The Contribution of R&D İnvestments to Technological Learning Capability: Evidence from Manufacturing İndustry Sectors of the Turkish Economy

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Abstract: - Learning-by-searching is the process of experience in the emergence of new high-value-added products with the new knowledge and skills that an enterprise achieves through the network system it establishes with its own R&D unit, other enterprises, universities, and other information sources. The most important factor that contributes to learning-by-searching is undoubtedly the investments made in research and development in economic sectors. A review of the literature on the subject reveals that R&D expenditures are only used as the second independent variable in linear learning curve models. For this reason, in the existing applied studies, only a fixed representative learning rate, which is the average of the learning rates in the period in question, is determined. In this study, a two-factor dynamic learning curve model is used to measure the cost-reducing effect of R&D expenditures. Thus, in addition to learning-by-doing ratios, the evolution of learning-by-searching ratios over time is also taken into account. The findings of the study support the view in the literature that the learning-by-doing rates in the one-factor dynamic learning model are biased. In addition, in the two-factor dynamic learning curve model, it was also found that in periods when learning-by-doing loses its effect, learning-by-searching increases its effect.

Key-Words: **-** Learning-by-doing, Learning-by-searching, Manufacturing Industry Sector.

Received: April 29, 2024. Revised: November 25, 2024. Accepted: December 23, 2024. Published: January 27, 2025.

1 Introduction

The determinants of economic growth have been one of the main topics of debate in the literature since the mid-20th century. The most important of these are technological development and human capital expenditures. Technological development emerges as a result of basic scientific research and innovation activities. In today's world where the technology race is gaining momentum, countries that do not want to lose their international competitiveness feel the need to develop and update their technological knowledge base more than ever. Human capital represents the knowledge, skills, and experience of the labor force. The common goal of technological development and human capital factors is to produce high-value-added products by increasing labor productivity in the production of goods and services.

The learning curve model predicts that an increase in cumulative output will increase labor productivity, which will naturally lead to a reduction in unit costs. There is a strong consensus in the existing literature that this model is the best measurement tool as it allows for the comparison of past learning levels. Moreover, the learning curve model allows for the estimation of long-run cost reductions at the individual, organizational and industrial levels, thus guiding economic policies in the areas of industry, energy and environment.

The idea that increased experience through hands-on learning would lead to improvements in productivity was first proposed in [1]. In [2] further is developed this basic approach and argued that new know-how created through learning-by-doing in the production stage can enter the production process as free input in the next production stage.

As production increases and costs fall, the new knowledge generated in this process will eventually spread to other firms in the sector, since it cannot be retained by the innovative company for a long time. Ultimately, this positive externality will affect other sectors of the economy and contribute to the economy as a whole.

In today's world of global competition, it has become even more important to increase productivity by improving technological learning capacity. Technological learning capability is defined as the ability to use technological knowledge effectively in production, engineering, and innovation processes. This capability can only be acquired through continuous technological learning in an economy with qualified labor, raw materials, capital, and strong institutions. Monitoring the sustainability of technological learning by using methods to measure the learning levels of the labor force employed in production is very useful in terms of guiding technology policies. Technological development is usually a long process involving several stages. [3] first described this process in the literature and proposed a model based on the triple paradigm of invention, innovation and diffusion. In this context, invention is defined as the generation of new knowledge and new ideas. In the innovation stage, inventions are further developed and transformed into new products. In the final stage, diffusion is the acceptance of new products by a broad segment of society. The process of technical change, which reflects the stages of technological progress, is not linear as it includes feedback loops between the components of the mode,l [4]. Knowledge of the stages and characteristics of this technological change process is also important for the economic analysis of renewable energy technologies, [5].

