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Learning Curve and Industry Structure: Evidences from Iranian Manufacturing Industries

Mohammad Ali Feizpour*[1], Abolfazl Shahmohammadi Mehrjardi[2], Marjan Habibi[3]

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Abstract

Empirical studies have shown that cost advantages can occur due to economies of scale and learning. However, a few studies have attempted to distinguish between these two effects on reducing costs. This paper is the first attempt to recognize the impact of learning on lowering costs by determining the effect of economies of scale in Iran. Therefore, this study aims to shed light on the cost benefits of industries based on learning and economies of scale in terms of their structures, as industries with various forms have different performances. Using industries at four-digit ISIC levels from 1997 to 2005, the findings show that learning rates are not uniform across industries. Learning rates are more than the effect of scale economies in only 11 among 31 industries. Moreover, the impact of learning in reducing costs in monopolistic industries is more than in oligopolistic and competitive industries; similarly, learning is more in oligopolistic than competitive industries. From a policy point of view, competitive industries should try to focus on achieving both dynamic and static dimensions of cost advantages to enhance their competitiveness and keep market shares.

Keywords: Competitive Industries, Industry Structure, Iranian Manufacturing Industries, Learning Curve, Market Structure.

JEL Classification: D22, L29, L52, O14.

1. Introduction

Economists have long been found that for producing a given unit, firm's cost curve may shift down over time as learning occurs. In fact, the plot

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1. Department of Economics, Business School, Yazd University, Yazd, Iran (Corresponding Author: feizpour@yazd.ac.ir).

2. Department of Economics, Business School, Yazd University, Yazd, Iran (shahamohamadi@stu.yazd.ac.ir).

3. Department of Economics, Kansas State University, Manhattan, USA (habibi@k-state.edu).

of the cost level against cumulative output is known as the learning curve or experience curve (Petrakis et al., 1996). Accumulated experience in production makes a firm more efficient in producing additional units which in turn yields lower unit costs (Morasch, 2013). A learning curve is also referred to as an ‘80% learning curve’ if the cost reduces by 20% every time the cumulative volume is doubled (Kar, 2007).

There are several strategic implications behind learning curve in stating that a firm’s unit cost declines with its cumulative production: Cabral and Riordan (1994) asserted four implication: “First, by moving down the learning curve faster than its rivals a firm gains a strategic advantage. Second, recognizing this potential for strategic advantage, firms compete aggressively and perhaps even unprofitably, to move down their learning curves. Third, even a mature firm might compete aggressively to prevent a rival from moving down its learning curve. Fourth, the strategic advantage conferred by learning may drive rivals from the market, creating an incentive for predatory pricing (Cabral and Riordan, 1994, p.1115)”. In the learning literature, dynamic learning effects also imply that a firm must consider the impact on future costs when deciding about the optimal output level for a given period. In an oligopolistic setting reducing future costs has a strategic dimension as it influences the competitive behavior of the other firms in the industry (Morasch, 2013).

Firm’s cost dynamics are usually determined by economies of scale and economies of learning (Windsperger, 1992). Economies of learning cause a downward shift in the long-run average cost (LAC) curve (movement from A to C in Figure 1), while economies of scale cause movement from point to another point on the same LAC curve (movement from A to B in Figure 1).

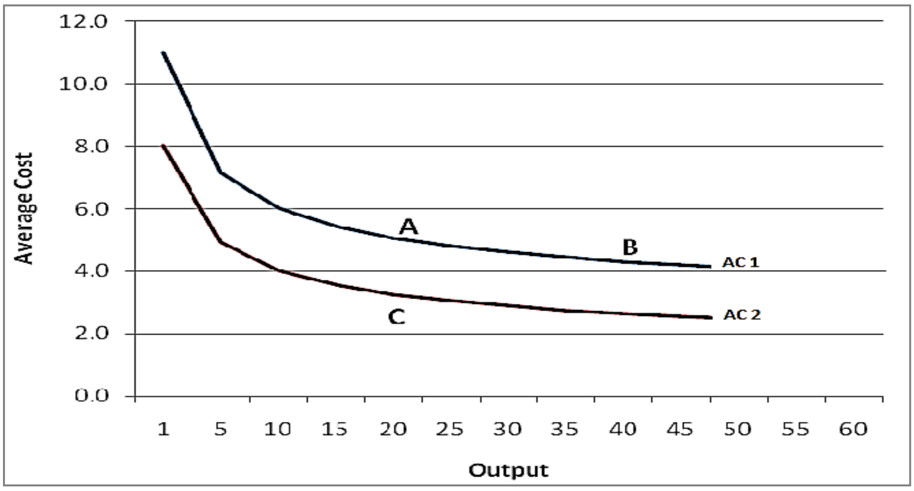

Figure 1: Increasing Return versus Learning (Heng, 2010)

Distinguishi*n*g the cost advantages in terms of economies of scale and economies of learning recently investigated and formulated in some studies. However, in this paper, we follow the study of Sadraei Javaheri (2007) to examine the learning rate. Therefore, in this paper, we focus on examining the nature of the cost advantage of Iranian manufacturing industries originated by economies of scale and economies of learning in terms of their structure.

