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The Learning by Doing Dimension of Extensive and Intensive Margins of Exports: the Case of Tunisia

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Abstract

The aim of this paper is twofold. The first consists in proposing the learning by doing approach as a theoretical background for which extensive and intensive margins of exports are jointly contributing to economic growth. The second is to verify if these margins are actual or not in Tunisia and if they are, as conjectured in this paper, a source of Gross Domestic Product expansion via a learning-by-doing process. The two margins of exports are assessed thanks to an export differentiation index à la Hirshman-Herfindahl which is computed, by using three digit standard international trade classification (SITC) data. The learning by doing process associated to exports margins is approximated not only by weighting the export differentiation index by a scale variable capturing the experience increase but also by assessing the latter variable for the whole economy and for the manufacturing sector where the sophistication of goods favors learning by doing. A Vector Autoregressive model is applied on Tunisian time series data covering the period (1970-2016). Export differentiation indexes are computed for the manufactured exports (500-899 in SITC) and all exported goods (001-899). Both margins of exports are proved to sustain a learning by doing process by favoring from, one hand, an increase of experience of workers and, from the other hand, technological spillovers between goods of increasing sophistication. The two exports margins are not impacting growth positively unless they happen in the manufacturing sector. The diversification of manufactured exports after a given maturity in producing already exported products is the principal insight in term of political economy.

Keywords: Learning by doing, Manufactured exports, Growth, Extensive and intensive margins of exports, Technological spillovers

JEL classification: F43, F62, F14, C32

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1. Introduction

In recent years, several problems are addressed through tackling the topic of extensive and intensive margins of exports (EIME). The intensive margin (IM) of exports correspond to a change in the intensity in an already attainment achieved in the exporting activity. The increase in quantities of already exported goods or the increase to the same partners is the most current way by which the export margin happens from the intensive side. At the extensive margin (EM), the change incorporates a structural achievement in exports activity. It consists in exploring new markets with already existing produced goods or thanks to an expanded variety of exported products which may be also commercialized to old destinations.

The deterioration of terms of trade at the origin of trade pessimism is the most debated issue that makes the distinction between EM and IM problematic. For Cong and Will (2007), a larger contribution of EM to exports growth that makes the outcome of exports expansion more optimistic comes from the expansion in varieties of exported products and from the improvement of the quality of these goods. EIME are also regarded as controversial in international trade literature with respect to the number of new trade partners (EM) and the exports changes 'volume in an established relationship (IM). Besedes and Purusa (2008), Felbermayr and Kohler (2006), Helpman et al (2008) and Amiti and Freund (2007) obtain different results in assessing the role played by the two margins in world trade. IM is found, for the majority of these studies, more frequent from the seventies. In the same line of ideas, Besedes and Purusa (2008) explain the developing countries poor performance at the IM by their incapacity to maintain and deepen their relationships. Another trail of exploration of the two margins of exports can also be found in the empirical literature that stresses on searching for the determinants of EIME occurring respectively by entry and exist of exporting firms and by average exports by firm. Hillberry and Hummels (2008), Lawless (2010) and Coughlin (2012) find that the two margins are influenced by distance to the foreign country and by its economic size.

Despite the diversity of approaches lying with EIME, explorations of this topic are useful for the insights that they involve in term of policies in a context of trade liberalization. This paper provides another promising route in exploring the margins of exports by analyzing their contribution to economic growth within a learning by doing (LBD) approach. This study provides also an assessment of EIME through a measure that hasn't been considered in the previous literature: the export differentiation index (EDI) constructed à la Hirshman-Herfindahl (HF) which accounts for change in the configuration of exports over time via horizontal and or vertical differentiation, on one hand, the dropping out of old products and the change in quantities of already exported products, on the other hand. The HF index is according to Krivka (2016) always the better in measuring firms' concentration in a given market. An analogical implementation of this index is made here by referring to diversity of exported products.

The LBD approach provides a robust justification on how is promising, for economic growth, the prevalence, of both EM and IM of exports in a developing country. LBD driven by the increase of exported products is the source of what has been called, by Lucas (1993), a growth miracle when he tried to break down, on its components, the spectacular experience of the South Korea. According to the author, LBD is supporting a dynamic process by which a fast growing economy is one that succeeds in concentrating its workforce on new goods and thus in accumulating human capital through the high rates of learning associated with new activities, on one hand, and through the spillover of this experience to the production of still newer goods, on the other hand. Korea engaged from the sixties in an outward oriented policy which gives it the possibility to open up the difference between the mix of goods produced and the mix consumed. For this country, a large volume of manufactured exports of increasing sophistication (EM) is auto-generating over time and is subsequently a source of learning based growth episode.

As we will show in the present paper, LBD associated to exporting manufactured goods, hypothetically of increasing technical content, is a way to perceive, in the case of Tunisia, how IM and EM of exports are prevalent, for the period (1970-2016) and how both are playing complementary roles in making more optimistic the output of exports expansion.

It is important to note that scarce are the export margins' empirical analysis focusing individually on Tunisia. Cross sectional studies on MENA (Middle East and North African) region give some insights on sets of homogenous countries incorporating Tunisia. In an attempt to evaluate the effect of the Euro-Mediterranean agreements on MENA countries, the Cremed (2010) indicate that only the North African countries enjoy a significant increase in exports consisting respectively in intensive margins for Tunisia, Algeria and Egypt and in extensive margins for Morocco. The report of the World bank (2010) gave also a preliminary answer to the question addressing the distinction between extensive and intensive margins of exports for the group of resource poor labor abundant countries (Tunisia, Lebanon and Morocco).

It is likely that no study tried to justify exports margins by taking the case of Tunisia individually, from one hand, and the learning by doing process associated to exports margins, from the other hand. Khalifa (2019) gave a first draft about the prevalence of EIME in Tunisia on an attempt to analyze the technological dimension of the link between exports and intermediate and capital goods imports. She finds two results that arouse trails of exploration of EIME-induced by learning by doing. The first is the payment of intermediate and capital goods thanks to exports differentiation. The second is in accordance with technological spillovers associated to manufactured exports providing the basis of the learning by doing process led by exports à la Lucas (1993).

In the present study, the possible theoretical conciliation between the two margins is made possible thanks to a tunisian empirical evidence whereby EIME are contributing significantly to economic growth by sustaining a learning by doing process. The main features of LBD on which our study is based are twofold. First, LBD occurs thanks to the experience increase of the labor force while engaged in productive activity. Second, the decreasing marginal returns of experience are counteracted by technological spillovers (TS) between manufactured exported products. Spillovers may be the consequence of the increase in production of the same exported good (IM) or the differentiation of the register of exported products (EM). A learning variable is than considered and constructed by weighting the scale variable by the EDI.