Research and Development (R&D) activities are undoubtedly one of the key drivers of technological progress. Basic research covers a wide range of innovations and addresses the initial stages of technological development. As is well known, installed capacity cannot increase until commercial sustainability is achieved through cost improvements and/or government intervention in the production process. Although market size and conditions are limited, R&D plays a leading role in technological progress. Commercial expectations and supportive measures will lead to increased R&D activity and capacity expansion. As technology gradually develops and matures, the impact of both R&D activities and their increased cumulative output will diminish. In practice, R&D activities are often associated with the innovation and diffusion stages of technological progress, [6]. In the related literature over the last 30 years, technological learning capability has been extended to include the learning capability acquired as a result of basic scientific research and R&D activities, which are the main sources of technological progress. Therefore, the level of learning-by-searching for employees in any sector or firm can only be explained by a two-factor learning curve model in which R&D expenditures are included in the model as an independent variable. The main objective of this study is to econometrically reveal the possible effects of cumulative production and R&D expenditures on labor productivity using the case of Turkey. In the study, manufacturing industry sub-sectors are first theoretically investigated in terms of technological learning capacity, R&D activities, learning curve, and technological characteristics, and then the related studies in the literature are comparatively reviewed. Finally, the learning-by-doing and learning-by-searching ratios in the Turkish manufacturing industry sub-sectors are statistically determined and according to the findings of the study, sectors with high productivity are selected, and support for these sectors is recommended.

2 Learning Curve Model

The learning curve model suggests that the reduction in the unit cost of a product is a function of the experience resulting from the cumulative increase in production. Since the 1930s, the learning curve has been used as a method for measuring technological change. The learning curve measures technical change that reduces costs through innovative activities. The concept of the learning effect as an indicator of technological change first appeared in the works of [1] and [7] has been commonly referred to as "learning-by-doing". Although the concept of the learning curve has been known for a long time, the need for innovation in energy technologies and environmental policy has led to a significant increase in interest in this area of research. In the 1930-1960 period, the first applications of the learning curve appeared in the manufacturing sector [7], [8], [9]. In the 1970-1980 period, it was applied to management, strategy, and business organization [10], [11], [12], [13], [14]. In addition, the learning curve has received considerable attention since the 1990s for its application in policy analyses and especially in renewable energy technologies, [15], [16], [17], [18].

The learning curve of a given technology can be defined by equation (1) below. Where, C_t is the unit production cost at time *t*; C_0 is the initial unit production cost; Q_t is the cumulative production quantity at time t and -a is the coefficient of learning elasticity. Equation (2) is the logarithmic form of equation (1). The progress ratio (d) is calculated using equation (3). The learning effect of increased capacity or cumulative output on unit cost is represented by the learning rate defined in equation (4).

$$C_t = C_0 \; Q_t^{-a} \tag{1}$$

$$LnC_t = LnC_0 - aLnQ_t \tag{2}$$

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

$$LR = 1 - d \tag{4}$$

The progress ratio (d) shows the change in unit cost compared to the initial value. The learning rate (LR) is the rate of decrease/increase in unit cost when cumulative production is doubled. The progress ratio shows that the unit production cost decreases by 2^{-a} when total production is doubled. When learning occurs in the production process, d is expected to be between 0 and 1. When this ratio approaches zero, it means that higher learning has taken place and when it approaches one, it means that lower learning has taken place. If d=1, there will be no change in unit production costs in the direction of increase or decrease. If d>1, there will be an increase in unit production costs or a loss in productivity.

At the macro level, it takes time to internalize new technologies in a country that lacks adequate institutionalization and qualified human resources. For this reason, a dynamic (S-shaped) learning curve showing the evolution of learning rates will reflect changes over time better than the classical linear learning curve. Moreover, the fact that technological learning is a costly and time-consuming process and that firms in the manufacturing industry sectors cannot internalize technological innovations due to their imperfect information also prolongs this process. For all these reasons, [19] determined that it would be more appropriate to use a third-order cost function, which is defined by equation (5) below, in accordance with the S-shaped learning curve developed by [20] and [21].

$$lnC_t = lnC_0 + \beta_1 (lnQ_t) + \beta_2 (lnQ_t)^2 + \beta_3 (lnQ_t)^3 \tag{5}$$

$$-a = \beta_1 + 2\beta_2 (lnQ_t) + 3\beta_3 (lnQ_t)^2 \tag{6}$$

Taking the first derivative of equation (5) with respect to lnQ_t gives the coefficient of elasticity of learning-by-doing (-a) defined in equation (6).

3 Literature Review

In studies based on the single-factor learning curve, reductions in unit costs caused by increases in production and capacity through technological change and innovation activities are accepted as a measurable indicator of technological progress [22]. However, the reduction of the independent variable to a single factor in the learning curve, which was originally designed for mature industries, has led to increasing criticism that this model is insufficient to keep pace with evolving technologies. The proactive approach, which views technological progress as endogenous, argues that a variety of factors should be used to encourage technological progress. An important shortcoming of the single-factor learning curve model is that it does not take into account the impact of R&D on cost reduction. In such a case, in other words, if the R&D variable is not included in the model, learning rates are likely to be biased.

