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The Impact of Learning on Technology Content of Iran's Industrial Export

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ABSTRACT

Over the past decades, technology has been considered as a major factor that affects economic and industrial development. The export technology content, which reflects the export goods characteristics, has also been of great importance at the international level. The export technology content influenced by knowledge which one of its sources is learning that according to economists, can be due to experience in production or export. The purpose of this paper is analyzing the learning-by-doing and investigating its impact on industrial export technology content at the level of two-digit ISIC codes in Iran's Industries using the Arellano-Band dynamic data estimation method from 2011 to 2015**.** For this purpose, different indicators are used to quantify the learning and another indicator is applied to compute the export technology content. The results of this study show that learning-by-exporting influences both a country's export composition and the export technology content more than learning-by-production. In addition, learning-by-doing has a positive and significant effect on the export technology content. Further, the variables of human capital, GDP per capita, trade openness, and Intra-industry trade index have a remarkable effect on the export technology content of two-digit ISIC codes industries.

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1. Introduction

It is generally accepted that exports based on technology-oriented industries, due to high value-added and their impact on other economic sectors, are the most important drivers of economic growth. According to Iran's customs statistics, Iran has not been successful in developing high-tech exports and had only $550 million in high-tech exports in 2011, which includes only 2.9% of the country's non-oil exports. In the last decade, the export unit value in Iran has not yet risen above $550 per ton and has even fallen to less than $400 per ton, while the imported goods unit value is between 1000 to 1600 dollars per ton. Within the next few years, production productivity or total factor productivity is likely to become an important component in international trade, and countries that have a large share of world exports have always tried to increase it in various ways.

Over the past decade, the quality of exports related to the technology content has been considered by economists (see Yang, 2006; Gokmen, 2013; Galindo and Verger, 2016; Peng and Zhang, 2020). Having technology-based advantages plays a key role in success in the international business environment. On the other hand, using new technologies in production in recent decades by developed countries has led to high profitability and reduced production costs. Nevertheless, the exports of the high-tech products, despite their high gain, have not been able to cover a significant share of the total exports of developing countries. In developed countries, export goods have high technology content, which is due to superior knowledge and technology, while the production and export performance of developing countries, including Iran, show a very small share of high-tech products. In fact, not only do both the raw and low value-added exports have a dominant share in the export of developing countries, but the export technology content is not also considered (Gani, 2009).

During the last fifty years, different countries have been growing at very different rates; besides, it is a fact that the product mix of the fast-growing nations contains a large portion of high technology goods. The output of each firm in an industry is a function of the amounts of inputs and the average level proficiency in the home country and the amount of the proficiency may be increased through learning-by-doing. As a result, the learning-by-doing mechanism is the most important factor that creates positive externalities; that in turn leads to the growth of production (Boldrin, 1988).

Learning has not been considered in Iran’s industries, especially in Iran's large industries; for these industries have often been state-owned or owned by public non-governmental organizations and the state manager does not pay attention to issues such as productivity, invention, innovation, and learning. Various laws in Iran try to facilitate the production of knowledge-based goods and the export process of such products and services, but no significant success has been achieved. Since the formation of knowledge-based companies has been emphasized by Iran's economic policymakers and Iran’s 1404 outlook document; therefore, the development of this kind of companies in high-tech industries, due to their importance in creating high value-added, employment, and increasing productivity, can play an effective role in economic growth and development. Besides, the resistance economics document has emphasized the knowledge-based economy and the organization of the national innovation system. One of the tools of resistance economics is the improvement of the production quality and its diversity, which requires learning-by-doing; for as previously mentioned, it is one of the effective factors in the accumulation of knowledge, technology, and human capital; and later in the enhancement of productivity and diversity. According to Galina and Murat (2003), “economists have long debated how learning-by-doing influences product proliferation, international trade, and economic growth[1]; Moreover, There is also the debate as to whether the gains from learning-by-doing are related to technological intensity. Then combining the interplay

1. A number of authors have emphasized the importance of learning by doing in economic growth, specialization and foreign trade. See Arrow (1962), Stokey (1991), Young (1991, 1993), Benarroch and Gaisford (2001), and Goh and Olivier (2002). Others have questioned the importance of learning by doing. See Clerides et al. (1998) and Thompson (2001).

between learning-by-doing with the technology content of production could be fruitful for better understanding the flows of foreign trade. Nonetheless, empirical study on how learning can affect the technology content of exports and foreign trade has so far been sparse".

According to studies as aforementioned, since knowledge plays a very important role in economic development, in Iran's economy, paying attention to the expansion of production of goods with high technology content that requires factors such as knowledge and learning can facilitate the way for economic growth and development. Accordingly, investigating the effect of learning-by-doing on the content of export technology in the oil-dependent economy and emerging industries of Iran is a new approach that has been addressed in this research. This research aims to analyze learning-by-doing and investigate its impact on industrial export technology content in Iran's industries.

The rest of the paper is organized as follows. Section 2 analyzes the theoretical foundations and Section 3 gives a brief overview of learning and export technology content, followed by the data, research method, empirical model and variables in section 4. The empirical results are outlined in section 5, and conclusions are drawn in the sixth and last sections.