The EDI is computed using exports data at the third digit level data of SITC. This index presents the opportunity to take into account either the vertical or the horizontal differentiation of exported products.

Backus and al (1993) test a model of LBD using cross country data 1970-1985[1]. However the change of the exports configuration as a way to favor growth, should be analyzed, in the case of developing countries, in the long term horizon. For instance, the out-oriented policy adopted by South Korea gives its fruits in term of economic growth after almost thirty years: the spectacular growth rate achieved in the 1990's, is about 8%, significantly higher than that of USA during the same period. Here we use a Vector Auto regressive (VAR) approach in order to take into account the dynamic process founding the learning led growth episode: learning contributing to growth is auto generating since growth is also conditioning learning thanks to the development of new goods that it enhances. Growth and learning are considered as the two endogenous variables of the model. They depend also on their lagged values. Some control variables are taken into account in the regressions: the share of foreign direct investment (FDI) in gross domestic product (GDP) and the share, in total labor force, of highly educated workers.

[1] Summers-Heston (1988) data set.

Another contribution of the present study consists in showing that EIME are significant in the case of manufacturing goods: the LBD on the course of exporting activity is not pertinent in generating growth unless it happens in the manufacturing sector. For this purpose, data of manufacturing sector are considered individually and are compared to the whole economy's data for which the EDI is computed by adding to the manufactured products the rest of products (Food, live animals, beverages and tobacco, Crude materials, fuels; minerals etc). We make two categories of regressions. First, GDP growth is regressed on LBD proxy using EDI computed on the basis of the whole register of traded products (000-899). Second, the manufacturing value added growth is regressed on LBD proxy using an EDI computed for manufactured products (500-899).

This paper is structured as follows. First there is an analysis on how LBD can be considered as a lubricant for EIME. The theoretical model, methodology and data constitute the subject of the second section. Results relative to tests using data on Tunisia, (1970-2016) are finally presented and discussed.

2. LBD as a lubricant for EIME

Different dimensions of EIME are analysed in the international trade literature. For Hummels and Klennow (2005), the absence of EM of exports implies the following predictions. Larger countries intensively export more the same goods and thus attend to lower prices of national products. Such terms of trade effects have two implications. Besides welfare changes they prevent real per capita incomes from diverging across countries with differing investment rates (Acemoglu and Ventura, 2002). The EM consisting in exporting both a wider array of goods or higher quality goods makes lower export prices no longer a necessary consequence of increase in size of exports.

For Pham and Martin (2007), the EM of exports offer an escape route from trade pessimism caused by the depress of terms of trade risk resulting from expansion in quantities of the same goods: if exports growth come from the expansion of the number of range of exported products, then exports growth perspective seems to be more promising.
For Besedeˇs and Prusa (2011), EM has no impact on long run developing countries' exports growth. Significant higher export growth would have been achieved through improvement of countries performance with respect to key components of the IM: survival of existing relationships and their deepening.

If for some studies, the performance of exports growth are attributed in preponderance to EM or to IM some other studies prove the importance of the two margins simultaneously. For Felbermayr and Kohler (2006), the EM played a larger role in the growth of world trade between 1950 and 1970 and again in the mid 1990s, while the IM was more important in the intervening periods. Helpman, Melitz and Rubinstein (2008) confirm the finding of Felbermayr and Kohler (2006) for the alternation of IM and EM in contributing to export growth: the majority of the growth of trade between 1970 and 1997 is attributable to the IM rather than the EM. However EM occurs occasionally.

LBD as a process tightly linked to EIME is implicitly explored by Backus and al (1992) who find a positive and significant correlation between economic productivity growth and an exports specialization index reflecting TS between sectors or firms which make, in turn, the scale increase effect continuous and not disrupted by diminishing returns of experience. The mathematical nature of the index, and the fine digit level data used to calculate it imply that TS favored by activities oriented to exports result from EM and IM of exports.

Stockey (1988) identifies a specification of LBD that supports the prevalence of exports margins. He considers that the accumulation of knowledge through economy wide LBD is the result of experience increase in production rather than a separate activity. LBD, which is displaying spillovers among goods, results in a sustained growth process thanks to the introduction of new and better goods. TS à la Stockey (1988), are an integrant part of the systematic development of new goods. In the case of open economies, international TS benefitting to local producers, are the source of EM of exports occurring within a dynamic mechanism thanks to regular improvement of goods and to knowledge spillovers associated to it. Without TS the LBD process is similar to that predicted by Krugman (1985): "Because each country learns only about the goods it has produced itself, the initial pattern of comparative advantage exacerbates as production occurs."

Chuang (1998) provides a theoretical argument about how LBD is, for the developed countries a lubricant for exports EM. For this author international spillovers result from exposing one self to competitive international markets. Over time, the exporting firm gradually learns and acquire adequate technology to produce more sophisticated goods and to market its capacities as an attractive potential supplier of other foreign purchasers. Two components of exports' EM are implicitly evoked by Chuang (1998), the increase in the number of more sophisticated goods and the exploration of new markets: participating in exports markets forces the country to develop in the direction of what the country can execute when trade begins. New goods are produced thanks to learning upgrading which allows the exporting of refined goods which leads subsequently to absorption of new skills and the development of still newer goods.

Lucas (1993) presenting a LBD explanation of the spectacular performance of South Korea makes implicitly reference to EIME. For this author, the alternation between IM and EM of trade happens in accordance with the alternation of accumulation of human capital and TS. Indeed the engagement of the country in manufacturing exports implies a further improvement of these goods through accumulation of human capital (by LBD) by producing at a first stage the same goods (IM) and thanks to the spillovers of the accumulated experience to the production of still newer goods (EM).