Research on the calculation of learning rates in the field of Renewable Energy Technologies (RET) has been conducted since the 1970s. Some of these studies have shown that learning-by-doing has accelerated with technological developments in photovoltaic (PV) solar energy and wind turbines, [18], [23], [24]. On the contrary, there are many studies showing the opposite, [25], [26], [27], [28], [29], [30], [31], [32]. According to the results of all these studies, it is normal that learning-by-doing rates for PV and wind technologies, which are more capital-intensive, gradually decrease over time. This is because it is known that R&D expenditures and the number of patents in RET have increased exponentially in the last 30 years, [33], [34]. Whether the declining learning-by-doing rates in RET have been replaced by an increase in learning-by-research rates can only be determined by a two-factor dynamic learning curve model.

A review of the relevant literature of recent years reveals that studies have focused on models that allow for the estimation of future learning rates. For example, qualitative research [35] estimated that in electricity generation with carbon capture and storage (CCS) systems in 1800 MW power plants in China, when the cumulative generation capacity reaches 100 GW, the cost of unit capital and electricity will decrease by 40% and 13-25%, respectively. Similarly, [36], forecasted that the unit capital investment cost of PV solar panel production in the UK will decrease from £5000 in 2007 to £1800 in 2030.

The single-factor dynamic learning curve model has also been the subject of empirical studies across economic sectors. Among these [19] conducted an important study on the subject for Turkey and detected that 28 manufacturing industry sub-sectors follow three different technological learning paths by using the Turkish data for the period 1980-2000 under the Least Squares (LS) method. In their study, they found that low and medium-low technology sub-sectors, which are defined as mature manufacturing industry sub-sectors, have experienced forgetting in recent years. On the other hand, they observed that high-tech sub-sectors, which are referred to as emerging sub-sectors, did not experience forgetting, while revitalized medium-high technology sub-sectors experienced forgetting at the beginning.

According to prior research [37], using the model and methodology in [19] with the NACE Rev.3 data of 25 manufacturing industry sub-sectors of the Japanese economy for the period 2000-2014, forgetting occurred in the initial period in high and medium-high technology sub-sectors of the manufacturing industry and in the last period in low and medium-low technology sub-sectors. Moreover, total factor productivity declined from 65% to 42% in the entire manufacturing industry sector. As a result, the capital-intensive nature of technological development in Japanese firms let unit production costs to not fall sufficiently in this situation where the level of learning did not increase.

An important question in the technological learning literature is the extent to which learning is driven by R&D expenditures or R&D-based know-how. The study of [38] was the first to incorporate cost improvements resulting from R&D expenditures into a single-factor learning curve model. Later studies have estimated learning rates for RET areas and tried to answer the question of whether there is a causal relationship between R&D expenditures and decreasing unit costs. For example [39] examined the effects of cumulative installed capacity and cumulative R&D expenditures on unit investment costs using a two-factor linear learning curve model and LS method on quarterly data on global wind turbine production for 1979-1997. According to their findings, the learning rates by doing and searching are 9.73% and 10%, respectively.

In another study using data on wind turbine technology [6], using the same model and methodology, investigated the impact of global production and R&D expenditures on the unit cost of electricity generation over the period 1980-1998. Finally, the learning rate was 13.1% and the learning rate by searching was 26.8%. Another study [40], using data from Germany (1990-1999), Denmark (1986-1999), Spain (1990-1999), Sweden (1991-2002) and the UK (1991-2000) in the same technology area, found that the learning-by-doing rate was 3.1% and the learning-by-searching rate was 13.2%. Similarly, [41], searched for the changes in investment costs in the period 1986-2000 and estimated the learning-by-doing rate as 17% and the learning-by-searching rate as 20%. The common result of all these studies is that the learning-by-searching rate is significantly higher than the learning-by-doing rate.