The paper proceeds as follows: In section 2 the literature regarding the learning curve is reviewed. Subsequently, in section 3 the basic structure of the formal model based on the study of Sadraei Javaheri (2007) is explained. Section 4 introduces the methods for achieving market structure. An overview of the data set, variables used in the model, and the process of industry selection are provided in section 5. Based on the model described in section 3, the learning curve is analyzed in section 6. Finally, the conclusion gives an overview of the main results of this paper and some policy implications.

2. Literature Review

Workers in many manufacturing operations tend to learn from their experiences due to performing repetitive tasks, doing so reduces the time and costs it takes to complete given tasks. Many empirical studies have so far attempted to investigate the learning curve. The theory of learning curve was first introduced by the seminal work of

Wright (1936) who was engaged in the production of airframes. According to Wright's findings, as the quantities produced by a given item, double the cost of that item decreases at a fixed rate. However, Wright asserted that this phenomenon occurs due to some features, such as diminishing rework over time, developing better tooling methods, designing more productive equipment, and detecting and correcting design bugs.

Following Wright's work, the learning curve theory has been studied extensively in economic literature in various industries. Baloff (1971) applied the concept of a learning curve to labor-intensive industries like automobile assemblies, apparel manufacturing, and production of large musical instruments. Lieberman (1984) and Sinclair et al. (2000) extended the learning concept to chemical manufacturing plants. Grochowski et al. (1996), Grubber (2000), Chung (2001), and Chen (2009) showed how the learning curves could be applied to semiconductors. Other studies in this direction have been made by Elias (2000) and Jarkas (2010) for the construction industry and Tsuchiya (2002) for predicting the cost of fuel cells.

While numerous studies have found that performance improves as organizations accumulate operating experience, the rate of learning has been shown to vary greatly across industries and even within subunits of the same firm as indicated by Yelle (1979) and Dutton and Thomas (1984). Webbink (1977) also found the cumulative production coefficient of -0.40, indicating a 24 percent decrease in cumulative average price as the cumulative output doubles. In a review of data on 37 chemical products, Liberman (1984) showed variations in the slope of the learning curve due to differences in R&D expenditures and capital intensity. Regarding the most recent studies, Pramongkit et al. (2000), using a cluster of manufacturing industries based on the ISIC classification, showed that heavy industries (which required heavy initial investments and technology) have steeper learning curves than light industries. Balasubramanian and Liberman (2010) also using plant-level data from the US manufacturing sector showed that learning rates vary considerably among industries and are higher in industries with greater R&D, advertising, and capital intensity. In another study, Heng (2010) estimated the learning rate for 20 industries in Singapore from 1980 to 2007. The findings demonstrated that the learning effect is not uniform across 20 industries. The unit labor input in the transport equipment industry reduced to 30 percent of the initial labor input when the experience doubles, while this amount was at the lowest amount about 2 percent in the rubber processing and plastic industry. Takahashi (2013) tried to test whether the progress ratio differs in various products. Based on the results, Takahashi asserted that it's superstition to accept equity of progress ratio for different products regardless of industry, firm, and product. Nevertheless, in some studies learning found not to be significant. For instance, in the study of Tan and Elias (2000) which was performed in Singapore construction, learning was found not to be significant, possibly due to the industry's high dependence on imported construction technology, industrial fragmentation as well as transient and largely unskilled, foreign workers.

Most learning curve studies had cumulative output as the only factor responsible for a reduction in labor hours which was privileged in the original formulations by Wright (1936). However, Productivity has been found to depend on other factors besides cumulative output as a proxy for experience. For instance, Conway and Schultz (1958) pointed out that the method of manufacturing is influenced by the rate of production and the estimated duration of production at this rate which gives the cumulative volume. Preston and Keachie (1964) found that unit labor costs are depended on the rate of output as well as on the amount of cumulative output. Their work showed the importance of including changes in the rate of output as well as cumulative output in assessing learning rates. Rapping (1965), Sheshinski (1967), and Stobaugh and Townsend (1975) have tested the hypothesis that learning is a function of time rather than cumulative output. These studies found that calendar time becomes statistically insignificant once the cumulative output is included in the analysis. Liebermann (1984) observed similar trends after he analyzed the three-year price change for 37 chemical products. He examined several other candidate explanatory variables of learning such as time, cumulated industry output, cumulative industry capacity, the annual rate of industrial output, the average scale of the plant, and rate of new plant investment, rate of new market entry, and level of capacity utilization. After analyzing all of the parameters he concluded that the cumulative industry output is the single best proxy for learning. Carrington (1989) also pointed out that total cost is a function of cumulative output as well as the firm’s rate of output.