3. The model and methodology

3.1. The model

Economy is composed by a finite number of industries. Value added Y_{it} of each industry i corresponds to:

$$Y_{it} = \gamma_i A_{it} N_{it}^{1-\alpha_i} K_{it}^{\alpha_i}, \quad i=1,2\ldots\ldots I. \tag{1}$$

N_{it} and K_{it} are respectively labor inputs and capital services
Ait is given by:

$$A_{it+1} = A_{it}(1+\beta_i Y_{it})^{\rho}, \tag{2}$$

β and ρ are positive constants. A_{it+1} measures the external effects of LBD (proxied by total output) between firms within the same industry i. Externalities, associated to learning increase are cumulative and counteract the diminishing returns to experience.
By defining yit= (Yit/Nt), kit = (Kit/Nt) and nit= (Nit/Nt) respectively as real output per capita, industry i's capital stock per worker and the share of industry i's workers on total labor force, (1) can be transformed to:

$$y_{it} = \gamma_i A_{it} n_{it}^{1-\alpha_i} k_{it}^{\alpha_i}, \tag{3}$$

Given the equation (2), the growth rate of output per capita is given by the following expression:

$$1+g(y_{it}) = \frac{y_{it+1}}{y_{it}} = (1+\beta_i Y_{it})^{\rho}\left(\frac{n_{it+1}}{n_{it}}\right)^{1-\alpha_i}\left(\frac{k_{it+1}}{k_{it}}\right)^{\alpha_i} \tag{4}$$

Mathematical transformation of equation 4, presented in detail by Backus et al (1993) and by Khalifa (2015) leads to the following expression of the whole economy's value added growth:

$$g(y_t) = \beta Y_t \sum_{i=1}^{I}\left(Y_{it}/Y_t\right)^2 \tag{5}$$

According to this equation, scale of production Y_t, revealing increase of experience and learning, raises the output growth rate. It is considered as reflecting quantitative learning effects on growth. Since the experience increase is subject to diminishing returns, scale of production is multiplied by a specialization index equal to the sum, of the squares of output shares of industries or goods on total output. This index reflects a qualitative weighting of experience increase. It reflects externalities between goods, sectors or industries.

Backus and al (1992) replace this index by a specialization index computed using data on exports by assuming that LBD and the relevant spillovers are significant only for high quality goods, the goods that a country is able to export. In such a case, the vertical and horizontal differentiation[2] allows a better evaluation of learning rate and the relevant spillovers associated to it since it happens in exported goods potentially of increasing technological content. For this purpose, the specialization index given by equation (5) is replaced by the EDI as in the following equation:

$$g(y_t) = \beta Y_t \sum_{i=1}^{I}\left(X_{it}/X_t\right)^2, \tag{6}$$

[2] See II.2 for more explanation.

In the present paper, the equation 6 is used in order to explore, in the Tunisian context, the effectiveness of EIME in a framework of LBD-led-growth. As illustrating a LBD process driven by the change in the exports configuration, equation 6 finds a robust justification by Lucas (1993) in his explanation of what he calls the south Korea's miracle. For this author, human capital accumulation on the job explains the wide productivity growth differences between Korea and Philippines, its homologous country during the sixties. From this date, Korea production of more sophisticated products is favored thanks to a strategy of manufactured exports promotion. According to Lucas, there is a systematic improvement in exported products of high technological content thanks to spillovers in export markets. As its own terms "a large volume of trade is essential to learning based growth episode". This enables a wide difference between the mix of products consumed locally and the mix produced: a difference that might occur slowly if all produced goods, even the manufactured ones, are intended for local use.

3.2. The EDI

This index presents a qualitative component of LBD process. Since it is calculated yearly, it takes in account the structure's products modification (the EM of exports) and also changes in quantities of products that persist in the list of exported products for many successive years in the period (the IM of exports). The EM illustrated by EDI may happen, à la Stockey (1988), thanks to entering of new products and dropping out of old products. EDI is tributary of exports categories change resulting, in turn, from a vertical or horizontal differentiation. It reveals more product structure's evolution if data on exports are disaggregated. Khalifa (2019) gives an illustration of EDI's evolution for manufactured exports. In this case, the third level of SITC disaggregation is considered. Figure I illustrates, for the same SITC disaggregation level, the evolution of EDI computed for the whole set of Tunisian exported products (500-899) within (1970-2016).

Table 1. Decomposition of exported products according to SITC

Chapters	Under chapters	Categories
Chapter I	I.1	I.1.1
		I.1.2
		I.1.3
	I.2	I.2.1
		I.2.6

Source: (the author, 2019).

Table 1 indicates how chapters of SITC are decomposed as to reveal horizontal (HD) or vertical differentiation (VD) of exports. SITC involves a decomposition of goods in chapters (first column), in under chapters (second column) in turn decomposed in different categories (third column). There is a VD of exported goods after a change of register of categories of an already existing under chapter. The HD happens after the appearance of a new category simultaneously with the appearance of the under chapter that it belongs to. Besides HD and VD, the EDI reveals also the disappearance of many exported products over time.

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It is obvious that the third (fourth) level of disaggregation of SITC is better than the second (third) one since it enables us to deepen the perception of either the HD or the VD. Working with the fourth level of SITC, gives a better illustration of HD and VD. Meanwhile what seems a HD in the case of the fourth level (the appearance at first of a category) may correspond to both HD or VD in the case of three digit level data.

Khalifa (2019) explains how EDI is a good way to measure the modification of exports' configuration. For Krivka (2016), a perfect value of this index is lesser than (0.1). Then its decrease over time indicates the prevalence of EM of trade that may correspond, in net terms, to appearance of new products over time if the entry of new products, to the set of exported goods, is more important than the disappearance of old products. The ability of the index to denote the increase of exported products is than a way to distinguish between experience spillovers across exported goods. This may be possible if data used for calculating this index is as finest as possible.

Given Lucas' central role of human capital accumulation in the course of producing manufactured exports, EDI is computed not only for the whole set of exported products but also for the set of manufactured exports given their specific technological content that increases over time.

3.3. The method of estimation

Regressions of the equation (6) are carried out according to a double sense of causality. The idea is to verify if growth is a consequence of LBD by exporting[3] or, at the opposite, if the former is a condition for the happening of the latter. Then we apply a VAR model on annual Tunisian data covering the period (1970-2016) according to which, the growth rate and proxy of learning by exporting indicated in (6) are explained each one as a function of the other and of its proper lagged values.

Equation (6) is the principal equation of the system. Its right hand side is made log-linear in order to separate the constant from the proxy of learning by exporting. This latter is, in turn, explained by the growth rate in the second equation. The system is the following:

$$\begin{cases} g(y_t) = \gamma_0^1 + \alpha_1^1 g(y_{t-1}) + \alpha_2^1 g(y_{t-2}) + \ldots + \alpha_p^1 g(y_{t-p}) + \beta_1^1 \log(Y_{t-1}I_{t-1}) + \\ \qquad \beta_2^1 \log(Y_{t-2}I_{t-2}) + \ldots + \beta_p^1 \log(Y_{t-p}I_{t-p}) + d_1 \log(Y_t I_t) + \varepsilon_{1t} & (7) \\ \log(Y_t I_t) = \gamma_0^2 + \alpha_1^2 g(y_{t-1}) + \alpha_2^2 g(y_{t-2}) + \ldots + \alpha_p^2 g(y_{t-p}) + \beta_1^2 \log(Y_{t-1}I_{t-1}) + & (8) \\ \qquad \beta_2^2 \log(Y_{t-2}I_{t-2}) + \ldots + \beta_p^2 \log(Y_{t-p}I_{t-p}) + d_2 g(y_t) + \varepsilon_{2t} \end{cases}$$

[3] Called also learning by exporting.

with It is the EDI, p the gap index of the endogenous variables, αij [i=0, 1, 2…p; j=1,2] is the coefficient of g(yt) lagged by i years, in equation j. Similarly [βij] is the coefficient of the proxy of learning by exporting ($Y_{t-i}I_{t-i}$).