In the related literature, another group of studies attempted to compare the impact of multiple technologies on unit costs. In the first of these [6] categorized technologies into four classes according to their maturity levels and examined the learning performances of technologies in each class. In his research, he found that emerging technologies have lower rates of learning-by-doing and learning learning-by- searching compared to other technologies. In his study, he argued that high capital intensity and market constraints slow down the rate of progress of emerging technologies. He also observed that evolving technologies have higher levels of learning-by-doing and learning-by-searching than other technologies. In the same study, [6], argued that even when firms face significant market constraints, revived technologies will respond positively to R&D and patent expenditures. On the other hand, other researchers [42] studied onshore wind power, offshore wind power, solar PV, and concentrated solar power (CSP) technologies for the period 1980-2012 and arrived that the learning-by-doing rates calculated with the two-factor model is lower than the learning-by-doing rates calculated using cumulative capacity alone.

In the literature it is also possible to find studies using learning curve models with more than two factors. In one of the first studies based on these models original study [43] found that 15% of the learning-by-doing effect in the production of 37 different chemical products in the US was due to economies of scale. In the same study, he also found that R&D expenditures and capital intensity are the most influential factors and that they significantly shift the learning curve downward in parallel. Supporting this result [44] detected that learning-by-searhinging resulting from R&D

investment expenditures is the most influential factor in US PV solar panel production. This was followed by economies of scale, silicon price, and cumulative production factors, respectively. On the other hand, [45] examined the production of the world's four largest solid oxide fuel cell (SOFC) manufacturers and found that the least influential variable on learning was R&D expenditures. They found that the learning rate was 5% at the initial commercialization stage, 27% at the pilot production stage, and 13-17% at the R&D stage. They also estimated a learning rate of 44% at the scale-up stage, 28% at the intensive equipment purchase stage, and 35% at the automation stage. In summary, the most influential factor was found to be economies of scale, followed by automation, input prices, and R&D expenditures. In the study of [46] it was determined that the most effective factors in cost reduction in Global PV solar panel production were cumulative capacity and silicon price. In addition, it was estimated that learning-by-doing had a 75% effect and input prices had a 25% effect.

4 Data and Econometrical Method

In the present study, 22 sub-sectors of the manufacturing industry in Turkey are analyzed. Annual data for the period 1990-2022 are used for the manufacturing industry sub-sectors. Among the variables used in the econometric analysis, R&D expenditures are obtained from the European Statistical Institute (EUROSTAT), while cumulative production and employment volume data are obtained from the Turkish Statistical Institute (TURKSTAT). The seasonally and calendar-adjusted industrial production index used in the study is also obtained from TURKSTAT. The data set used in the study is defined in Table 1.

Table 1. Definition of Variables

Name	Symbol	Explanation
Unit Cost (TL)	C_t	Employment volume divided by reel cumulative output.
Real Cumulative Production (TL)	Q_t	Firstly, the turnover of the relevant sector is divided by the consumer price index of that year (CPI: 2003=100) and the real cumulative production amount of the relevant year is calculated in Turkish Lira (TL). Then, real cumulative production amounts were obtained by adding the total real cumulative production amount of the previous year to this amount.
Real Cumulative R&D Expenditures (TL)	RD_t	Dividing R&D expenditures by the consumer price index of that year (CPI: 2010=100), the amount of real R&D expenditures of the relevant year was calculated in TL. Real cumulative R&D expenditures were then calculated by adding this amount to the total real R&D expenditures of the previous year.
Employment Volume (Person)	L_t	Number of employees by sub-sector in year t.

In the econometric analysis of the study, learning-by-searching is defined as a second factor, and the learning curve function is modified as shown in equation (7) below.

$$C_t(Q, RD) = C_0 \, (Q_t)^{-a} (RD_t)^{-b} \tag{7}$$

In equation (7), "-b" is the coefficient of the flexibility of learning-by-searching. RD_t represents the real cumulative R&D expenditures in the relevant sub-sector at time t. Replacing C_t in equation (5) with $C_t(Q, RD)$ in equation (7) yields the following two-factor dynamic learning curve equation.

$$lnC_t = \beta_0 + \beta_1 (lnQ_t) + \beta_2 (lnQ_t)^2 + \beta_3 (lnQ_t)^3 + \beta_4 \; lnL_t + \beta_5 (lnRD_t) + \beta_6 (lnRD_t)^2 + \beta_7 (lnRD_t)^3 + \varepsilon_t \tag{8}$$

when the first derivative of equation (8) is taken with respect to $lnRD_t$, the coefficient of elasticity to learning-by-searching (-b) calculated by equation (9) below is obtained.

$$-b = \beta_5 + 2\beta_6 (lnRD_t) + 3\beta_7 (lnRD_t)^2 \tag{9}$$

The rate of improvement in research (d_r) and the rate of learning-by-searching (RR) is calculated as shown in equations (10) and (11), respectively.

$$d_r = 2^{-b} \tag{10}$$

$$RR = 1 - d_r \tag{11}$$

In the econometric analysis part of the study, the following regression models were separately estimated for each sector.