Several studies have attempted to find those underlying factors affecting cost reduction. In one study, Hollander (1965) investigated the sources of efficiency increase and found that most of the efficiency gains were due to technology and learning, while only 10-15% of the efficiency gains were accounted for scale economies effects. However, as the large part of the cost reduction from technology improvement was due to a series of minor technical changes, Hollander resulted that these minor technical changes could be taken into account to some extent as learning by observation. Rapping (1965) analyzed additional factors such as economies of scale in assessing learning rates and found that although productivity gains associated with cumulative output were not due to increased inputs of labor or capital or increasing exploitation of economies of scale, evidence of learning remained strong when they were taken into account. Stobaugh and Townsend (1975) and Lieberman (1984) have also shown that scale economies are typically significant, but much smaller in magnitude than learning-related cost reduction. Sinclair et al. (2000) also looked at those factors regarding cost reduction and observed that technology triggered cost reductions were largely the result of small technological changes in production and manufacturing based on R&D and related activities.

Developing firm operational strategies has also investigated on significant work using learning curves. For instance, Spence (1981) developed a model of competitive interaction and industry evolution in the presence of a learning curve and concluded that the firm achieves higher profits in the long run by moving further down the learning curve faster than its competitors. Spence’s analysis also showed that the largest barriers to entry occur when there are moderate rates of learning rather than when there is either very slow or very fast learning. The Dasgupta-Stiglitz (1988) article on analyzing the influence of learning on the evolution of market structure, have shown that market concentration increases as learning proceeds when a small initial cost advantage grants to one firm (i.e. an oligopoly with initially asymmetric costs eventually becomes monopolized).

Recently, Mukhopadhyay et al. (2011) examined learning curves in an information Technology-Enabled Physician Referral Systems to determine whether agents achieve performance improvements from cumulative experience at different rates and how information technologies transform the learning dynamics in this setting. They determined The IT-PRS exhibits a learning rate of 4.5% for emergency referrals, 7.2% for non-emergency referrals, and 12.3% for non-emergency out of network referrals as well.

Della Seta et al. (2012) studied the optimal investment in technologies characterized by the learning curve. They indicated that technologies with the intermediate speed of learning were most susceptible to losses and risk. Morasch (2013) investigated the competition or cooperation solution in markets with network externalities or learning curves. The results indicated that the alliance solution could be chosen for medium values of a learning curve or network effects. Kredler (2014) studied a vintage human capital model and showed that the experience premium is always positive but diminishes as technology ages. Sampedro and Gonzalez (2014) calculated the Spanish photovoltaic (PV) learning curve over the period 2001– 2012. The results indicated a curve with a strong structural change in the speed of cost reduction in October 2009. Feizpour et al. (2015) explored the influence of education level on Firm's Learning in Non-metallic mineral products manufacturing firms in Iran. The results indicate that there is needed to a certain threshold of the percentage of higher educated employees to affect the learning of firms by about 30 percent. Baltwilks et al. (2015) tried to improve the application of the learning curve for forecasting costs of renewable technologies in integrated assessment models (IAMs). They provided a new estimated learning curve for wind turbines and PV technologies. Hong et al. (2015) estimated the decrease of photovoltaic power generation cost in Korea based on the learning curve theory. The 2FCL analysis indicated that the cost decreases by 2.33% every time the cumulative photovoltaic power generation is doubled and by 5.13% every time R&D investment is doubled. Oyapıcıto et al. (2016) tried to develop a way to better estimate the learning curve which is an exponentially decreasing function based on multiplicative Lagrange interpolation. The results of this study indicated that the proposed multiplicative method of learning curve provides more accurate estimates of labor costs when compared to conventional methods.

Smith et al. (2016) estimated the learning curve using both global and North American compact fluorescent lamp (CFL) data during the period of 1990–2007. The results showed a learning rate of approximately 21% between 1990 and 1997, and 51% and 79% in global and North American datasets, respectively, after 1998.

Wei et al. (2017) used the learning curve to determine the learning rates for six selected technologies. They showed that there is a downward bend in the experience curve for 5 out of the 6 energy-related technologies.

Hayashi et al. (2018) examined how an accumulation of experience and knowledge by wind farm developers and turbine manufacturers contributed to productivity gains in China's wind power industry during its rapid expansion phase between 2005 and 2012. The results revealed that the experience and knowledge accumulation did not result in improvements in generation performance, turbine size, or unit turbine costs of the Chinese wind farm.

To our knowledge, this study is the first to provide a quantitative comparison of learning rates across such a broad set of industries and their interaction with industry structure in Iran.

3. Basic Structure of the Formal Model

Considerable empirical pieces of evidence have been documented the existence of learning curves in an abundant variety of industries. Learning curve studies have experimented with a variety of functional forms to describe the relationships between cumulative capacity and cost (Nemet, 2006). Wright’s model, also referred to as the “Log-linear Model”, is perhaps the first formal model with the following mathematical representation:

$$c_t = c_0 Q_t^{\lambda} \tag{1}$$

$$PR = 2^{-\lambda} \tag{2}$$

$$LR = 1 - PR \tag{3}$$

where c_t is the unit cost of production at the time t, c_0 unit cost of production in the initial production period and t, Q is a cumulative number of units that have been produced (a proxy for experience). The parameter λ is the slope of the learning curve, which can be used to calculate the progress ratio (PR) and learning ratio (LR) (Anzanello and Fogliatto, 2011). Equation (1) also represents that the labor force learns from gained experience during the production process which leads to reducing cost.