2. Literature Review

The first systematic study on learning curves in the economic literature was carried out in 1936 by Wright. His observations indicated that by doubling the amount of production, the number of working hours for producing one unit of product decreases. According to Yelle (1979), various authors have sometimes referred to the learning curve and related concepts using alternative terms such as the progress curve (Alchian, 1950), the improvement curve (Carlson, 1973), and the experience curve (Bodde, 1976). Learning-by-doing is one of the effective factors in increasing high quality production and consequently the economic growth. Learning-by-doing is expressed as an explanation for realizing the production potential of new technologies. As a result, the development of such technologies and their use in the production of new or existing goods is likely to lead to rapid learning-by-doing in the first place (Young, 1991).

The characteristics of learning-by-doing have not been widely addressed. Some economists maintain that learning-by-doing is an externality of human capital accumulation and a by-product of the use of labor and capital in new production processes, leading to the development of human capital, thereby increasing productivity (see Daton and Tumas, 1984; Lucas, 1988; young, 1991). Most of the learning curve's gains are achieved by reducing labor costs and increasing productivity as well as growth. The traditional approach of economic growth considers physical capital and human capital as growth inputs, while knowledge is assumed as an input that increases marginal productivity in Roemer's long-term growth model. Learning-by-doing can be conceptualized as a cost-saving activity accomplished in situations in which the productive facilities remain unaltered. Learning-by-doing is one of the most sustainable and important resources in creative and innovative activities (Fellner, 1969). Learning reduces the average cost over time along with increasing cumulative production, therefore, most of the benefits of the learning curve are achieved by reducing labor costs, increasing productivity and increasing growth. (Elshurafa, 2018)

Job training, learning-by-doing and education are important elements of human capital formation. The learning effects usually appear at the beginning of the activity at a high rate and then slow down. At high levels of activity, that is, when all the production factors are sufficiently skilled, the learning effects are discharged and the learning curve becomes horizontal and smooth (Lucas, 1988).

Exogenous technical change is one engine for sustainable growth (as in Solow, 1959; Diamond, 1965; Shell, 1967), and positive production's externalities or learning-by-doing are another motivator (as in Arrow, 1962; Romer, 1983, 1986; and Lucas, 1988). Also, the knowledge accumulation through learning-by-doing, which is the result of experience in production, will have positive external effects on the production process (Stokey, 1988).

Within the existing literature, learning has been defined as a matter of experience. Learning can only take place through an attempt to solve a problem and therefore can only take place through an attempt to solve a problem and while doing an activity. Learning is basically related to repetition and leads to acquiring skills and experience in production; therefore, the goods will be produced with high speed, high quality and low cost. The attainment of knowledge, which is usually called learning, will improve production performance over time. According to Arrow (1962), one of the most important issues is selecting the appropriate variable to quantify experience. Arrow (1962) considered the cumulative output (the total output from the beginning) and cumulative gross investment (cumulative production of capital goods) as an index of experience (Arrow, 1962).

It has been suggested that importing capital goods is another source of learning. By importing capital goods with lower price and also increasing investment, domestic producers begin to imitate and copy foreign technology. As a result, goods are produced with higher quality and lower cost, which is conceptualized as learning-by-doing. Learning is the result of knowledge spillover and will lead to diversification of production, exports and economic growth (Ambler et al., 1999). The increase of productivity from learning-by-doing occurs not only in the companies producing goods but also in other companies that import goods and copy imported technology due to positive external effects as well as spillover effects (Goh and Oliver, 2002). As a result of learning-by-doing, domestic production can gain a comparative advantage and an ability to compete internationally. Kim and Chang (2012) estimated the learning curve using the nuclear power generation cost in Korea and compared it with that of renewable energy sources.

In the industrial economics literature, “Learning Curves” (LCs) is defined as the relationship between cumulative output and the average costs incurred over time to produce the goods. LCs supply a mathematical description of the learning process and have been applied to evaluate the time needed to accomplish production runs and the reduction in production costs as learning takes place (Anzanello and Fogliatto, 2012). In general, learning is concerned with reduction in average cost over time with increasing cumulative output and can be measured through the learning curve and its slope. Furthermore, learning is not limited to workers but it also occurs in machineries and equipment as a result of the increase in production and the use of higher technology equipment. As learning occurs, unit cost decreases over time, resulting in a decrease in product price as well as an increase in the competitive advantage of industry.

The export technology content shows the combination and quality of export for each economy. Successful developing countries change their production structure incrementally by replacing high value-added activities and more specialized products with non-specific and low value-added activities. Therefore, the country’s ability to accumulate skills and knowledge determines its ability to diversify, increase value-added and promote technology domestically, resulting in the production of more specialized and competitive goods in international markets and competition with current developed countries in terms of technological possibilities. The knowledge acquired through formal education and social networks such as families and communities also enhances skills increasing export technology content (Khirinakz et al., 2014).

International trade models classify commodities by labor productivity (Ricaridan model), factor intensity (H-O model), variety and quality (monopolistic competition models) as well as their relationship with heterogeneous firms. By merging the insights of all international trade models, the same goods from various countries could be completely different in terms of quality (Melitz, 2003). Hausemann et al. (2005) developed a new method and proposed that goods be ranked based on their per capita income content. With higher GDP per capita of countries exporting a commodity, the per capita income content of these commodities is also higher. This measure determines the complexity of a commodity with regard to the real GDP per capita of the exporting country. Therefore, the quality issue is discussed and the quality difference between exporting countries in a specific group of goods should be taken into consideration in measuring the technology content of export goods.