Model 1 : $lnC_t = \beta_0 + \beta_1 (lnQ_t) + \beta_2 (lnQ_t)^2 + \beta_3 (lnQ_t)^3 + \varepsilon_t$

Model 2 : $lnC_t = \beta_0 + \beta_1 (lnQ_t) + \beta_2 (lnQ_t)^2 + \beta_3 (lnQ_t)^3 + \beta_4 \; lnL_t + \varepsilon_t$

Model 3 : $lnC_t = \beta_0 + \beta_1 (lnQ_t) + \beta_2 (lnQ_t)^2 + \beta_3 (lnQ_t)^3 + \beta_4 \; lnL_t + \beta_5 (lnRD_t) + \beta_6 (lnRD_t)^2 + \beta_7 (lnRD_t)^3 + \varepsilon_t$

Model 2 was produced by adding employment volume (L_t) as a control variable to Model 1. Model 3 is defined as a two-factor dynamic learning curve model and as a result of the estimation of this model, learning-by-doing and learning-by-searching rates are obtained.

Before proceeding with the model estimations, unit-root analyses of the time series analyzed for all sub-sectors were performed by using [47], [48], [49] and all series were found to be stationary at their levels. In the estimated regression equations, the autocorrelation problem was checked by using [50]; the heteroscedasticity problem was investigated by using [51] and when it is necessary, variance-covariance matrices were corrected by using [52].

5 Empirical Results

Using the data of 22 manufacturing industry sub-sectors of the Turkish economy for the period 1990-2022, Models 1, 2, and 3 were estimated under the Ordinary Least Squares method in the NACE Rev.2 category (Table 2) as 2-digit.

Table 2. NACE Rev.2 Codes

10	Food products
13	Textiles
14	Wearing apparel
15	Leather and related products
16	Wood products, except furniture
17	Paper and paper products
18	Printing and reproduction of recorded media
19	Coke and refined petroleum products
23	Other non-metallic mineral products
24	Basic metals
25	Fabricated metal products, except machinery
26	Computer, electronic and optical products
27	Electrical equipment
28	Machinery and equipment not classified elsewhere
29	Motor vehicles
30	Other transport equipment
31	Furniture
32	Other manufacturing
33	Repair and installation of machinery and equipment

The statistical findings show that only learning-by-doing is effective in the food, wood products, printing and publishing, petroleum and coke, basic metal industry, and motor vehicles sub-sectors. On the other hand, it is understood that only learning-by-searching is effective in the electrical equipment sub-sector, while both two learning types are effective in the remaining 15 manufacturing industry sub-sectors. Moreover, all F values are statistically significant at the 1% level and adjusted R^2 values are between 0.569 and 0.990.

The annual technological progress ratios obtained as a result of learning-by-doing for the sectors coded 10-20 were presented in Table 3. Each column in Table 3 represents the technological learning levels for a particular sub-sector according to NACE Rev.2 codes. The learning levels over unity are grey-colored to separate the years of forgetting. In the same table, each one of the learning levels indicates the reductions or increases in unit production costs for each doubling of production in a given year for a given sub-sector. Changes in the annual learning levels from one year to another suggest that the level of technological learning differs each year. For example, the annual learning levels for the textiles sub-sector, with 13 NACE Rev.2 codes, are 1.24, 0.97, and 0.83 in 1991, 1992, and 1993, respectively. These learning values represent the per unit cost efficiency gained or lost in that particular year. This means that, in 1991, the textiles sub-sector lost some efficiency and the unit production cost increased 24% for each doubling of the production. However, in 1993, unit production costs decreased to 83% of the previous value for each doubling of production.