The linear form of the Equation (1) to estimate learning effects will be:

$$\ln c_t = \ln c_0 + \lambda \ln Q_t + \varepsilon_t \tag{4}$$

where λ, as mentioned above, is the elasticity of learning (i.e. percentage change in unit cost for a given percentage change in cumulative output). And ε_t is a random error term to allow for unobservable or immeasurable shocks. And it is assumed that $E(\varepsilon) = 0$. Although this equation demonstrates the learning curve, we can differentiate between economies of learning and economies of scale. Accordingly, based on the proposed model by Sadraei Javaheri (2007), Wright's model integrated with the Cobb Douglas cost function as follows to separate the economies of learning and the economies of scale.

Cobb Douglas cost function for each industry is written in Equation (5).

$$C = (\alpha + \beta)\left[A\alpha^{\alpha}\beta^{\beta}\right]^{-1/\sigma} Y^{1/\sigma} r^{\beta/\sigma} W^{\alpha/\sigma} \tag{5}$$

where C is the nominal total cost, Y is output, r is the capital price, W is labor price, and σ is the rate of return to scale ($\alpha + \beta$). In the above Equation, $(\alpha + \beta)\left[A\alpha^{\alpha}\beta^{\beta}\right]^{-1/\sigma}$ can be considered as h and so the linear form of the equation can be rewritten by Equation (6) as follows:

$$\ln C = \ln h + {}^{1}\!/_{\sigma} \ln Y + {}^{\beta}\!/_{\sigma} \ln r + {}^{\alpha}\!/_{\sigma} \ln W + \varepsilon_t \tag{6}$$

By deflating the nominal cost function into real one using price deflator of Gross National Product (GNPD) in which assumed weights in price deflator of GNPD is a representation of input use (L, K) by firms, we have:

$$\mathrm{lnGNPD}_t = \frac{\beta}{\sigma} \ln r_t + \frac{\alpha}{\sigma} \ln W_t \tag{7}$$

$$C'_t = \frac{C_t}{GNPD_t} \Rightarrow \ln C'_t = \ln C_t - \ln GNPD_t \tag{8}$$

$$\ln C' = \ln h + {}^{1}\!/_{\sigma} \ln Y + \varepsilon_t \tag{9}$$

Two differences can be observable in Wright's model and the Cobb Douglas cost function. The first one is contributed to the lack of existence of Q_t in the Cobb Douglas cost function and A in Wright's model. To solve this problem, it is assumed that there is a similarity between Q_t and A because experience (Q_t) can be related to technology (A). Advances in knowledge can be related to learning. Therefore, it is assumed that $A_t = Q_t^{(-\lambda)}$. By substituting $Q_t^{(-\lambda)}$ in Equation (9) instead of A , we have:

$$\ln C'_t = \ln h' + {}^{\lambda}\!/_{\sigma} \ln Q_t + {}^{1}\!/_{\sigma} \ln Y_t + \varepsilon_t \tag{10}$$

where $h' = \sigma\left[\alpha^{\alpha}\beta^{\beta}\right]^{-1/\sigma}$.

The second differences originate from the dependent variable in Cobb Douglas cost function and Wright's model which is the total cost and average cost, respectively in the first and second model. Therefore, the total cost should be converted to the average cost. This way leads us to the following Equation:

$$\ln c_t = \ln h' + \frac{\lambda}{\sigma} \ln Q_t + \frac{1-\sigma}{\sigma} \ln Y_t + \varepsilon_t \tag{11}$$

where c_t is the average cost. Therefore, for estimating the coefficients the following linear equation can be used:

$$\ln c_t = \beta_0 + \beta_1 \ln Q_t + \beta_2 \ln Y_t + \varepsilon_t \tag{12}$$

where c_t is the real unit cost of production at the time t, Q_t is the cumulative number of units produced up to and including period t (a proxy for experience) and Y_t is output at the time t. Based on the coefficient of λ and σ which can be calculated as $\frac{\beta_1}{1+\beta_2}$ and $\frac{1}{1+\beta_2}$, respectively, rate of learning can be estimated by $1-2^{-\lambda}$.

4. Market Structure

There are several measures of concentration in which concentration ratio (CR) and Herfindahl-Hirschman Index (HHI) have a powerful theoretical foundation and are the most frequently used. Summing only the market shares of the k largest firms in the market, concentration ratio takes the form:

$$CR_n = \sum_{i=1}^{n} S_i \tag{13}$$
$$i = 1, 2, 3, \ldots, k, k \geq n$$

where k defines the number of firms in an industry, n is the number of large firms, and S_i is the market share of i th firm. The index gives equal emphasis to the k leading firms but neglects the many small banks in the market. The concentration ratio is a one-dimensional measure ranging between zero and unity. The index approaches zero for an infinite number of equally sized firms and it equals unity if the banks included in the calculation of the concentration ratio make up the entire industry (Donsimoni et al., 1984). The most common concentration ratios are the CR_4 and the CR_8, which means the market share of the four and the eight largest firms. Concentration ratios are usually used to show the extent of market control of the largest firms in the industry and to illustrate the degree to which an industry is oligopolistic.