Xu (2006) introduced the quality multiplier for calculating the export technology content which adjusts the per capita income content index of Hausmann, Hwang and Rodrik (2005). Per capita income content measures the average technology content of a commodity without considering quality differences within that commodity. To obtain the technology content differences among products as well as within one product, the export technology content index is defined as the per capita income content multiplied by the quality multiplier. This index has two elements: a base and a multiplier. The base component is the per capita income content index, introduced by Hausmann et al. (2005), which considers products' average technology levels in relation to the development levels of all their exporting countries. The multiplier measure is a relative qualitative index, which calculates the ratio of the technology level employed in the quality of a country's production to other exporting countries.

The first classification, which is widely used to compare the trade technology content in all countries, was developed by OECD in 1984 in the basis of the intensity of research and development. In the 1984 report, the R&D intensity index was created as the ratio of R&D costs to production using 11 country's data and 21 industries during 1970-1980 weighted by industry and country. This index was divided to three groups to show the industries with high, medium and low R&D intensity.

The ECLAC[1], the second classification, used the proposed method by Lall (1998; 2000). This method categorizes technology groups using the second-edition of three-digit SITC codes and the information of both developed and developing countries. Inspired by Pavitt's (1984) classification, Lall (1998; 2000) created four groups: Resource-based, low-tech, medium-tech and high-tech. Drawing on the concept of product complexity, Lall et al. (2006) and Hausmann et al. (2007) introduced the

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technology complexity index, which explains that high-income countries export higher value-added products. Complexity provides a new and useful analytical method of international trade and location patterns and tracks competitiveness in developing countries.

Xu (2007) pointed out that the unit price index can be used to measure differences in the quality of exported goods. In other words, the particular final goods exported by a developed country differ from those exported by a developing country in terms of technology content which is reflected in the price of goods. A key problem with much of the literature regarding technology content index (TCI) is that there is no agreement on the definition of this index.

An and Iyigan (2004) argued that a more relevant proxy for learning-by-doing is cumulative output as well as cumulative export. They maintained that learning-by-doing raises the skills, experience, abilities and proficiencies of the labor, thereby enhancing more specialized and high-technology products. According to this study, countries with relatively little experience in production and export specialize in producing and exporting more standardized products as well as lower technology goods. In contrast, countries with greater experience in both production as well as export and higher learning-by-doing are more likely to produce and export high-technology products.

3. Related Literature

Various studies have been conducted in the field of learning and export technology content. Some studies estimated the learning curve in different sectors and analyzed the effects of learning-by-doing on the economic variables and on international trade. Some other studies have attempted to provide an index for the export technology content and examined the relationship between learning-by-doing and the export technology content.

Peng and Zhang (2020) indicated that technology content of export products may not completely come from the home country. This study calculates the domestic technology content of China's manufacturing industry from 2000 to 2014 by using the data of World Input–Output

Database (WIOD). The results showed that: the technology content of the China’s manufacturing exports are increasing, and the domestic technology content grows faster than overall technology content.

Estimating the learning curve of balance-of-system costs in photovoltaics for more than 20 countries, Elshurafa (2018) created a global benchmark LC for the BOS for small-scale systems. Also, Panas and Pantouvakis (2017) used the learning curves to estimate the construction productivity and found that the labor skill is one of the most important components of labor productivity. They illustrated the direct correlation of the labor skill coefficient with the learning curves. In this study, the straight line model was applied to explore the learning curve. The results indicated that the labor skill coefficient was influenced by the learning rate and the specification of the standard production stage, denoting the completion of the learning phenomenon.

Aboal et al. (2017) suggested a new method to classify products using data at both industry and product levels. They employed information on direct and indirect R&D expenditure by public and private sources in services, agriculture and manufacturing sectors. This information was combined with the complexity index and was improved for product quality and for tariffs employing trade data. In this study the R&D intensity and the complexity index were divided by the median values to create a four-category classification: highly, potentially and locally dynamic products as well as non-dynamic products.

Considering learning-by-doing externalities, Teignier (2013) investigated the welfare effects of various trade policies in an economy with two sectors (in a two-sector economy). Within one of the sectors, productivity grew owing to the learning-by-doing externalities, while in the other sector, production technology remained constant. The main conclusion was that free international trade decreased the economic growth of a poor country. Nevertheless, the quantitative results showed that if the poor country were smaller than its trade partner and the learning-by-doing externality size were not large enough, international trade undoubtedly would increase the welfare and the optimal import tariff would be zero. If the externality were large enough, the country's welfare would raise when the country set a production subsidy in the externality sector, and then eliminated it after achieving a competitive advantage in the production of goods.

Clarke (2008) introduced a new method for estimating the learning-by-doing parameters applying datasets that are commonly available. Contrary to previous studies on learning-by-doing which have mainly focused on production function based on microeconomics, this study offered the evaluation of learning-by-doing index using an estimation of first-order condition of a structural model which allowed for the production experience accumulation. The numerical results showed that the dynamic structure employed by the structural model was largely compatible with industry-level data for knowledge-based industries. On the other hand, the proposed model was generally rejected for other industries, indicating that learning-by-doing probably did not present a substantial function in creating productivity dynamics for these industry groups.

Expanding the learning-by-doing model of Young (1991), Mao (2012) compared the dynamic impacts of learning-by-doing in autarky condition with those of two-country free trade condition. The main results revealed that learning-by-doing was the key variable of sustainable economic growth in the long run. Indeed, increasing the rate of either population growth or saving enhanced the real GDP per capita growth rate and long-run technical improvement in the autarky situation as well as free trade condition. It should be noted that the growth rate of GDP per capita and technical improvement in autarky condition were slower than those in free trade condition.

