Learning and Productivity Performance in Arab Manufacturing Industries

Riadh Ben Jelili

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Abstract

Enhancing workforce productivity in manufacturing industries requires a broad range of technological capabilities which can be acquired only by a long and costly process of learning. For most developing countries, the key to technological change is technological catch-up through learning, which means acquisition, diffusion and upgrading of technologies that already exist in more technologically advanced countries, than undertaking R&D to push the global knowledge frontier further. Continuous measuring of an ever-changing technological learning is then crucial for building technological capability and managing industrial policies in these countries. The key contribution of this paper is to provide direct estimates of learning effect using a panel of annual data and three-digit level International Standard Industrial Classification (ISIC) manufacturing industries for five Arab countries (Egypt, Jordan, Morocco, Oman and Tunisia) and two reference countries (Korea and Turkey).

التعلم والأداء الإنتاجي في الاقتصادات الصناعية العربية

رياض بن جليلي

ملخص

يتطلب تحسين إنتاجية قوة العمل في الصناعات التحويلية إطاراً واسعاً من الإمكانات التقنية، التي يستوجب تحقيقها عملية طويلة ومُكلفة للتعلم. إن مفتاح التغير التقني في معظم الدول النامية لا يتأتى من مباشرة عملية البحث العلمي والتطوير التقني في المجال الصناعي، ولكن من خلال إدراك التقانة عن طريق التعلم، وهو ما يعني التزود وانتشار وتطوير التقنيات المعمول بها في الدول المتقدمة. تكمن المساهمة الرئيسية لهذه الورقة في إعطاء تقديرات مباشرة لآثار التعلم باستخدام جدول من البيانات السنوية للصناعات التحويلية لخمس من الدول العربية (مصر، الأردن، المغرب، عُمان، وتونس) موزعة على الحد الثالث للتصنيف الصناعي القياسي الدولي، ولدولتين مرجعيتين (كوريا وتركيا).

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Introduction

Economic analysis of productivity improvements is vital to the understanding of economic growth and development. Such improvements may be achieved by continuous technological learning. The importance of a firm>s effective performance has been emphasized in the literature (Arrow, 1962; Kim, 2001; Figueiredo, 2002). Even when it has a technologically superior product, a new manufacturing firm must learn other skills to position its product successfully in the market and develop the competencies that are necessary for better economic performance.

As mentioned by Platt and Wilson (1999), technological learning can be understood as a process of accumulation of knowledge, information, skills, competencies, and experience in order to generate changes in a productive system, accumulate technological capability over time and sustain competitiveness in price and quality. It is a cumulative and costly process in the sense that it utilizes as inputs the existing knowledge base embedded in humans, machines and organizational routines in a great variety of ways. It also requires sufficient level of financial resources to acquire these necessary inputs.

To improve competitiveness, both governments and firms should be concerned with capability building. Of course, activities that aim to increase ability to make effective use of technological knowledge in production and engineering take place largely at firms. However, a government's public policy can establish important infrastructure and promote conducive environments favoring the strengthening of learning and innovation capabilities and the continuous technological development at the sectoral level.

From the microeconomic point of view, it is considered that a firm with a workforce that exhibits greater willingness to learn and develop skills through cumulative production experience is able to achieve lower unit cost of production and substantive improvement in productivity. Learning curve (*LC*), as a line displaying the relationship between unit production time and the cumulative number of units produced, is a recording result of this cumulative production experience. The curve suggests that as the quantity produced is doubled, unit cost is reduced in some percentage. The learning has facilitated to achieve greater efficiencies in a workplace. As workers become more familiar with their tasks, their efficiency improves.

LC constitutes a precious tool for modeling technical change, evaluating the dynamic efficiency and competitiveness of firms and industries in the economy, and informing policy decisions related to manufacturing technology. Its theoretical foundation is based on three assumptions: Hypothesis 1: The amount of time required to complete a given task or unit of product will be less each time the task is repeated; Hypothesis 2: The unit time will decrease at a decreasing rate; and Hypothesis 3: The reduction in time will follow a predictable pattern. In general, each of these assumptions has been found to hold true in manufacturing industries (Magee, Copacino and Rosenfield, 1985).