Herfindahl-Hirschman Index is also taken the form of:

$$H = \sum_{i=1}^{N} \left(\frac{X_i}{X} \right)^2 \tag{14}$$

$$H = \sum_{i=1}^{N} (S_i)^2 \tag{15}$$

where S_i is the market share of i th firm and N defines the number of firms in an industry. The index stresses the importance of larger firms by assigning them greater weight than smaller firms. The HHI can range from zero in a market having an infinite number of firms to 10,000 in a market having just one firm (with a 100% market share). The industry is regarded to be a competitive market if the HHI is less than 1000, somewhat concentrated market if the HHI lies between 1000 and 1800, and a very concentrated market if HHI is more than 1800.

This paper has used these two measures of market concentration for estimating and evaluating the learning curve and their interaction with industry structure in terms of three criteria of employment, output, and value-added as a way for achieving industry structure.

5. Data and Variables

Most learning curve studies have focused on better specifying the aggregate learning effect, primarily concentrating on the selection of proxies for experience and cost. Cumulative output was privileged in the original formulations by Wright (1936) and by many later studies. Hirschleifer (1962) and Alchian (1963) distinguished between the rate of output and the scheduled volume of output. Sheshinski (1967) examined cumulative investment as an alternative to cumulative output. Cooper and Charnes (1954), Sheshinski (1967), Fellner (1969), Stobaugh and Townsend (1975) discussed time as an alternative or complement to cumulative output. A dependent variable that measures workers' performance in LC models includes time to produce a single unit, number of units produced per time interval, costs to produce a single unit, and percent of non-conforming units (Teplitz, 1991; Franceschini and Galetto, 2002).

This research focuses on cumulative output as an original proxy for experience. Moreover, since output function in short-term is the function of only one variable, generally labor force, it is assumed that all the variable costs of a firm only consist of wage and salary as well as fringe benefits to employees and therefore the present research takes the view that average cost is defined by annual wages, salaries and fringes to employees. Besides, wage deflator as well as price deflator has been applied to convert the nominal wage and salary and the nominal output into the real ones, respectively.

Data of this paper also extracted from the Statistical Center of Iran (SCI). In this regard, entrance firms in 1997 which have been followed until 2005 are considered for the empirical investigation. It should be noted that the data used in this research is at the firm level, despite the continual references of the researchers of this study to the Statistics Center of Iran (SCI) for receiving new data for recent years, But this period used in this study is the best and last available data that published by SCI. During this period, only those firms that do not exit from underlying industries and also do not change their industries have been contributed to the investigation. Also, industries have been determined based on four-digit ISIC codes. Accordingly, 80 four-digit ISIC codes industries have been selected.

6. Estimation of Learning Rate

Data used in this paper have the nature of Panel data due to the existence of cross-section and time series. Therefore, the Panel data method is performed to estimate the equation (12) presented in section 3 for four-digit ISIC codes industries. The analyses start by testing the stability of the available data using the panel unit root test. Levin, Lin, and Chu (2002) and Im, Pesaran, and Shin's (2003) tests are used and the results provide evidence on the rejection of the null hypothesis at a five percent significance level for all industries. Besides, using the Likelihood ratio test, the hypothesis based on the existence of homoscedasticity in variances is rejected and thus, the model has heteroscedasticity. In this case, the best way to estimate the model is the method of Generalized Least Square (GLS). In doing so, the results of estimated coefficients are presented in

Table 1. No insignificant models and coefficients are included.

According to the estimated coefficients and base on the calculated value of λ and σ, dynamic and static dimension of cost advantage is calculated. The value of LR (i.e. rate of learning) is calculated by the formulation of $1-2^{\lambda}$ and reported in Table 2 along with the value of ES (i.e. scale of economies) for industries listed in Table 1.

Table 1: Estimation of Models' Coefficients

ISIC	Industry	β_0	β_1	β_2
1516	Meat	4.708	-0.151	-0.575
1531	Grain mill products	1.648	-0.367	-0.130
1532	Starch Manufacturing	-0.619	-0.812	0.510
1533	Animal feeds	4.339	-0.395	-0.317
1544	Macaroni, spaghetti, vermicelli, and noodles products	4.262	-0.424	-0.280
1546	Confectionery	1.811	-0.107	-0.472
1547	Tea manufacturing	9.911	-0.322	-0.707
1548	Other food products	2.256	-0.260	-0.283
2212	Newspapers and magazines publishing activities	1.367	-0.289	-0.204
2320	Petroleum products manufacturing	-3.834	-0.447	0.265
2413	Plastic materials and synthetic rubber manufacturing	0.098	-0.254	-0.185
2423	Medicinal chemical and botanical manufacturing products	-4.136	0.157	-0.341
2429	All other miscellaneous chemical products	0.811	-0.212	-0.256
2511	Tires and inner tubes and tire retreating	-2.874	-0.541	0.331
2519	All other rubber products manufacturing	-0.581	-0.129	-0.261
2520	Plastic products manufacturing Except footwear	-0.749	-0.137	-0.257
2611	Flat glass manufacturing	10.947	-0.494	-0.357
2691	Non Clay refractory manufacturing	-8.580	-0.422	0.544
2695	Concrete, cement and gypsum products manufacturing	2.651	-0.342	-0.261
2696	Cut stone and stone products	1.064	-0.341	-0.173
2697	Brick manufacturing	-2.283	-0.558	0.328