Table 3. Progress Ratios Obtained as a Result of Learning-by-doing

	10	13	14	15	16	17	18	19	20
1990	0.94	1.99	0.55	1.37	0.78	0.85	0.75	1.61	0.29
1991	0.95	1.24	0.71	1.01	0.64	1.12	0.86	1.11	0.45
1992	0.93	0.97	0.79	0.96	0.59	1.26	0.89	0.95	0.58
1993	0.91	0.83	0.85	0.91	0.55	1.31	0.91	0.88	0.70
1994	0.89	0.75	0.89	0.89	0.52	1.29	0.91	0.84	0.81
1995	0.87	0.69	0.93	0.87	0.51	1.26	0.91	0.83	0.86
1996	0.85	0.65	0.96	0.86	0.50	1.22	0.91	0.82	0.95
1997	0.83	0.62	1.01	0.86	0.49	1.18	0.90	0.82	0.98
1998	0.81	0.60	1.03	0.86	0.49	1.14	0.89	0.82	0.99
1999	0.79	0.58	1.05	0.86	0.48	1.11	0.88	0.83	1.00
2000	0.78	0.57	1.06	0.86	0.48	1.10	0.87	0.84	0.99
2001	0.76	0.56	1.07	0.86	0.48	1.04	0.86	0.85	0.97
2002	0.75	0.55	1.08	0.87	0.48	1.00	0.85	0.86	0.94
2003	0.73	0.54	1.09	0.88	0.48	0.96	0.84	0.88	0.90
2004	0.72	0.54	1.10	0.89	0.48	0.92	0.83	0.90	0.86
2005	0.70	0.54	1.11	0.89	0.48	0.88	0.82	0.92	0.81
2006	0.69	0.54	1.12	0.90	0.48	0.85	0.81	0.94	0.75
2007	0.68	0.53	1.12	0.90	0.48	0.92	0.79	0.97	0.71
2008	0.66	0.53	1.12	0.91	0.48	0.79	0.78	0.99	0.66
2009	0.65	0.53	1.13	0.92	0.49	0.76	0.77	1.03	0.60
2010	0.64	0.53	1.13	0.93	0.49	0.73	0.76	1.05	0.55
2011	0.62	0.53	1.13	0.94	0.50	0.70	0.74	1.08	0.50
2012	0.61	0.53	1.13	0.95	0.50	0.67	0.73	1.12	0.46
2013	0.60	0.53	1.14	0.97	0.51	0.64	0.71	1.16	0.41
2014	0.59	0.53	1.14	0.98	0.51	0.60	0.70	1.20	0.37
2015	0.57	0.53	1.14	0.99	0.52	0.57	0.69	1.24	0.33
2016	0.56	0.53	1.14	1.01	0.52	0.54	0.68	1.27	0.30
2017	0.53	0.53	1.14	1.02	0.52	0.50	0.66	1.30	0.27
2018	0.51	0.53	1.14	1.04	0.53	0.46	0.66	1.33	0.25
2019	0.50	0.54	1.14	1.05	0.53	0.44	0.65	1.37	0.24
2020	0.49	0.54	1.14	1.06	0.54	0.43	0.64	1.41	0.23
2021	0.49	0.55	1.14	1.07	0.54	0.39	0.63	1.45	0.22
2022	0.48	0.55	1.14	1.08	0.55	0.37	0.62	1.48	0.21

Similarly, the annual technological progress ratios obtained as a result of learning-by-searching for the sectors coded 24-33 are given in Table 4. Looking at this table, the annual learning levels for the repair of machinery sub-sector, with 33 NACE Rev.2 codes, are 0.67, 0.88, and 1.08 in 2013, 2014, and 2015, respectively. In other words, in 2013 unit production costs decreased to 67% of the previous value for doubling of production. Whereas, in 2015, the repair of machinery sub-sector lost some efficiency and the unit production cost increased by 8% doubling of the production.