The key contribution of this paper is to provide estimates of learning parameters using a panel of annual data and three-digit level International Standard Industrial Classification (ISIC) manufacturing industries for five Arab countries namely: Egypt, Jordan, Morocco, Oman and Tunisia and two reference countries, i.e. Korea and Turkey. It goes without saying that enhancing the levels of learning mechanisms is an important policy objective for the considered Arab countries, which are supposed to make concerted efforts to enhance learning process within sectors and capitalize on competence available within the firms in order to respond to global competition and remain competitive particularly in manufacturing industries.

The choice of these five Arab countries is primarily related to data availability at three-digit industry-level, and also motivated by the lack of knowledge among economists and policy makers about their learning capabilities. Korea is chosen because along with Turkey, it is often considered as a benchmark comparator for evaluating manufacturing competitiveness in the Arab world.

The Learning Curve: An Overview

The learning curve (*LC*) originates from observations that workers in manufacturing plants become more efficient as they produce more units. Drawing on the concept of learning in psychological theory, Arrow (1962) formalized a model explaining technical change as a function of learning derived from the accumulation of experience in production. In its original conception, the *LC* referred to the changes in the productivity of labor which were enabled by the experience of cumulative production within a manufacturing plant. It has since been refined by many authors, for example, Bahk and Gort (1993) made the distinction between labor learning, capital learning, and organizational learning. Others developed the experience curve to provide a more general formulation of the concept, including not just labor but all manufacturing costs (Conley, 1970) and aggregating entire industries rather than single plants (Dutton and Thomas, 1984).

Though different in scope, each of these concepts is based on Arrow's explanation that learning-by-doing provides opportunities for cost reductions and quality improvements. As a result, these concepts are often grouped under the general category of learning curves. An important implication of the experience curve is that increasing accumulated experience in the early stages of a technology is a dominant strategy both for maximizing the profitability of firms and the societal benefits of technology-related public policy.

The *LC* model operationalizes experience as the explanatory variable using a cumulative measure of production or use. Changes in cost typically provide a measure of learning and technological improvement, and represent the dependent variable. *LC* studies have experimented with a variety of functional forms to describe the relationship between cumulative capacity and cost (Yelle, 1979). The log-linear function is most common, perhaps for its simplicity and generally high goodness-of-fit to observed data.

The central parameter in the *LC* equation is the exponent defining the slope of a power function, which appears as a linear function when plotted on a log–log scale. This parameter is known as the learning coefficient (b) and may be used to calculate the progress ratio (PR) and the learning ratio (LR) as shown below where C is labor unit cost and $QCUM$ represents cumulative output:

$$C_t = C_0 \left(\frac{QCUM_t}{QCUM_0} \right)^{-b} \qquad \text{(Equation 1)}$$

$$PR = 2^{-b} \qquad \text{(Equation 2)}$$

$$LR = (PR - 1) \times 100 \qquad \text{(Equation 3)}$$

The *LR* indicates the percentage decrease in labor cost when the cumulative output is doubled. The larger the *LR* is, the greater is the cost reduction gain.

The *PR* states that doubling total production reduces unit production costs by a factor of 2^{-b}. When learning takes place, values of the progress ratios are expected to be between 0 and 1. As the ratio gets closer to zero, learning becomes better while getting close to one indicates lower levels of learning. *PR* > 1 suggests unit cost increase instead of cost reduction. It signals increase in unit production costs and a loss in efficiency as the total production increases. The progress ratio can easily be interpreted. For example, a 60% progress ratio means that the value of per unit production cost would cut 40% and reduce to its 60% value whenever the production doubles. Case studies conducted in a broad range of industries showed that the typical progress ratios listed in the literature range between about 60% and 95% for all technologies.

The *LC* provides a suitable model for several reasons. Firstly, the availability of the two empirical time series required to build an experience curve (cost and production data) facilitates testing of the model. As a result, a rather large body of empirical studies has emerged to support the model (Yelle, 1979; Badiru, 1992; Promongkit, Shawyun and Sirinaovakul, 2000; Karaoz and Albeni, 2005). Secondly, earlier studies of the origin of technical improvements, such as in the aircraft industry (Alchian, 1963) and shipbuilding (Rapping, 1965) provide narratives consistent with the theory that firms learn from past experience. Thirdly, studies cite the generally high goodness-of-fit of power functions to empirical data over several years, or even decades, as validation of the model. Fourthly, the dynamic aspect of the model ─ the rate of improvement adjusts to changes in the growth of production ─ makes the model superior to those which treat change purely as a function of time. Finally, the reduction of the complex process of innovation to a single parameter, the learning rate, facilitates its inclusion in manufacturing supply equation and more general macroeconomic models.

