation between observations and make use of more temporal information. The selection between these two approaches depends on the research transactions and assumptions [11].

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 comprised 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 [12]. The study innovates by utilizing a longer time series and focusing on industries where the Iranian economy has a comparative advantage (*Table 1*).

[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 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 | Findings

4.1 | Correlation Coefficients

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

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

	lnIq	lnX	lnX2	lnX3	lnI
lnIq	1.0000				
lnX	0.8718	1.0000			
	0.0000				
lnX2	-0.8821	0.9981	1.0000		
	0.0000	0.0000			
lnX3	-0.8892	0.9928	0.9983	1.0000	
	0.0000	0.0000	0.0000		
lnI	0.1467	0.3169	0.3067	0.2952	1.0000
	0.1098	0.0004	0.0007	0.0011	

Source: Research findings.

4.2 | 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 production levels increase, the required workforce per production unit decreases. Therefore, it is advisable to increase production levels and take advantage of economies of scale in selected industries.

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

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 in *Table 3*, the coefficients of determination (R-sq) are high, and the regression is statistically significant. The coefficient of determination indicates that the explanatory variables account for 93% of the variation in the dependent variable.

5 | Conclusion

The findings of this research have a direct impact on industrial management and administrative decision-making. The study examined the learning curves of six industries: 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 to increase production levels and leverage economies of scale 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 to processes and activities, leading to significant reductions in overall plant costs and productivity. Moreover, skilled workers tend to make fewer mistakes, thereby reducing rework and raw material repurchase costs. In short, workforce learning can improve performance and reduce costs in the factory.

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Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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