Xu (2006) developed a new index of export technology content (ETC) and used it to China's economy. This ETC measure is combined with both technology complexity ranking and the quality ranking of country differences among product. The findings displayed that country-level ETC became consistent with China's development level after the 1990s while the China's product-level ETC had a significant difference with the benchmark and this difference was increased during 1991-2001. The results showed a positive relation between the growth of export share and ETC at both the product and industry levels. In fact, the effect of export share was probably the main factor amplifying China's ETC growth.

An and Iyigan (2004) empirically tested whether countries with relatively little experience in production and export have lower learning-by-doing level and specialize in producing and exporting more standardized commodity as well as low-technology goods. And whether countries with greater experience in both production as well as export and higher learning-by-doing are more likely to produce and export high-technology products. They used panel data estimation for 127 countries from 1970 to 1997 and found that export experience was positively correlated with export technology content. The experience in export affected a country's export combination more than production experience, which implied that the learning-by-doing component might be considered in international trade specialization.

Considering the positive impact of learning-by-doing as well as innovation on economic growth and also the countries interactions over international trade, Nakajima (2003) studied how the global income was distributed through the time. The main conclusion was that the improvement was feasible and transitional dynamics could occur in the both models, although these transitional dynamics were more valuable in the three-country model than in the two-country one. More specifically, it was found that the improvement might happen in sequence. It was also mentioned that there might be an initial phase where the middle-income country grew sharply, as a result, its gap with the high-income country was reduced while the income difference with the low-income country was increased. Subsequently, the low-income country improved in the next phase.

Lall et al. (2006) considered complexity in their model and prepared a new and effective measure to examine both spatial patterns and international trade in developing countries and trace competitiveness in such countries. This measure was concerned with exported goods in terms of technology and classified them into five different groups which had been superior to the existing indicators. The main results showed that complexity was absolutely related to technology and source-based exports were not related to the income level of country. In general, complexity was not directly related to growth rate, and the degree of regional complexity was in line with expectations in the developing countries.

Nourani Azad and Khodadad Kashi (2017) attempted to calculate the intensity of learning and examine its effects on the function of Iran's manufacture industries using a learning curve. In this study, they used 130 industry datasets in four-digit ISIC codes from 1996 to 2013. The results indicated that the slope of the learning curve in all sub-sectors of Iran's industries was negative and the effect of learning intensity was significantly positive. In addition, the rate of learning in high value-added industries was high due to the use of high technology.

Feizpour and Habibi (2016) evaluated the effect of various levels of technology on learning in Iranian manufacture industries. They considered the Cobb Douglas cost function within the Log-Linear model and used the OECD's classification of industries based on technology levels. They concluded that although learning had occurred in most industries, the impact of learning on cost reduction was less than economies of scale. Furthermore, the highest level of learning is associated with the high-technology industries. Therefore, these groups of industries can receive further attention and investigation.

Elahi et al. (2015) analyzed the technological content, the complexity of the export portfolio and the revealed factor intensities for Iran's export. In this paper, they used the method introduced by Lall (2000) to describe export's technological composition. Also, they apply Hausmann, Hwang, and Rodrik (2006) method to estimate changes in export complexity as well as Shirotori et al. (2010) method to determine the revealed factor intensities in Iran's export. The results showed that Iran's export basket was always dependent on primary products and technological changes in the composition of export towards knowledge based and high value-added goods was not successful. Indeed, the findings suggested that the complexity of Iran's export was low level. In addition, the intensity of physical capital and the intensity of human capital embodied in export was also low level.

Reviewing research background related to Iran’s economy shows that coherent research has not been conducted to investigate the factors affecting the export technology content. In addition, the few studies that have been done in this area, have either introduced and defined the technology content index or considered high-tech export factors. Therefore, it seems the present study is the only study that defines different indicators of learning-by-doing and examines their impact on the Iran's export technology content. Furthermore, this study investigates the effect of learning-by-doing due to production and export on the export technology content in the industrial sector using Arelano Bond dynamic data estimation method, which has not been done before.

4. Data and Model Specification

Economists have paid special attention to the export technology content over the recent years. Xu (2006) stated that factors affecting product quality and the R&D level could influence the export technology content. The effect of export share is also introduced as an effective factor in export technology content. Other studies have emphasized the importance of capabilities and skills in the export technology content and stated that capabilities could be created as a result of acquired knowledge in the formal education process and in social networks (Khirinaks et al., 2014). Aboal et al. (2017) combined industry-based indicator (internal R&D index) with product-based one (complexity index) to calculate the export technology content. The internal R&D index was proposed by the OECD and the complexity index was measured by product quality and trade policy. Also, An and Iyigan (2004) used the ratio of the R&D level to the gross sales as the proxy of technology content for each industry.

As mentioned above, this study set out to investigate the impact of learning on the export technology content in Iranian industries. For this purpose, three indicators are introduced: two indicators for learning and one indicator for the export technology content. Then two different models, in each of which one indicator has been entered as a substitute for learning, are estimated. Using the same method of An and Iyigan (2004), this study was built on the assumption that countries with relatively little experience in production and export specialize in producing and exporting more standardized products as well as lower technology goods. In contrast, those with greater experience in both production as well as export and higher learning-by-doing are more likely to produce and export high-technology products.