Besides the two endogenous variables specified above, we control by the regressions of the system by the high education level of workers, the capital stock growth rate and the share of foreign direct investment in GDP.

3.4. The data

3.4.1. EDI Calculations

EDI is computed, according to the third-digit level of SITC data (Yearbook of International trade Statistics), yearly, for two sets of products: the manufactured exports classified[4], between 500 and 899[5] and the entire set of exported products containing besides manufactured goods, the subset of goods classified between (001 and 899)[6]. The system (7)-(8) is then respectively estimated by using data on manufacturing sector (the manufacturing sector value added and its rate of growth) and data on the whole economy (GDP level and GDP growth).

Comparing the case using manufactured data and the case where all goods are cumulated is a way to verify for which category of products, the expansion of exports (EIME) over time is actually the force behind systematic learning and long term productivity gains.

3.4.2. Data about the model's variables

The endogenous variables of the system 7-8 are $g(y_t)$ and $\log(Y_t I_t)$. Data relative to y_t corresponding to GDP per capita or the manufactured value added per capita is collected from the Tunisian national accounts. Variables are evaluated at constant prices of 2005.

Exogenous variables used in our case are respectively the share of foreign direct investment (FDI) in GDP or in manufacturing sector value added and also the share of highly educated workers in total workers in the manufacturing sector or in the whole economy. Both, are provided by the Tunisian Institute of Competitiveness and Quantitative Studies (TICQS). Augmented Dicky Fuller test for stationary condition of all the model's variables are made but not presented here . Non stationary condition is found significant for the learning variable

[4] In the case of Tunisia, the maximum level of disaggregation of exports given the availability of data for the whole period is the third level of SITC.
[5] This subset includes chemical and related products, manufactured goods classified by material, machinery and transport equipment and miscellaneous manufactured articles.
[6] This subset includes food and live animals, beverages and tobacco, crude materials, mineral fuels, lubricants, animals and vegetable oil, fats and waxes.

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$\log(Y_{t-1}I_{t-1})$ called below EDIWLV and also for FDI variables. High education level of manufacturing workers is also non stationary. The first difference of these variables is then considered while estimating the system 7-8.

4. Results and discussions

Results of estimations of the system 7-8 are presented in tables 2 and 3. In each case, two rows are devoted for results of regressions using respectively manufacturing data and those using data on the whole economy. The VAR specification implies the use of different lags of the endogenous variables. Ten regressions of system 7-8, with lags of endogeneous variables ranging from one to ten, are carried out. Only the cases of eight and nine lags, slightly similar, are presented here (tables 2 and 3). The optimality of lags number is presented in table 4.
One common feature of the three categories of regressions is the significativity, in the first equation of system 7-8, of the coefficient relative to the learning variable when dealing with the manufacturing sector data. This variable is problematic in our study since it incorporates the index that reveals the effectiveness of EIME. It is also composed by a scale variable denoting the experience change of workers even for the whole economy or for the manufacturing sector. The multiplication of the scale variable by the EDI index reflects the LBD dimension of the EIME. Indeed, growth is driven thanks to experience increase (increase of the scale variable) of workers via LBD. However, productivity gains are counteracted by the diminishing returns of experience. Weighting the scale variable by the exports differentiation index is a way to take into account spillovers resulting from the production of new or already exported goods. Thus, LBD generates productivity gains thanks to higher paths of experience resulting from regular change in exported products as a consequence of participating in export markets.

According to results in tables 2 to 3, the optimal lag corresponds, when dealing with the manufacturing data, to the ninth. In this case significant and interesting results are obtained only for the first equation of the system (7-8). Coefficients of the learning variables given by the first equation of the system start to be significant from the eight lags case. For tables 2 to 3, the learning variable is significant for the third and for some anterior lags: the impact of LBD is lasting over time. Its impact on growth is not immediate but it becomes to make its fruits at least after three years. In the optimal case, the contribution of LBD to growth is actual even after five and eight years: the LBD leads to productivity gains periodically when the increase of workers experience and relevant spillovers attain their maturity and become potentially able to generate growth.
At the ninth lag (table 3), the coefficients of the learning variable are significant and the highest. In addition, there is an improvement in values of R^2 which attains 0.97. This high explaining power of the regression is confirmed by the important value of $\overline{R}^2$ (about 0.84). According to Bourbonnais (2000) an important value of $\overline{R}^2$ reinforces the quality of the adjustment justified by R^2.

As well as R^2, the Akaike criterion (AIC), that of Schwarz (SC) and other criterions prove also to be the optimal according to optimal lag structures.
The EIME is favorable to growth via LBD while exporting. The amplitude of the effect of learning by exporting appears alternatively more and less important. Always with the optimal lag

case, a 100% increase of the variable $Y_{t-i}I_{t-i}$, which is the EDI weighted learning variable (EDIWLV), implies an impact of the first difference[7] of this variable on growth about 1.6%, 0.37% and 0.824% respectively for the third, the fifth and the eighth lag. The variation of the scale of production in the manufacturing sector denoting experience-led productivity, from one hand, and the decrease of the EDI from the other hand, are jointly influencing growth via EIME that they reflect. If the value added of the manufacturing sector (the first component of EDIWLV) implies just an increase of workers experience, the EDI is a way to weight this experience measure qualitatively since it describes the extent to which there is differentiation and diversification of exported products. EDI incorporates also an increase of the experience which happens when only quantities of some exported goods change: the IM and the EM of exports are both prevalent thanks to the LBD- led growth process that they enhance.

The impact of the more recent learning variable (at the third lag) is more important since it is weighted by EDI computed using more recent register of exported products. EIME result in better productivity gains: when change of exported products is more recent, its impact on growth is more important: the coefficient associated to EDIWLV is more important for three lags than for five and eight lags. This result may be attributed to the increase of technological content of the exported products over time from one hand, and also to the immediacy of rewards coming from exporting new register of products, on the other hand. The reward is taking place either in the form of LBD-led technological diffusion among goods or from LBD-led productivity thanks to experience increase. In this case, the experience increase is due, partially, to IM of exports consisting in the quantities increase of some exported goods. EM of exports generate the move on a new LBD path thanks to TS between goods. Since the lag of the EDIWLV is not important it is more plausible that the intensive margin is more important since the experience increase is generating yet productivity gains and doesn't reach the phase of diminishing returns to experience. The effect of more lagged EDIWLV seems to reside rather in that of TS where the diminishing returns to experience is actual.
Results in table 3 show a higher coefficient associated to the eighth lag than that of the fifth. Although, the reverse seems to be more plausible, this result is interpreted as follows. First, the period that is separating t-8 to t-3 is more important than that separating t-8 to t-5. Than the change in the register of exports may be more important for a longer period and implies a greater effect on learning and productivity. In the intermediate period (t-5), the change of the list of products is not enough important as it is the case in the extreme periods (t-3) and (t-8). Additionally, the impact of learning happening eight years earlier may take place via TS associated to such learning.