Table 4. Progress Ratios Obtained as a Result of Learning-by-doing

	24	25	26	28	29	30	31	32	33
1990	0.96	0.19	2.19	1.24	0.80	0.03	2.21	1.19	0.55
1991	0.59	0.29	1.86	0.69	0.87	0.08	1.77	0.74	0.59
1992	0.48	0.36	1.51	0.53	0.90	0.20	1.29	0.52	0.65
1993	0.43	0.37	1.28	0.44	0.2	0.32	1.05	0.41	0.71
1994	0.40	0.39	0.94	0.40	0.93	0.41	0.95	0.36	0.78
1995	0.40	0.41	0.75	0.38	0.93	0.50	0.86	0.32	0.86
1996	0.40	0.42	0.60	0.36	0.93	0.56	0.80	0.30	0.98
1997	0.41	0.43	0.49	0.34	0.93	0.60	0.75	0.29	1.08
1998	0.42	0.44	0.41	0.34	0.93	0.63	0.72	0.28	1.18
1999	0.43	0.44	0.37	0.33	0.93	0.65	0.69	0.27	1.27
2000	0.44	0.44	0.34	0.33	0.92	0.66	0.67	0.26	1.38
2001	0.45	0.44	0.32	0.33	0.92	0.67	0.67	0.26	1.49
2002	0.47	0.44	0.30	0.30	0.92	0.68	0.66	0.26	1.61
2003	0.49	0.44	0.30	0.34	0.91	0.68	0.66	0.30	1.75
2004	0.51	0.43	0.30	0.34	0.90	0.69	0.66	0.38	1.80
2005	0.54	0.43	0.31	0.35	0.90	0.69	0.67	0.50	1.84
2006	0.56	0.42	0.33	0.36	0.89	0.69	0.67	0.62	1.83
2007	0.59	0.42	0.35	0.37	0.88	0.69	0.68	0.77	1.78
2008	0.62	0.41	0.38	0.38	0.88	0.69	0.69	0.94	1.65
2009	0.65	0.40	0.41	0.39	0.88	0.68	0.70	1.09	1.53
2010	0.69	0.40	0.46	0.41	0.87	0.68	0.71	1.21	1.37
2011	0.73	0.39	0.51	0.43	0.87	0.67	0.71	1.35	1.18
2012	0.76	0.38	0.57	0.45	0.86	0.65	0.72	1.52	1.06
2013	0.80	0.38	0.64	0.47	0.85	0.64	0.73	1.65	0.95
2014	0.83	0.38	0.70	0.50	0.84	0.62	0.74	1.73	0.92
2015	0.87	0.37	0.77	0.53	0.83	0.60	0.75	1.81	0.88
2016	0.90	0.37	0.86	0.57	0.82	0.57	0.76	1.88	0.94
2017	0.93	0.37	0.94	0.60	0.81	0.56	0.78	1.95	0.79
2018	0.94	0.36	1.01	0.64	0.80	0.54	0.80	1.99	0.77
2019	0.98	0.35	1.15	0.67	0.79	0.52	0.83	2.03	0.75
2020	1.03	0.34	1.26	0.69	0.78	0.50	0.86	2.08	0.73
2021	1.08	0.33	1.33	0.73	0.77	0.48	0.89	2.12	0.69
2022	1.13	0.32	1.39	0.77	0.76	0.46	0.93	2.16	0.67

According to Figure 1, which presents the time course of learning-by-doing levels, contrary to the findings of [19], [37], [53], there is no forgetting in any period in the medium-high-tech chemical products, motor vehicles, machinery and equipment not classified elsewhere and other transportation vehicles sub-sectors, while there is no forgetting even in the middle of the period in high-tech computer-electronics and in the medium-low-tech rubber and plastic and petroleum products sub-sectors. In the high-tech pharmaceuticals sub-sector, forgetting was observed in the last period. On the other hand, forgetting occured in the low-tech furniture, textiles, and paper products sub-sectors in the baseline period. Moreover, in the low-tech food, wooden products, and printing of recorded media sub-sectors and in the medium-low-tech fabricated metal products sub-sector no forgetting was reported in any period. The fact that the end-period forgetting observed in the low-tech clothing and other manufacturing and the medium-low-tech basic metals sub-sectors is in line with the findings of the aforementioned 3 studies in the same field in the literature.

	Forgetting periods	Related Sub-sectors
Convex with minimum	No forgetting in the middle	Rubber and plastic, petroleum products, leather products, computer-electronics
	No forgetting in any period	Machinery and equipment and classified elsewhere
	Forgetting in the end	Basic metals, other manufacturing
Concave with maximum	No forgetting in the middle	Repair of machinery and equipment, non-metallic mineral products
	No forgetting in any period	Chemical products, motor vehicles, other transportation vehicles
	Forgetting in the beginning	Furniture, textile, paper products
Convex without reaching minimum	No forgetting in any period	Food, fabrcated metal products, wooden products, printing of recorded media
Concave without reaching maximum	Forgetting in the end	Clothing, pharmaceutical products