Methodology

As mentioned above, the *LC* has been formulated in a variety of ways. A common version expresses the logarithm of the average cost of production as a linear function of the logarithm of the cumulative output. In this paper and for data availability considerations, value added per worker is used instead of unit cost as the dependent variable. When employees in an industry learn and gain experience by producing more of the same product, the value created per employee or the productive performance of the worker will increase; and the cost per unit of output will accordingly decline.

To quantify the learning effect, the following assumptions are adopted (Heng and Thangavelu, 2005):

Hypothesis 1: The value-added per worker (*VAW*) is a function of the cumulative production (*QCUM*). In logarithmic form, the *LC* can be written as :

$$Log(VAW_t) = \alpha + \beta Log(QCUM_t^*) \qquad \text{(Equation 4)}$$

where *QCUM** is a latent variable measured by the weighted average of past *QCUM*:

$$Log(QCUM_t^*) = \lambda_0 Log(QCUM_t) + \sum_{i=1}^{\infty} \lambda_i Log(QCUM_{t-i}) \qquad \text{(Equation 5)}$$

Hypothesis 2: The weights λ_i, $i=1,\ldots,\infty$, follow a geometric series which gives larger weight to recent observation than those in the past:

$$\lambda_i = \lambda_0 (1-\lambda_0)^i,\ i = 1,\ldots,\infty \quad \text{with} \quad \sum_{i=0}^{\infty} \lambda_i = 1 \qquad \text{(Equation 6)}$$

Replacing Equations 5 and 6 in Equation 4 gives the estimable function:

$$Log(VAW_t) = \alpha\lambda_0 + \beta\lambda_0 Log(QCUM_t) + (1-\lambda_0) Log(VAW_{t-1}) \qquad \text{(Equation 7)}$$

The learning index (*LIV*) is defined as:

$$LIV = \left(2^{\beta} - 1\right) \times 100 \qquad \text{(Equation 8)}$$

It indicates the percentage increase in value-added per worker (labor productivity) when the cumulative output is doubled. The larger the *LIV* is, the greater is the productivity gain.

The estimation of the *LC* is conducted separately for each of five Arab countries namely: Egypt, Jordan, Morocco, Oman and Tunisia; and each of the two reference countries to wit: Korea and Turkey, using a panel of annual data and three-digit level ISIC Revision 2 code manufacturing industries. Period coverage as well as sector coverage differ for each considered Arab country as shown in Appendix 2, Table A1. The data for manufacturing output, value added and labor are from the UNIDO Industrial Statistics Database (Indstat3, 2006 ed). The GDP deflator indices are from the IMF World Economic Outlook database.

In deriving the data series on the cumulative output for each country and industry, it is assumed that the initial cumulative stock of output in the starting year is 3 times that of the output in the previous year. The values of cumulative output for the other years are obtained by the recurrent formula:

$$QCUM_t = QCUM_{t-1} + Q_{t-1} \qquad \text{(Equation 9)}$$

where Q_{t-1} is the output in year t – 1. Output and value added are accordingly deflated by the GDP deflator indices.

Empirical Results

Equation 7 has been estimated using pool procedure presented in Appendix 1. The *LIV* is derived from the learning elasticity β by using Equation 8. The estimated values of β and *LIV* for the manufacturing clusters ranked in descending order are presented in Appendix 2, Tables A2 to A8. One way to summarize the detailed results is to look at the average of the five highest *LIV* for each country. Figure 1 presents these averages.