The diminishing returns to experience are proven thanks to lags where no significant contribution of learning variables is found: t-1, t-2, t-4, t-6 and t-7. The increase of experience stops to generate productivity gains if the goods are repeating. For Backus and al (1992) "LBD in the same activities can not generate sustained growth". This happens also when the EIME is not significantly important: the increase of experience is a continuous source of growth only if new manufactured exports are introduced over time. The EIME is put in evidence over time when the register of products is enough differentiated. In this study, EIME contributes to growth at different moments after a significant change, over time, of the register of manufactured exports. Here, the effect of learning by exporting is able to generate productivity gains not only after three

[7] Given the non stationnarity of this variable we replace it by its first difference: stationnarity tests are not presented here.

years but also after five and eight years. This implies that categories of products are changing three years, five or eight years ago. When the change of these products isn't important, its effect on productivity is not significant since experience increase is subject to diminishing returns to scale. In the same order of ideas, Lucas gives some evidence against Krugman's (1987) formulation relative to the permanently different learning potentials of different goods: there is no reinforcement of the comparative advantage in open economies given the decrease of growth of total factor productivity across both industries and time, on one hand, and the learning path on narrowly defined product lines characterized by high initial learning rates, declining over time as production cumulates, on the other hand.

The second three rows' bloc of table 3 is presenting results of regressions using data on the whole economy. According to the first equation of system (7-8), the LBD is not impacting the GDP growth since the total output is cumulated for all the sectors of the economy. These results imply that EIME are actual only in the manufacturing sector where goods are horizontally and vertically differentiated. The set of products dealt with in whole economy's regression is so heterogeneous since it incorporates besides the manufacturing goods (500-899), products classified under the set (0-499) of SITC such us animals, mineral fuels, crude materials etc. These results are in line with those of Backus and al (1992) using dataset of Summers-Heston (1988). By focusing on LBD-led scale effects, the authors show that the evidence of learning in the course of exporting goods is weak at the national level. However, there is a positive correlation between the learning variable and productivity growth in the regressions using manufacturing variables. There is also a justification of these results in Lucas (1993) who makes reference to the learning-based spillovers technology as the main feature of the East Asian miracles all of which have favored sustained movement of the workforce from less to more sophisticated products.

Another aspect of the optimal estimation is the positive and significant coefficient of proxies of FDI and that of workers' high education level. The introduction of these variables is crucial given the improvement of the quality of the regression[8]: higher R-squared and F-statistic and lesser Akaike and Shwarz criterions. A 100% increase of the first difference of FDI proxy (manufacturing sector workers' high education level) is associated to an increase in manufacturing sector's value added growth of 0.71 % (0.128%). Both of these control variables increase the significant power of the lagged learning variable. Furthermore, their introduction makes the non significant coefficient of the fifth lagged learning variable positive and significant. These results enable to conclude that more workers are educated, better is their learning and their ability to profit from TS. In our country, the presence of foreign capital firms is accelerating the learning process since they compose networks where TS are diffused within the manufacturing sector, from one hand, and since these firms are engaged in production of goods of increasing sophistication, from another hand.

When comparing tests using total economy data and data on manufacturing sector, the obvious difference regarding the contribution of the LBD variable to growth is theoretically founded by the LBD approach as that presented by Stockey (1988) and Lucas (1993). These authors propose a learning spillover technology consistent with permanent development of goods of higher quality. For Lucas, high learning spillovers across goods is the force behind sustained growth because, as it is also underlined by Stockey, these spillovers allow the improvement of existing goods for which productivity gains associated to experience increase are not permanent. More

[8] Results relative to the optimal estimation without FDI measure and high education workers not presented here.

precisely, growth is driven by the accumulation of human capital on the job, higher learning rates associated to new goods and the spillovers of the cumulated experience for the production of still newer goods. For Stockey, there is no learning in the traditional sector: the absence of such spillovers enhances systematically static gains of trade. As suggested by Krugman (1987) "without spillovers displayed, LBD reinforces the existing pattern of production which works against the introduction of new goods and the discontinuance of old ones".
Our results are kind with this theoretical hypothesis. The effect of the learning proxy variable on growth is quasi-absent when data on the whole economy are dealt with. Learning is mitigated for the whole set of exported goods: they are not all of increasing sophistication as it is proven for manufactured products. Their introduction works in favor of a dynamic process incorporating alternative contribution to growth of experience increase, learning spillovers and further improvement of goods.

In our case, this new products' induced learning dynamics may be used to support the prevalence of EIME which correspond in our case to quantitative and qualitative change of the three-digit SITC manufactured exported products. Some products are dropping out through the whole period; some products are persisting for a given period with a change in their quantities and some new products appearing from period to period. As a consequence, the effect of EDIWLV is not continuous over time.
For some intermediate periods, its contribution to t year's growth becomes obsolete. The LBD approach can offer a background to how IM and EM of exports are complementary and are subsequently providing an optimistic route to exports expansion. Similar results regarding the distinction between IM and EM are drawn by the Cremed's empirical study (2010) on MENA countries. It indicates that only the North African countries enjoy a significant increase in exports consisting in intensive margins for Tunisia, Algeria and Egypt and in extensive margins for Morocco. The plausible hypothesis that explains these results is, the Euro-Mediterranean agreements rules allowing the integration of better quality/less expensive intermediate goods in production which has positive effects on MENA exports of sophisticated manufactured products. By focusing particularly in the case of Tunisia the results of Khalifa (2019) revealing the reverse causality sense between exports and intermediate and capital goods imports give a first draft about the prevalence of both EM and IM of exports in that exports are revealed enough diversified in order to insure payments of diversified imported goods. The world bank (2010) have given also a preliminary answer to the question addressing the EM and IM of exports: the decline of concentration indexes (Herfindhal, Theil and Gini) for the group of resource poor labor abundant countries (Tunisia, Lebanon and Morocco) have been largely attributable to lower concentration of traditional products and relatively limited progress in the introduction of new products.