According to the purpose of this study, we used an analytical-quantitative model in order to identify learning and its impact on Iran's export technology content. The data were obtained from the Iran's Statistics Center and the Central Bank databases during the period of 2011-2015 at the level of two-digit and four-digit codes for Iranian industries with 10 or more employees. In the proposed model of this study, the dependent variable is the "technology content index" (TCI) and the independent variables include "learning-by-doing" (LBD), "human capital" (School), "per capita income" (GDPCAP), "degree of economy openness" (OPEN) and "intra-industry trade index" (IIT). Two alternative variables are also introduced for learning-by-doing: the first one, originally identified by Arrow (1962), is cumulative production experience (learning-by-doing due to production) denoted by LBD(Y) and the second one, proposed by Chuang (1997), is the cumulative export experience (learning-by-doing due to export) indicated as the LBD(EX). Nominal variables have been adjusted by the price index of the industrial goods, the exported goods and the imported goods in constant 2011 and the software application employed to analyze the data was Eviews. The variables and data sources are presented in Table (1).

Table 1. Introduction of Variables of Technology Content Model during the Period of 2011-2015

Variable	Definition	Data Sources
***ln* TCI**	Logarithm of export technology content	Statistical Center of Iran
***Ln*GDPCAP**	Logarithm of gross	Statistical Center of Iran and Central Bank

	domestic product per capita	of the Republic of Iran
***ln* IIT**	Logarithm of intra industry trade index	Statistical Center of Iran
***ln* OPEN**	Logarithm of degree of openness	Statistical Center of Iran and Central Bank of the Republic of Iran
***ln* School**	Logarithm of human capital index	Statistical Center of Iran
***ln*LBD(EX)**	Logarithm of learning-by-exporting	Statistical Center of Iran
***ln* LBD(Y)**	Logarithm of learning-by-Production	Statistical Center of Iran and Central Bank of the Republic of Iran

Source: Research finding.

The effect of cumulative learning experience on export technology content may be simply verified by estimating the following equation according to and An and Iyigan (2004). They maintained that learning-by-doing raises the skills, experience, abilities and proficiencies of the labor, thereby enhancing more specialized and high-technology products.

$$TCI_{jt} = \mu_i + \lambda_t + \beta_1 TCI_{jt-1} + \beta_2 LBD_{jt-1} + \beta_2 School_{jt} + \beta_3 GDPCAP_{jt} + \beta_4 IIT_{jt} + \beta_5 OPEN_{jt} + \varepsilon_{jt} \quad (1)$$

TCI_{jt} is the export technology content at the level of two-digit codes for industries. The index *j* represents the industries with two-digit codes and the index *t* indicates time. Our experimental set up is practically the same as the one proposed by An and Iyigan (2004). TCI_{jt} is defined as followes:

$$TCI_{jt} = \frac{\sum_i [(R\&d/sales)_i * e_i]_{jt}}{\{\sum_i [(R\&d/sales)_i * e_i]_{jt}\}_{j=max}} \quad (2)$$

In equation (2), the index *i* represents the industries with four-digit codes, $R\&d/sales$ is the ratio of research and laboratory costs to the sale of industries in billion Rials. $e_i = \frac{EXP_i}{\sum_i EXP_i}$ demonstrates the ratio of exports of the four-digit industry *i* to the total exports of the two-digit industry *j*. This variable has been adjusted by the export commodity price index in constant 2011 and the value of this variable in industries and during the period under review varies between 0.0001 and 0.79

LBD_{jt} denotes the learning-by-doing which increases the competitiveness of firms and the quality of exported products by enhancing labor productivity and reducing the production cost (Felner, 1989; Porter, 1990). Two indicators for learning-by-doing, proposed by Arrow (1962) and An and Iyigan (2004), are used in this article. The first indicator is "learning-by-doing" from production (LBD(Y)) and the second indicator is "learning-by-doing" from exports (LBD(EX)). These two indicators are derived as follows:

$$LBD(Y)_{jt} = \frac{\sum_0^t (Y_{jt}/N_{jt})}{max \sum_0^t (Y_{jt}/N_{jt})} \qquad (3)$$

Where Y_{jt} denotes the manufacturing value added of industry j at time t and N_{jt}denotes the number of labor force of industry j at time t. Y_{jt} has been adjusted using the price index of industrial goods in constant 2011. In fact, equation (3) measures the ratio of the cumulative per capita product of industry j to the highest cumulative per capita product of studied industries for each year. The value of this variable in industries and during the period under review varies between 0.0029 and 0.88

$$LBD(EX)_{jt} = \frac{\sum_0^t (EX_{jt}/N_{jt})}{max \sum_0^t (EX_{jt}/N_{jt})} \qquad (4)$$

Where EX_{jt} indicates the export of industry *j* at time *t* and N_{jt}denotes the number of its labor force at time t. EX_{jt} has been adjusted by the price index of exported goods in constant 2011. In fact, equation (4) measures the ratio of the cumulative per capita export of industry j to the highest cumulative per capita export of the industries under investigation for each year. The value of this variable in industries and during the period under review varies between 0.0002 and 0.49.

$School_{jt}$: This variable represents the human capital index in industry *j* at time *t* which is the ratio of employees with beyond to total employees in the industries with 10 or more employees. Increasing the number of employees with higher education will enhance the quality of the workforce. On the other hand, increasing the ratio of highly educated employees with improved level of knowledge and expertise provides more specialized and more competitive products. As a result, exports of goods with higher technology content in the international markets will be enhanced.

$GDPCAP_{jt}$: This variable denotes the Gross Domestic Product (GDP) per capita of industries with 10 or more employees in billion Rials in constant 2011 for industry *j* at time *t*. It is expected that the content of industries' income per capita will increase by raising GDP per capita and consequently the value-added and the technology content of exports will rise.