ISIC	Industry	β_0	β_1	β_2
2698	Other structural clay products manufacturing	-1.901	0.641	0.397
2699	All other miscellaneous non-metallic mineral products manufacturing	0.364	-0.283	-0.161
2731	Metal and steel foundries	1.576	-0.276	-0.237
2812	Boiler, tanks and other similar products manufacturing	-6.907	-0.651	0.695
3120	Power, distribution. and transformer manufacturing	11.339	-0.538	-0.495
3150	Electric lamp bulb and lighting equipment manufacturing	-6.058	-0.265	0.262
3311	Orthopedic, and surgical appliances manufacturing	0.533	-0.173	-0.290
3312	Navigational, measuring and control instruments manufacturing	-3.645	-0.369	0.210
3320	Instrument manufacturing for optical and photography	16.959	-0.631	-0.774
3520	Railroad equipment and repairing	7.042	-0.503	-0.261

Table 2: Learning Elasticity, Learning Rate, Rate of Return to Scale & Economies of Scale

ISIC	Industry	λ	LR	σ	ES
1516	Meat	-0.36	21.9	2.36	135.8
1531	Grain mill products	-0.42	25.4	1.15	14.9
1532	Starch Manufacturing	-1.66	68.4	2.04	104.5
1533	Animal feeds	-0.58	33.1	1.47	46.6
1544	Macaroni, spaghetti, vermicelli, and noodles products	-0.59	33.5	1.39	38.9
1546	Confectionery	-0.20	13.1	1.89	89.4
1547	Tea manufacturing	-1.10	53.3	3.41	241.3
1548	Other food products	-0.36	22.3	1.39	39.5
2212	Newspapers and magazines publishing activities	-0.36	22.2	1.26	25.6
2320	Petroleum products manufacturing	-0.35	21.7	0.79	-20.9
2413	Plastic materials and synthetic rubber manufacturing	-0.31	19.4	1.23	22.7
2423	Medicinal chemical and botanical manufacturing products	-0.29	18.5	0.86	-13.6
2429	All other miscellaneous chemical products	-0.28	17.9	1.34	34.2
2511	Tires and inner tubes and tire retreating	-0.81	42.9	1.49	49.5
2519	All other rubber products manufacturing	-0.17	11.3	1.35	35.3

2520	Plastic products manufacturing Except for footwear	-0.18	12.0	1.35	34.6
2611	Flat glass manufacturing	-0.77	41.3	1.56	55.5
2691	Non Clay refractory manufacturing	-0.27	17.3	0.65	-35.2
2695	Concrete, cement and gypsum products manufacturing	-0.46	27.4	1.35	35.5
2696	Cut stone and stone products	-0.41	24.9	1.21	20.9
2697	Brick manufacturing	-0.42	25.3	0.75	-24.7
2698	Other structural clay products manufacturing	-0.46	27.2	0.72	-28.4
2699	All other miscellaneous non-metallic mineral products manufacturing	-0.34	20.8	1.19	19.2
2731	Metal and steel foundries	-0.36	22.3	1.31	31.2
2812	Boiler, tanks and other similar products manufacturing	-0.38	23.4	0.59	-41.0
3120	Power, distribution. and transformer manufacturing	-1.07	52.3	1.98	98.4
3150	Electric lamp bulb and lighting equipment manufacturing	-0.21	13.6	0.79	-20.8
3311	Orthopedic, and surgical appliances manufacturing	-0.24	15.6	1.41	41.0
3312	Navigational, measuring and control instruments manufacturing	-0.30	19.1	0.83	-17.4
3320	Instrument manufacturing for optical and photography	-2.79	85.6	4.42	342.5
3520	Railroad equipment and repairing	-0.68	37.7	1.35	35.3
Average		-0.56	28.7	1.45	44.9

Source: Research findings.

The learning rate expresses the relative decline in production cost with a doubling of the cumulative production. As can be seen in Table 2, the learning effect is not uniform across considered 31 industries and differs between 11 percent and 86 percent. Among these industries at four-digit levels, the learning effect is strongest in instrument manufacturing for the optical and photography industry (ISIC 3320), while all other rubber products manufacturing industry (ISIC 2519) has the smallest one. These results indicate that when experience doubles, the unit cost in that industry is reduced based on the rates indicated in Table 2. A graphical exposition of this information is provided in Figure 2 in ascending order according to the magnitude of their learning rate.