Fig. 1: Time Course of Learning-by-doing Levels

	Forgetting periods	Related Sub-sectors
Convex with minimum	No forgetting in the middle	Chemical products, other transportation vehicles, repair of machinery and equipment, non-metallic mineral products
	Forgetting every period	Fabricated metal products
Concave with maximum	Forgetting in the middle	Computer-electronics, furniture, pharmaceutical products, textile, leather products, paper products, other manufacturing, rubber and plastic
	No forgetting in any period	Electrical equipment
Convex without reaching minimum	Forgetting in the beginning	Clothing

Fig. 2: Time Course of Learning-by-searching Levels

The course of learning-by-searching levels over time is presented in Figure 2. According to this table, it is observed that in most of the sub-sectors of the manufacturing industry, the progress ratios obtained through learning-by-searching (d_r) move symmetrically in the opposite direction to the progress ratios obtained through learning-by-doing (d). Namely, in the computer-electronics, chemical products, machinery and equipment not classified elsewhere, repair of machinery and equipment, non-metallic mineral products, rubber and plastics, leather products, clothing, other transportation vehicles and other manufacturing sub-sectors, learning-by-doing levels declined during the period when learning-by-searching levels increased. Similarly, while learning-by-doing levels of the fabricated metal products sub-sector did not show forgetting in any period, learning-by-searching levels demonstrated forgetting in the entire period analyzed. Again, forgetting, which was initially observed in the learning-by-doing levels of the clothing sub-sector, was reported in the last period in the learning-by-searching levels.

6 Conclusion

In the literature, learning curve models are used as one of the ways to measure labor productivity during production. The first empirical study based on these models was T.P. Wright's single-factor linear learning curve model in 1936. Over time, Wright's single-factor learning curve model was further developed and the new models developed were named as experience curve, Moore's law, and Stanford B model. Since the early 2000s, it has been used as a dynamic learning curve model. Nowadays, especially in empirical studies, learning curve models with two or more factors are widely used instead of single-factor learning models. The main reason for this is that the learning rates calculated with the single-factor model are overestimated. Many empirical studies suggest that technological learning levels change and can also change over time, [19]. The assumption that technological learning can change over time is only possible with a dynamic learning curve model. Thus, according to the course of learning levels over time, the effect of the relevant independent variables on cost reductions can be measured. Therefore, whether R&D investments in any of the sub-sectors of the manufacturing industry yield the desired results can be easily monitored with this model and the findings obtained from the related study can be used as a basis for future research.

In this study, three different versions of the dynamic learning curve model are estimated to obtain the learning-by-doing and learning-by-searching rates of 22 manufacturing industry sub-sectors of the Turkish Economy for the period 1990-2022. In the one-factor dynamic learning model, the independent variables obtained by taking the cumulative output, its square and cube are separately used. Employment volume is then included as a control variable. In the two-factor dynamic learning model, the independent variables obtained by taking real cumulative R&D expenditures, its square and cube are also included in the model. According to the findings of the econometric analysis of the study, the time course of learning-by-doing levels obtained from the study differs significantly from the time course of learning-by-doing levels in similar studies using the one-factor model. Moreover, in the majority of manufacturing industry sub-sectors, the graph of learning-by-doing curves obtained from the estimation of the two-factor dynamic learning curve model moves symmetrically in the opposite direction to the graph of learning-by-doing curves estimated using the same model. This supports the view in the literature that the learning-by-doing rates obtained from the single-factor model estimation is biased. Finally, it is recommended that the high-tech computer electronics, pharmaceuticals, medium-high-tech chemicals, machinery and equipment not classified elsewhere, electrical equipment, medium-low-tech rubber-plastics, non-metallic mineral products and low-tech textiles, clothing, leather products, and paper products sub-sectors should be supported with more R&D incentives. With this study, the course of learning-by-doing and learning-by-searching rates in manufacturing industry sub-sectors over time has been obtained. Thus, the contribution of R&D investments in these sub-sectors to their technological learning capabilities has been revealed.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

The authors wrote, reviewed and edited the content as needed and they have not utilised artificial intelligence (AI) tools. The authors take full responsibility for the content of the publication.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

No funding was received for conducting this study.

Conflict of Interest

The authors have no conflicts of interest to declare.