$open_{jt}$: The degree of openness is another independent variable that indicates the degree of direction of a country in the context of world's trade. In this study, the degree of openness in industry *j* at time *t* is calculated based on the ratio of industry's trade to its GDP and is defined as follows:

$$Open_{jt} = \frac{Export_{jt} + Import_{jt}}{GDP_{jt}} \tag{5}$$

where $Export_{jt}$ denotes the export of industry *j* at time *t* and has been adjusted employing the price index of exported goods in constant 2011. $Import_{jt}$ indicates the import of industry *j* at time *t* and has been adjusted using the price index of imported goods in constant 2011. GDP_{jt} variable is gross domestic product of industries with 10 or more employees in billion Rials and has been adjusted using the price index of industrial goods in constant 2011. The degree of an economy's openness can be thought as a channel for transferring higher technology to the economy which will enable the growth of export technology content.

IIT_{jt}: Intra-industry trade index is another explanatory variable that is operationally defined and calculated as follows:

$$IIT_{jt} = 1 - \frac{|EX_{jt} - IM_{jt}|}{EX_{jt} + IM_{jt}} \tag{6}$$

In equation (6), EX_{jt} represents the export of industry *j* at time *t* in constant 2011. IM_{jt} denotes the import of industry *j* at time *t* in constant 2011. The value of this index is between 0 and 1. If the value of this variable is close to 1, it means that intra-industry trade will be at its maximum. Higher intra-industry trade allows countries to access technologies that may not exist in their own countries and enables them to increase the export technology content by improving production knowledge and technology.

After introducing the export technology content model and learning indicators, it is now possible to estimate the empirical model. In this study, in order to estimate model (1), the GMM estimation method and Arellano-bond estimation have been used. This method was chosen because the lagged dependent variable is considered as an explanatory variable in the model. Hence, the model is dynamic and the data are cross-sectional. Due to the existence of the lagged dependent variable (TCI_{jt-1}) as an explanatory variable in the equation and consequently autocorrelation between the lagged dependent variable and the disturbing component, the ordinary least squares estimators are inconsistent. Therefore, a generalized method of moments (GMM) for estimating dynamic panel data models is used. In this method, the instrument matrix is used to eliminate the autocorrelation between the lagged variable and other explanatory variables. The instrument matrix validity is also checked using the Sargan test. Model (1) is written in logarithmic form and the impact of learning on the export technology content in Iranian industries is evaluated using the GMM method.

5. Empirical Results

As mentioned above, two models are estimated that in each of them an indicator has entered as a proxy for learning. As mentioned in equations (3) and (4), LBD(Y) and LBD(EX) are introduced as a proxy for learning-by-doing and are entered in the first and second models, respectively. The estimation results of both models are presented in Table (2).

Table 2. Dynamic Panel Data Model for Technology Content Index

Models	Variables	Coefficient	t-value	Probability
First model LBD(Y)	$LTCI_{j,t-1}$	0.5	3.06	0.000
	$LLBD(Y)_{j,t-1}$	0.39	1.9	0.06
	$LSchool_{j,t}$	2.2	0.65	0.51
	$LGDPCAP_{j,t}$	0.08	0.09	0.9

Models	Variables	Coefficient	t-value	Probability
First model LBD(Y)	$LIIT_{j,t}$	0.4	1.78	0/077
	$LOPEN_{j,t}$	0.46	1.7	0.085
	Sargan test	J-statistic =5.24 prob=0.38		
	Arrelano-bond test	M-Statistic-AR(1)= 1.17 prob=0.000 M-Statistic-AR(2)=0.25 prob=0.29		
Second model LBD(EX)	$LTCI_{j,t-1}$	0.27	1.81	0.07
	$LLBD(EX)_{j,t-1}$	0.72	2.10	0.039
	$LSchool_{j,t}$	4.8	2/04	0.044
	$LGDPCAP_{j,t}$	1.13	1/91	0.06
	$LIIT_{j,t}$	0.55	2/5	0.01
	$LOPEN_{j,t}$	2.7	3/8	0.000
	Sargan test	J-statistic =4.30 prob= 0.50		
	Arrelano-bond test	M-Statistic-AR(1)=-0.65 prob=0.000 M-Statistic-AR(2)=-0.07 prob=0.59		

Source: Research finding.

According to Table (2), the value of probability statistic and Sargan test checking the instrument matrix validity show that the null hypothesis as a non-correlation between instruments and disturbing components cannot be rejected. Therefore, the instruments used to estimate the model have the necessary validity. Also, according to Arellano and Bond test and according to M_1 and M_2 statistics, the degree of autocorrelation of disturbing components shows that the null hypothesis as a first order non-autocorrelation is rejected, while the second-order non-autocorrelation is not rejected. Therefore, there is no specification bias in the model and the Arellano and Bond method is an appropriate method for eliminating the fixed effects of the model. In addition, the results reveal that LBD(EX) and LBD(Y) as the learning indicators have a positive and significant effect on the export technology content in Iran's industries in the both models, confirming the theoretical expectations.

In the first model, which LBD(Y) is entered as a proxy for learning-by-doing, the lagged technology content variable, trade openness and intra-industry trade indicator have a significant and positive effect, while human capital index and GDP per capita variable have a positive but insignificant effect on the export technology content in Iranian industries. In the second model, in which LBD(EX) is introduced as a proxy for learning-by-doing, the lagged technology content variable, trade openness, intra-industry trade index, human capital index and GDP per capita variable have a positive and significant effect on the export technology content in Iran’s industries. It is interesting to note that LBD(EX) as an export experience indicator affects the export technology content more than LBD(Y) as a production experience index and their coefficients are 0.39 and 0.72 in the first and second models, respectively.