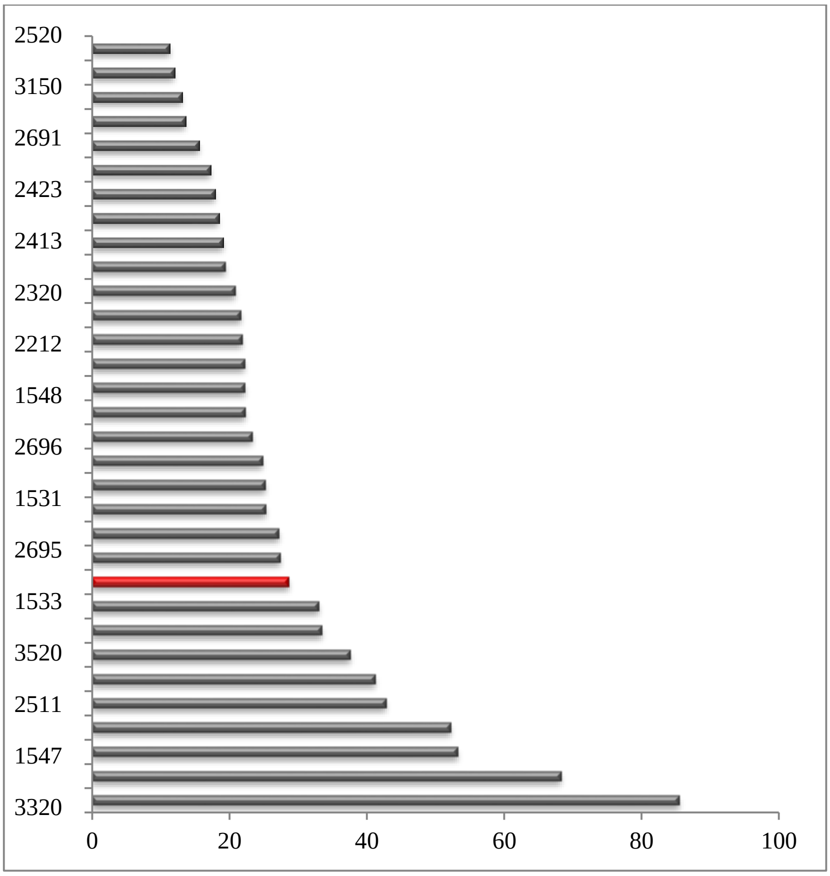

Figure 2: Learning Rates of Industries at Four-Digit ISIC Levels in Ascending Order

Table 2 also includes the static dimension of cost advantages that is economies of scale. It is observable that eight industries including petroleum products manufacturing (ISIC 2320), medicinal chemical and botanical manufacturing products (ISIC 2423), non-clay refractory manufacturing (SIC 2691), brick manufacturing (ISIC 2697), other structural clay products manufacturing (ISIC 2698), boiler, tanks, and other similar products manufacturing (ISIC 2812), electric lamp bulb and lighting equipment manufacturing (ISIC 3150) and navigational, measuring and control instruments manufacturing (ISIC 3312) enjoy diminishing rate of return to scale. However, they all have a positive rate of learning which indicates that all the reduction in cost is contributed to the learning effect. This fact is displayed in Figure 3 for only four selected industries. The trend of cost shows that despite the diminishing rate of return to scale, the real cost is reduced just because of the effect of learning. Nevertheless, the average of economies of scale is about 45 percent which is more than average of the learning rate. It indicates that scale economies play a more important role in reducing cost than the learning effect as a whole. However, the effect of learning is relatively higher than the effect of scale economies in some industries which are highlighted in Table 2.

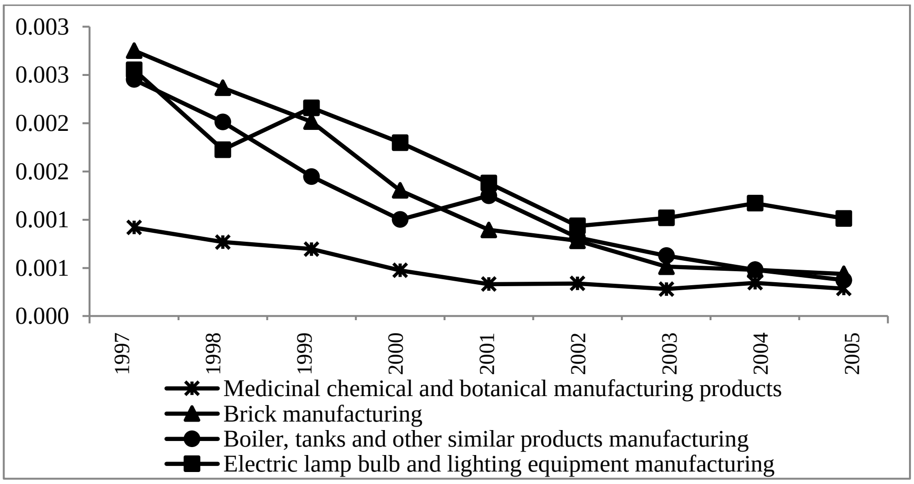

Figure 3: The Trend of Unit Cost in Selected Industries Enjoying Diminishing Rate of Return to Scale

To sketch the outlines of the link between learning rate and industry structure, CR_4, and HHI based on the employment criteria are calculated and inserted in Table 3.