The delayed contribution of EDIWLV to growth gives confirmation of the conjectured spillovers à la Lucas (1993) which are another indicator about the prevalence of EIME. Indeed TS externalities are at the heart of the dynamic process of learning- induced growth since they are the source of continuous higher paths of learning. Results in table 3 show that the spillovers make time to occasion high learning rates and to imply a stimulus in term of increase of high learning of other goods. Moreover, If the EDIWLV affects the growth after few years this is because the diffusion of externalities among goods and over time may persist even eight years and enhance productivity gains after having led to further learning thanks to development of newer goods. This is a proof that the EIME are auto-generating within a dynamic process. Higher learning rates and EIME are evolving alternatively with mutual reinforcement of each other. Technological spillovers linked to the change in exports quantities and in exports categories at the heart of this dynamic process are particularly highlighted in the empirical study of Khalifa (2019). The main finding of Khalifa (2019) is the important contribution of manufactured exports of Tunisia on its economic growth thanks to technological spillovers. By contrast to cremed (2010), Khalifa considers a deeper level of disaggregation of data in evaluating the extent to which exports are changing quantitatively (IM) and qualitatively (EM). It is only this change that ensures the continuance of learning by doing process since it is ensuring technological spillovers between goods, stopping decreasing returns to experience, enhancing long term economic growth and so on.

Table 2 - Results of the estimations of the system (7)-(8) with 8 lags

	GVAPC	D(LOGVAIS)		GPIBPC	LOGYI
GVAPC(-1)	-0.159186	-2.766788	GPIBPC(-1)	0.713549	3.820476
	(0.22565)	(1.49774)		(0.47638)	(2.10937)
	[-0.70547]	[-1.84730]		[1.49787]	[1.81120]
GVAPC(-2)	-0.577782	-1.122364	GPIBPC(-2)	0.035835	1.577885
	(0.25347)	(1.68244)		(0.34289)	(1.51830)
	[-2.27947]	[-0.66710]		[0.10451]	[1.03925]
GVAPC(-3)	-0.758534	0.575516	GPIBPC(-3)	0.192807	1.116235
	(0.27541)	(1.82807)		(0.42446)	(1.87947)
	[-2.75418]	[0.31482]		[0.45425]	[0.59391]
GVAPC(-4)	-0.316344	-3.380148	GPIBPC(-4)	-0.359523	0.385917
	(0.27513)	(1.82623)		(0.30885)	(1.36757)
	[-1.14978]	[-1.85089]		[-1.16408]	[0.28219]
GVAPC(-5)	-1.418179	-2.428559	GPIBPC(-5)	0.277918	1.746247
	(0.35399)	(2.34962)		(0.35123)	(1.55521)
	[-4.00630]	[-1.03360]		[0.79128]	[1.12284]
GVAPC(-6)	-1.217446	-3.360988	GPIBPC(-6)	0.285490	1.721114
	(0.31686)	(2.10322)		(0.34672)	(1.53526)
	[-3.84216]	[-1.59802]		[0.82340]	[1.12106]
GVAPC(-7)	-0.283621	-3.902093	GPIBPC(-7)	-0.075832	-1.984138
	(0.29196)	(1.93791)		(0.25860)	(1.14506)
	[-0.97144]	[-2.01356]		[-0.29324]	[-1.73278]
GVAPC(-8)	-1.015087	-3.203202	GPIBPC(-8)	0.068971	-0.325320
	(0.30336)	(2.01359)		(0.26027)	(1.15247)
	[-3.34613]	[-1.59079]		[0.26500]	[-0.28228]
D(LOGVAIS(-1))	0.022170	-0.286368	LOGYI(-1)	-0.046650	0.058567
	(0.05138)	(0.34107)		(0.08292)	(0.36717)
	[0.43144]	[-0.83961]		[-0.56258]	[0.15951]
D(LOGVAIS(-2))	0.040269	0.222532	LOGYI(-2)	-0.055669	-0.058262
	(0.05630)	(0.37373)		(0.07360)	(0.32591)
	[0.71520]	[0.59544]		[-0.75634]	[-0.17877]
D(LOGVAIS(-3))	0.307573	0.490829	LOGYI(-3)	0.007032	0.247438
	(0.06730)	(0.44671)		(0.06102)	(0.27017)
	[4.57013]	[1.09875]		[0.11525]	[0.91585]

D(LOGVAIS(-4))	-0.038440	0.633498	LOGYI(-4)	0.084379	0.376951
	(0.05760)	(0.38230)		(0.06275)	(0.27787)
	[-0.66741]	[1.65707]		[1.34461]	[1.35657]
D(LOGVAIS(-5))	0.089781	0.184794	LOGYI(-5)	-0.034855	-0.281273
	(0.06059)	(0.40217)		(0.04719)	(0.20894)
	[1.48178]	[0.45949]		[-0.73864]	[-1.34616]
D(LOGVAIS(-6))	0.040048	-0.156188	LOGYI(-6)	-0.081888	-0.260802
	(0.05157)	(0.34227)		(0.04715)	(0.20876)
	[0.77665]	[-0.45633]		[-1.73694]	[-1.24931]
D(LOGVAIS(-7))	-0.000398	0.162137	LOGYI(-7)	0.183217	0.682349
	(0.05251)	(0.34853)		(0.07073)	(0.31320)
	[-0.00758]	[0.46521]		[2.59029]	[2.17864]
D(LOGVAIS(-8))	0.174013	-0.143239	LOGYI(-8)	-0.128496	-0.696404
	(0.05704)	(0.37861)		(0.05445)	(0.24109)
	[3.05068]	[-0.37833]		[-2.36000]	[-2.88855]
C	-0.097126	0.697619	C	0.565757	7.107644
	(0.10660)	(0.70754)		(0.50352)	(2.22956)
	[-0.91116]	[0.98597]		[1.12361]	[3.18791]
D(LOGIDEMAN)	0.008686	0.008353	D(LOGIDE)	-0.009105	-0.040716
	(0.00878)	(0.05827)		(0.00724)	(0.03206)
	[0.98941]	[0.14334]		[-1.25758]	[-1.27002]
LOGSUPMANUF	0.023520	-0.024290	D(LOGSUP	0.697242	3.246875
	(0.01139)	(0.07559)		(0.36547)	(1.61829)
	[2.06545]	[-0.32136]		[1.90779]	[2.00636]
R-squared	0.889304	0.745120	R-squared	0.745915	0.955785
Adj. R-squared	0.557215	-0.019520	Adj. R-squared	0.174222	0.856302
Sum sq. resids	0.001787	0.078727	Sum sq. resids	0.001792	0.035127
S.E. equation	0.017257	0.114547	S.E. equation	0.014965	0.066264
F-statistic	2.677909	0.974472	F-statistic	1.304749	9.607516
Log likelihood	83.85336	36.53464	Log likelihood	91.56541	51.39109
Akaike AIC	-5.188268	-1.402771	Akaike AIC	-5.375216	-2.399340
Schwarz SC	-4.261923	-0.476425	Schwarz SC	-4.463331	-1.487455
Mean dependent	0.019269	0.013976	Mean	0.017989	7.741874
S.D. dependent	0.025935	0.113446	S.D.	0.016468	0.174803

Source: (calculations of the author, 2019).