6. Conclusion

This study was carried out with the aim of analyzing learning-by-doing and investigating its impact on Iranian industrial export technology content at the level of two-digit ISIC codes using the Arellano and Band dynamic data estimation method over the period from 2011 to 2015. For this purpose, two different indicators have been introduced to quantify learning and one indicator has been defined to measure export technology content. According to the related literature, improving the export technology content is one of the basic necessities for the development of industrial exports in developing countries. For this reason, Iran's export technology content has been studied and the effects of some economic variables including learning-by-doing on export technology content has been investigated.

As expected, our empirical study demonstrates that both learning-by-doing indicators, LBD(EX) and LBD(Y) in the export technology content model, have a positive and significant effect on the export technology content of two-digit ISIC codes in Iran’s industries. According to the results of estimations, learning variable coefficients in the first and second models are 0.39 and 0.72, respectively. Learning-by-doing increases the skills, abilities and expertise of the labor, thereby increasing the production of more specialized and high-tech products. As a result, countries with less experience specialize in the production and export of low-tech goods and countries with more experience focus on the production and export of high-tech and developed products. The findings of this study are consistent with those of An and Iyigan (2004), Yang (2004) and Vali Beigi and Rezaei (2003). Also, our results support the idea that targeted import of intermediate and capital goods with the aim of absorbing foreign technology and realizing learning, as well as supporting the infant industry to achieve learning in Iranian industries, should be considered by politicians. As mentioned in the previous section, one of the learning indicators in this research is cumulative export. Due to the greater impact of cumulative exports on the export technology content in comparison with cumulative production, supporting and emphasizing the activities of firms with appropriate export background can grow the export-oriented products and also export technology content.

The empirical results of the human capital's effect on the export technology content in Iranian industries show that this variable has a positive but insignificant effect in the first model; however, this variable has a positive and significant effect in the second model. As shown in Table (2), its coefficient in the second model is 4.8, implying that our empirical results are consistent with those of An and Iyigan (2004), Xu (2006), and Khirinaks et al. (2014). Therefore, the evidence from this study suggests that in the process of industrial export, the presence of high-skilled and high quality labor force can play a crucial role in the development of the industrial export technology content through innovations, creativity and absorption of superior imported technology. In general, these results suggest that developing countries, including Iran, must invest in higher education and in-service courses to improve the quality and skills of the labor and to accumulate human capital in their economy.

In addition, according to the results of Table (2), the GDP per capita variable (GDPCAP) has a positive and insignificant effect in the first model, while it has a positively significant effect on the export technology content in the second model and its coefficient is 1.13. Our result for this variable is consistent with those of Hausman et al. (2005), Lall et al. (2006), and An and Iyigan (2004). Accordingly, countries with higher per capita income export more value-added products and higher technology content goods. Furthermore, the empirical evidence of this study emphasize that it is necessary to produce and export high value-added products in replacement with the production and export of raw and low value-added products in the Iran’s export basket. Therefore, the development of knowledge-based companies in high-tech industries, due to the importance of this sector in creating high value added, employment and increasing productivity, can play an effective role in the growth of Iran’s industrial production as well as export technology content.

The next variable is openness (Open), according to the results of Table (2), which has a positive and significant effect on the industrial export technology content as expected in both models and its coefficients in the first and second models are 0.46 and 2.7, respectively. Trade openness affects exports through various channels: a) it improves export technology content through the import of capital goods transferring technology to the country and b) the economy with a higher degree of trade openness has more potential to absorb targeted technology from developed countries. Therefore, according to the present findings, further communication with the international markets in order to gain experience and to accumulate knowledge and innovation from industrialized countries in the field of industrial production, especially in high-tech industries, should be considered by the Iranian economic policy makers.

Finally, the last variable is IIT representing the intra-industry trade index. According to the results, it has a positively significant effect on both models and its coefficients in the first and second models are 0.40 and 0.55, respectively. These results are consistent with those of previous studies such as An and Aigan (2004) and Khirinaks (2014). Therefore, it is necessary for Iranian economic policy makers to pay more attention to the targeted import of intermediate and capital goods with the intention of imitating and absorbing foreign technology.

Considering that learning has had a positive effect on Iran's industrial export technology content, so it is suggested that first, industries whose technology is compatible with learning and second, learning resources Identify in each field of activity. In addition, it is suggested that economic agents be given the necessary incentive, such as tax incentives, to activate learning resources, including in-service training.

References

Aboal, D., Arza, V., & Rovira, F. (2017). Technological Content of Exports. *Economics of Innovation and New Technology*, *26*(7), 661-682.

Ambler, S., Cardia, E., & Farazli, J. (1999). Export Promotion, Learning by Doing and Growth. *Journal of Economic Dynamics and Control*, *23*(5-6), 747-772.

An, G., & Iyigan, M. F. (2004). The Export Technology Content, Learning by doing and Specialization in Foreign Trade. *Journal of International Economics*, *64*, 465-483.

Anzanello, M. J., & Fogliatto, F. S. (2012). Selecting the Best Clustering Variables for Grouping Mass-Customized Products Involving Workers' Learning. *International Journal of Production Economics*, *92*, 11- 19.

Arrow, K. J. (1962). The Economic Implications of Learning by Doing. *Review of Economic Studies*, *29*, 155-173.

Bardhan, P. K. (1971). Economic Growth, Development and Foreign Trade. *Industrial Economics*, *14*, 275-282.