Table 3: Industries Structure Based on CR_4 and HHI (Employment)

ISIC	Industry	CR_4		HHI	Structure
1516	Meat	0.234	Competitive	266	Competitive
1531	Grain mill products	0.086	Competitive	66	Competitive
1532	Starch Manufacturing	0.809	Monopoly	2217	Monopoly
1533	Animal feeds	0.224	Competitive	269	Competitive
1544	Macaroni, spaghetti, vermicelli, and noodles products	0.048	Competitive	58	Competitive
1546	Confectionery	0.388	Competitive	565	Competitive

ISIC	Industry	CR_4		HHI	Structure
1547	Tea manufacturing	0.095	Competitive	113	Competitive
1548	Other food products	0.198	Competitive	199	Competitive
2212	Newspapers and magazines publishing activities	0.829	Monopoly	2642	Monopoly
2320	Petroleum products manufacturing	0.697	Oligopoly	1958	Monopoly
2413	Plastic materials and synthetic rubber manufacturing	0.746	Oligopoly	2297	Monopoly
2423	Medicinal chemical and botanical manufacturing products	0.276	Competitive	321	Competitive
2429	All other miscellaneous chemical products	0.298	Competitive	368	Competitive
2511	Tires and inner tubes and tire retreating	0.678	Oligopoly	1459	Oligopoly
2519	All other rubber products manufacturing	0.272	Competitive	364	Competitive
2520	Plastic products manufacturing Except footwear	0.168	Competitive	133	Competitive
2611	Flat glass manufacturing	0.720	Oligopoly	1793	Oligopoly
2691	Non Clay refractory manufacturing	0.258	Competitive	414	Competitive
2695	Concrete, cement and gypsum products manufacturing	0.205	Competitive	206	Competitive
2696	Cut stone and stone products	0.056	Competitive	32	Competitive
2697	Brick manufacturing	0.033	Competitive	15	Competitive
2698	Other structural clay products manufacturing	0.474	Competitive	719	Competitive
2699	All other miscellaneous non-metallic mineral products manufacturing	0.108	Competitive	86	Competitive
2731	Metal and steel foundries	0.451	Competitive	702	Competitive
2812	Boiler, tanks and other similar products manufacturing	0.625	Oligopoly	1738	Oligopoly
3120	Power, distribution. and transformer manufacturing	0.538	Oligopoly	982	Competitive
3150	Electric lamp bulb and lighting equipment manufacturing	0.618	Oligopoly	1673	Oligopoly
3311	Orthopedic, and surgical appliances manufacturing	0.498	Competitive	1425	Oligopoly
3312	Navigational, measuring and control instruments manufacturing	0.716	Oligopoly	1878	Monopoly
3320	Instrument manufacturing for optical and photography	0.882	Monopoly	2477	Monopoly
3520	Railroad equipment and repairing	0.866	Monopoly	2435	Monopoly

Source: Research findings.

As can be seen in this table, methods of CR_4 and HHI do not show the same picture of concentration in these industries. In other words, if some industries are more concentrated than other industries in terms of CR_4, they are not more concentrated in terms of HHI. However, we cannot differentiate between the learning rates in competitive industries from those industries with oligopoly or monopoly structures. In other words, competitive industries do not fare badly in comparison with oligopolistic or monopolistic industries.

Nevertheless, based on the average learning rate shown in Table 4, we can assert that monopolistic industries have more advantages of learning rate than competitive and oligopolistic structures in terms of both methods of CR_4 and HHI. Also, oligopolistic industries fare better than competitive industries in both groups.

Table 4: The Average of Learning Rates and Economies of Scale in Competitive, Oligopolistic and Monopolistic Structures Based on CR_4 and HHI

Structure	CR_4		HHI	
	LR	ES	LR	ES
Competitive	23.3	36.8	25.2	39.7
Oligopoly	29.2	37.1	27.3	52.5
Monopoly	53.5	67.7	39.2	51.8

As can be seen in Table 4, in comparison with competitive industries, the average learning rate of oligopolistic industries is more than competitive industries. Nevertheless, it should be noted that the average of economies of scale in all three structures is more than the learning rate. Therefore, we can allude to the fact that the reducing costs have been more influenced by the benefits of economies of scale than the learning rate in all structures.

7. Conclusion

Despite several previous studies on learning curve analysis, this issue has not been taken into account in Iran. In this paper, we focus on the effect of learning in Iranian manufacturing industries during 1997-2005. The empirical results demonstrate that the learning rate is not uniform across 31 industries and varies in the range of 11 to 86 percent. Moreover, distinguishing the effect of learning and the effect of economies of scale, it's found that the effect of learning in a few industries (i.e. 11 industries among 31 industries) is more than their effect of economies of scale. The cost advantages in these industries are mostly due to learning impact. Comparison of the average of learning in various structures demonstrates that monopolistic industries get the more advantage of learning than oligopolistic and competitive industries and similarly, learning is more in oligopolistic than competitive industries. Nevertheless, economies of scale play a significant role in reducing costs in all three structures. From a policy point of view, competitive industries should try to focus their efforts on achieving both dynamic and static dimension of cost advantages to enhance their competitiveness to keep their market shares.

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