Table 3 - Results of the estimations of the system (7-8) with 9 lags

	GVAPC	D(LOGVAIS)		GPIBPC	LOGYI
GVAPC(-1)	-0.290705	-4.681933	GPIBPC(-1)	0.778677	3.680580
	(0.31450)	(3.69449)		(0.56454)	(2.03034)
	[-0.92435]	[-1.26728]		[1.37931]	[1.81279]
GVAPC(-2)	-0.626842	-2.014738	GPIBPC(-2)	0.144731	3.874281
	(0.19770)	(2.32241)		(0.54120)	(1.94638)
	[-3.17070]	[-0.86752]		[0.26743]	[1.99050]
GVAPC(-3)	-0.903075	-1.215474	GPIBPC(-3)	0.132170	1.871832

	(0.32003)	(3.75951)		(0.52659)	(1.89384)
	[-2.82182]	[-0.32331]		[0.25100]	[0.98838]
GVAPC(-4)	-0.481289	-4.934686	GPIBPC(-4)	-0.332972	2.584520
	(0.30311)	(3.56077)		(0.48466)	(1.74306)
	[-1.58781]	[-1.38585]		[-0.68702]	[1.48275]
GVAPC(-5)	-1.383877	-4.230334	GPIBPC(-5)	0.213424	1.736144
	(0.29486)	(3.46383)		(0.42653)	(1.53399)
	[-4.69330]	[-1.22129]		[0.50037]	[1.13178]
GVAPC(-6)	-1.530257	-7.155465	GPIBPC(-6)	0.312340	3.304024
	(0.61449)	(7.21859)		(0.46074)	(1.65704)
	[-2.49029]	[-0.99125]		[0.67790]	[1.99393]
GVAPC(-7)	-0.176517	-7.621252	GPIBPC(-7)	-0.115155	-0.775582
	(0.44732)	(5.25482)		(0.37688)	(1.35545)
	[-0.39461]	[-1.45034]		[-0.30554]	[-0.57220]
GVAPC(-8)	-1.077599	-5.047493	GPIBPC(-8)	0.041401	-0.182816
	(0.30689)	(3.60508)		(0.30493)	(1.09667)
	[-3.51139]	[-1.40010]		[0.13577]	[-0.16670]
GVAPC(-9)	0.179428	-3.438402	GPIBPC(-9)	-0.148673	-0.250436
	(0.35325)	(4.14977)		(0.33895)	(1.21901)
	[0.50793]	[-0.82858]		[-0.43863]	[-0.20544]
D(LOGVAIS(-1))	0.067308	-0.494390	LOGYI(-1)	-0.049693	0.001144
	(0.03412)	(0.40087)		(0.09469)	(0.34055)
	[1.97244]	[-1.23330]		[-0.52478]	[0.00336]
D(LOGVAIS(-2))	0.037131	0.264433	LOGYI(-2)	-0.080554	-0.427055
	(0.03380)	(0.39707)		(0.10837)	(0.38976)
	[1.09851]	[0.66595]		[-0.74331]	[-1.09570]
D(LOGVAIS(-3))	0.347825	0.710383	LOGYI(-3)	0.031846	0.330618
	(0.05901)	(0.69320)		(0.08890)	(0.31972)
	[5.89442]	[1.02479]		[0.35822]	[1.03409]
D(LOGVAIS(-4))	-0.037177	1.451534	LOGYI(-4)	0.085738	0.237576
	(0.10549)	(1.23919)		(0.07497)	(0.26962)
	[-0.35243]	[1.17136]		[1.14363]	[0.88114]
D(LOGVAIS(-5))	0.081009	0.321299	LOGYI(-5)	-0.025569	-0.017706
	(0.03855)	(0.45290)		(0.06736)	(0.24227)
	[2.10119]	[0.70942]		[-0.37957]	[-0.07309]
D(LOGVAIS(-6))	0.016366	0.193811	LOGYI(-6)	-0.095018	-0.327402
	(0.04598)	(0.54018)		(0.06109)	(0.21970)
	[0.35591]	[0.35879]		[-1.55543]	[-1.49022]
D(LOGVAIS(-7))	-0.013602	0.250892	LOGYI(-7)	0.184716	0.557858
	(0.03205)	(0.37644)		(0.08305)	(0.29870)
	[-0.42447]	[0.66648]		[2.22405]	[1.86762]
D(LOGVAIS(-8))	0.179922	-0.120285	LOGYI(-8)	-0.123288	-0.359167
	(0.03441)	(0.40421)		(0.08017)	(0.28834)
	[5.22890]	[-0.29758]		[-1.53774]	[-1.24562]
D(LOGVAIS(-9))	0.089452	0.236404	LOGYI(-9)	-0.006367	-0.349197
	(0.06716)	(0.78890)		(0.05270)	(0.18953)

	[1.33200]	[0.29966]		[-0.12082]	[-1.84239]
C	-0.136370	0.390703	C	0.608681	10.24140
	(0.08284)	(0.97319)		(0.74363)	(2.67443)
	[-1.64611]	[0.40147]		[0.81852]	[3.82937]
LOGSUPMANUF	0.028389	0.049352	D(LOGIDE)	-0.010332	-0.038852
	(0.01280)	(0.15039)		(0.00875)	(0.03146)
	[2.21752]	[0.32816]		[-1.18108]	[-1.23494]
D(LOGIDEMAN)	0.015668	-0.002969	D(LOGSUP2)	0.637577	2.018038
	(0.00572)	(0.06722)		(0.46184)	(1.66098)
	[2.73803]	[-0.04416]		[1.38052]	[1.21496]
R-squared	0.973776	0.810872	R-squared	0.754108	0.971773
Adj. R-squared	0.842656	-0.134766	Adj. R-squared	-0.065530	0.877681
Sum sq. resids	0.000423	0.058417	Sum sq. resids	0.001734	0.022426
S.E. equation	0.010287	0.120848	S.E. equation	0.016999	0.061136
F-statistic	7.426616	0.857487	F-statistic	0.920050	10.32794
Log likelihood	101.8548	40.26427	Log likelihood	92.00794	57.44937
Akaike AIC	-6.468386	-1.541141	Akaike AIC	-5.259848	-2.699953
Schwarz SC	-5.444530	-0.517286	Schwarz SC	-4.251975	-1.692080
Mean dependent	0.019269	0.013976	Mean dependent	0.017989	7.741874
S.D. dependent	0.025935	0.113446	S.D. dependent	0.016468	0.174803

Source: (calculations of the author, 2019).