Boldrin, M., & Scheinkman, J. A. (1988). Learning-by-doing, International Trade and Growth: A Note (285-300). In *The Economy as an Evolving Complex System*. Florida: CRC Press.

Chuang, Y. (1997). Learning by Doing, the Technology Gap, and Growth. *International Economic Review*, *39*(3), 697-721.

Clarke, A. (2008). Learning-by-Doing and Productivity Dynamics in Manufacturing Industries. *University of Melbourne*, *Working Paper*

Series, 1032, 1-50.

Elahi, N., Khodadad Kashi, F., & Sagheb, H. (2018). Technology Content, Sophistication and Revealed Factor Intensities in Export of Iran. *Quarterly journal of Industrial Economic Researches*, *2*(3), 57-70.

Elshurafa, A. M., Albardi, S. R., Bigerna, S., & Bollino, C. A. (2018). Estimating the Learning Curve of Solar PV Balance–of–System for over 20 Countries: Implications and Policy Recommendations. *Journal of Cleaner Production*, *196*, 122-134.

Fafchamps, M., El Hamine, S., & Zeufack, A. (2008). Learning to Export: Evidence from Moroccan Manufacturing. *Journal of African Economies*, *17*(2), 305-355.

Feizpour, M., & Habibi, M. (2018). Learning Curve and Technology Levels of New Firms in Iranian Manufacturing Industries. *Quarterly journal of Industrial Economic Researches*, *2*(3), 7-22.

Fellner, W. (1969). Specific Interpretation of Learning by Doing. *Journal of Economic Theory*, *1*, 119-140.

Goh, A. T., & Olivier, J. (2002). Learning by Doing, Trade in Capital Goods and Growth. *Journal of International Economics*, *56*(2), 411-444.

Hausmann, R., Hwang, J., & Rodrik, D. (2005). What You Export Matters. *NBER*, *Working Paper*, *11905*, 1-25.

Khodadad Kashi, F. (2012). *Industrial Economics (Theory and Practice).* Tehran: Samt.

Kim, D. W., & Chang, H. J. (2012). Estimated the Learning Curve Using the Nuclear Power Generation Cost in Korea and compared it with that of Renewable Energy Sources. *Energy Policy*, *40*, 361-373.

Lall, S. (2000). The Technological Structure and Performance of Developing Country Manufactured Exports, 1985–98. *Oxford Development Studies*, *28*(3), 337-369.

---------- (1998). Exports of Manufactures by Developing Countries: Emerging Patterns of Trade and Location. *Oxford Review of Economic Policy, 14*(2), 54-73.

Lall, S., Weiss, J., & Zhang, J. (2006). The "Sophistication" of Exports: A New Trade Measure. *World Development*, *34*(2), 222-237.

Leahy, D., & Neary, J. P. (1999). Learning by Doing, Precommitment and Infant-Industry Promotion. *The Review of Economic Studies*, *66*(2), 447-474.

Lucas, R. E. (1988). On The Mechanics of Economic Development. *Journal of Monetary Economics, 22*, 3-42.

Mao, Z. Y. (2012). Learning-by-Doing and Its Implications for Economic Growth and International Trade. *MPRA, 42186*, 1-47.

Melitz, M. J. (2003). The Impact of Trade on Intraindustry Reallocations and Aggregate Industry Productivity. *Econometrica, 71*, 1695-1725

Nakajima, T. (2003). Catch-up in Turn in a Multi-Country International Trade Model with Learning-By-Doing and Invention. *Journal of Development Economics*, *72*, 117- 138.

Norani Azad, S., & Khodadad Kashi, F. (2017). Learning Intensity and Its Effects on Performance of Iranian Manufacturing Industries. *Quarterly Journal of Applied Theories of Economics*, *4*(1), 173-196.

Panas, A., & Pantouvakis, J. P. (2018). On the Use of Learning Curves for the Estimation of Construction Productivity. *International Journal of*

Construction Management, *18*(4), 301-309.

Pavitt, K. (1984). Sectoral Patterns of Technical Change: Towards a Taxonomy and a Theory. *Research Policy*, *13*(6), 343-373.

Peng, J., & Zhang, Y. (2020). Impact of Global Value Chains on Export Technology Content of China's Manufacturing Industry. *Sustainability*, *12*(1), 1-19.

Salazar Xirinachs, J. M., Irmgard, N., & Richard Kozul, W. (2014). *Creating Change in the Economy, Industrial Policy in the Service of Growth, Employment and Development* (Trans. by a Group of translators). Tehran: Institute of Business Studies and Research, Commercial Publishing Company (in Persian).

Stokey, N. L. (1988). Learning by Doing and the Introduction of New Goods. *Journal of Political Economy*, *96*(4), 701-717.

Teignier, M. (2013). Trade Policy Analysis under Learning-by-Doing Externalities: Is the Dutch Disease a Disease? Retrieved from University of Barcelona.

Valibeigi, H., Rezaee, M. (2014). The Effective Factors in High-tech Exports. *Iranian Journal of Trade Studies*, *18*(72), 61-82.

Xu, B. (2006). Measuring the Technology Content of China's Exports. Retrieved from China Europe International Business School (CEIBS).

Yelle, L. E. (1979). The Learning Curve: Historical Review and Comprehensive Survey. *Decision Sciences*, *10*(2), 302-328.

Young, A. (1991). Learning by Doing and the Dynamic Effects of International Trade. *The Quarterly Journal of Economics*, *106*(2), 369-405.