Table 4 - The optimal number of lags

Lag	LogL	LR	FPE	AIC	SC	HQ
0	80.48813	NA	1.04e-05	-5.799051	-5.409010	-5.690870
1	81.55779	1.625871	1.34e-05	-5.564623	-4.979563	-5.402352
2	82.61911	1.443395	1.74e-05	-5.329529	-4.549448	-5.113167
3	85.49917	3.456074	2.00e-05	-5.239933	-4.264833	-4.969482
4	89.42611	4.084018	2.17e-05	-5.234089	-4.063968	-4.909547
5	92.90329	3.059922	2.55e-05	-5.192263	-3.827122	-4.813631
6	95.54089	1.899074	3.41e-05	-5.083272	-3.523111	-4.650549
7	100.2637	2.644783	4.25e-05	-5.141098	-3.385917	-4.654285
8	137.8742	15.04420*	4.50e-06	-7.829938	-5.879737	-7.289035
9	161.1233	5.579776	2.12e-06*	-9.369864*[9]	-7.224642*	-8.774870*

Source: (calculations of the author, 2019).

Conclusion

In the recent international trade literature, the impact of EIME on economic growth has been neglected and too much emphasis has been placed on the contribution of EM and or IM to exports growth. In an attempt to propose a new method in evaluating jointly the two exports margins, this study proves the prevalence of both IM and EM in Tunisia via their LBD effect on

[9] * indicates lag order selected by the criterion LR: sequential modified LR test statistic (each test at 5% level)

economic growth along a period of 45 years. The HF index computed by using fine data accounts for the introduction of exported goods horizontally and vertically differentiated the change in quantities of already exported goods and the dropping out of old goods. This EDI is considered as a weight in the learning variable. The decrease of such index, implying a change in the exports configuration over the period, induces positive and significant effect of the learning variable on the manufacturing sector‘s value added growth but not on GDP growth.

The absence of a significant impact of the learning variable on GDP growth implies that EIME has actual benefits when exported goods are, as for manufactured goods, of a relatively high technological content. The new framework proposed by this study to provide theoretical grounds to EIME is also confirmed by these results. There is a LBD dimension of EIME given the technological change of exported goods that they imply. Indeed, LBD results in decreasing returns to scale unless there is improvement of goods. However, the prevalence of EIME, implying an increase in quantities of some exported products, an improvement of existing goods or an introduction of new goods over time, , makes the decreasing returns counteracted by TS between manufactured exported goods. Thus EIME are an integrant part of a growth process driven by LBD dynamics where TS induced by highly technological goods are favorable to producing still newer goods.

A distinction between the effects of EIME may be possible by the relative alternation found, over time, between the significant and non significant impact of the learning variable on manufacturing value added growth. It seems that productivity gains of experience increase cease after a given change on quantities of already exiting goods (IM of exports). IM of exports are however positively determinant of LBD-led growth when they are reinforcing, on the course of exporting more quantities, the experience increase. In such a case, the first learning phase associated to productivity gains is, yet, not overtaken. .
In the case of Tunisia, a significant change of goods occurs in average after three years (EM). However, the significant impact of the learning variable may be due to productivity gains associated to significant spillovers favored, in a first stage, by the increase of experience. Although extensive and intensive margins of exports are proved to be complementary, too much work has to be carried out in order to distinguish the amplitude of each one in providing a promising route about exports expansion.

Economic policy insights, that this study implies, are similar to those of Lucas (1993). According to this author, South Korea, by contrast to a historically similar country as Philippines, has become a large exporter of manufactured goods of increasing sophistication and has achieved a growth miracle in the nineties. This spectacular performance is attributed to Korean's specific discrepancy between the mix of goods consumed and the mix produced. Philippines continued to produce its traditional goods and has been deprived of profiting from technological learning spillovers. South Korea succeeds in shifting its workforce onto the production of goods not formerly produced there and allows a learning based growth episode to occur thanks to TS favored by manufactured products exports promotion.

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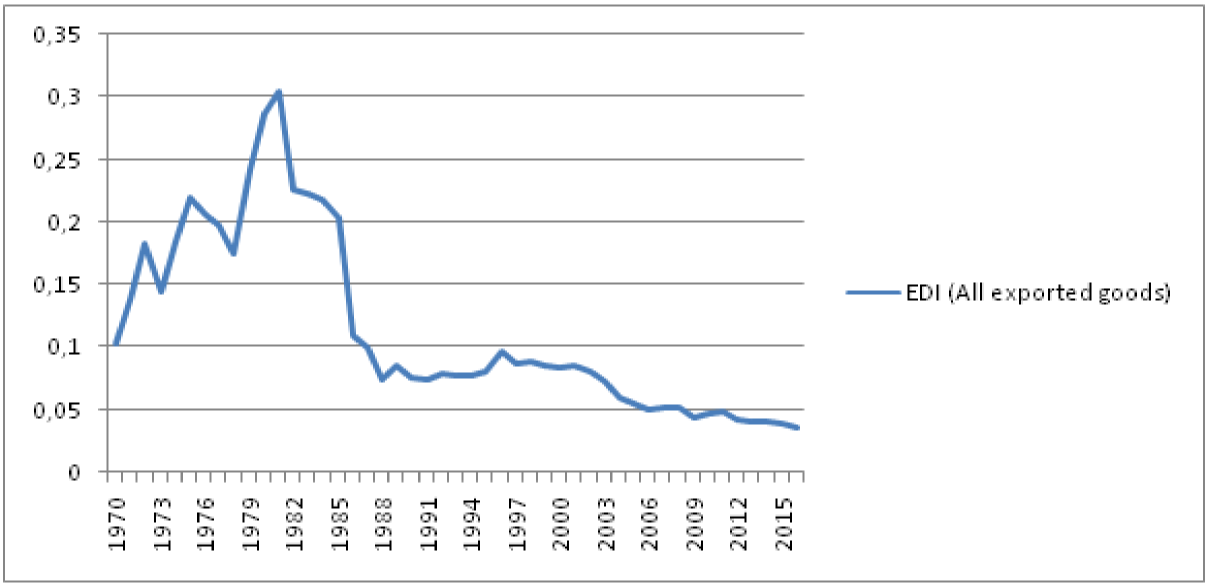
Appendix



Source: calculations of the author, 2019.

Figure 1 - Evolution, between 1970 and 2016, of the EDI for all exported goods (001-899)

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