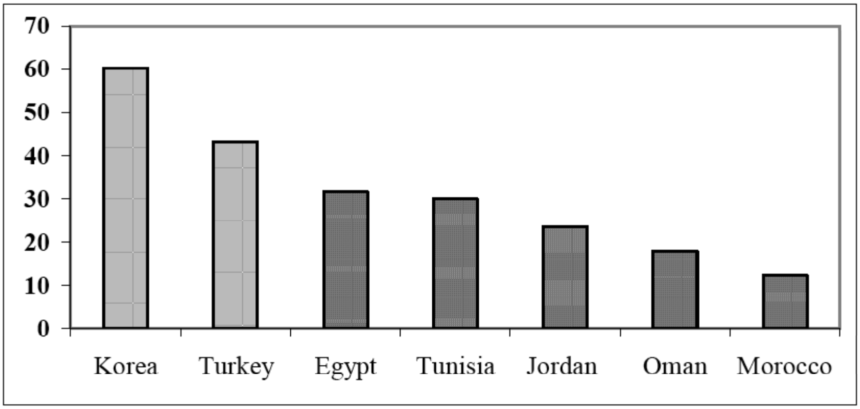

Figure 1. Average of five higher manufacturing *LIV*.

As shown in Figure 1, Korea ranks top among the considered countries with an average of five higher manufacturing *LIV* of 60.1 %. The gap with the average *LIV* for the five Arab countries is about 37%. Within the five considered Arab countries, Egypt and Tunisia perform best for this indicator, with 31.5 % for Egypt and 29.8 % for Tunisia.

No Arab country has achieved *LIV* above 35 % in any manufacturing sector. Even for Arab countries that are supposed to have developed manufacturing sectors, the *LIV* is relatively low particularly in industries which are often classified as "high tech" such as professional and scientific equipment, machinery as well as chemical products and which are supposed to have relatively good learning scores (cf. Figure 2). The average learning index is 28.3 %, 27.5 %, 21.4 %, 16.1% and 10.8 % respectively in Egypt, Tunisia, Jordan, Oman and Morocco, compared to 40.5 % in Korea.

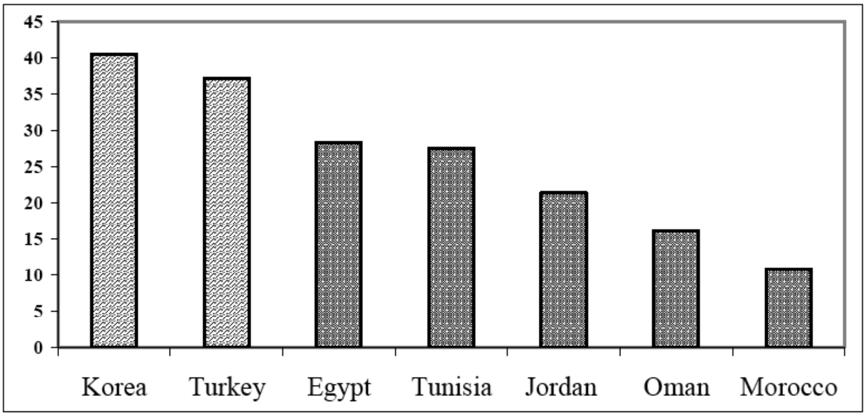

Figure 2. Average of “high tech” manufacturing *LIV*.

Although relatively small, the variability of the learning rates in each Arab country is much less important than in Korea and Turkey. The standard deviation of the estimated *LIV* is 2.04, 1.98, 2.3, 2.72 and 1.54 for Egypt, Jordan, Morocco, Oman and Tunisia respectively compared to 10.84 for Korea and 10.94 for Turkey. This probably reflects a generalized low learning process in Arab countries compared to a richer experience in comparator countries.

From Appendix 2, Tables A1-A8, Table 1 below summarizes the *LIV* results for the best and worst performers for manufacturing clusters.

Table 1. Best and Worst Performers for Manufacturing Clusters

	ISIC Code	Industry	*LIV (%)*
Best Performers			
Korea	355	Rubber products	64.7*
Turkey	372	Non-ferrous metals	47.7
Egypt	353	Petroleum refineries	34.2
Tunisia	390	Other manufactured products	31.2
Jordan	372	Non-ferrous metals	24.3
Oman	353	Petroleum refineries	23.8
Morocco	371	Iron and steel	14.8
Worst Performers			
Korea	381	Fabricated metal products	19.6
Turkey	354	Misc. petroleum and coal products	6.7
Egypt	321	Textiles	23.4
Tunisia	311	Food products	24.9
Jordan	311	Food products	17.3
Oman	322	Wearing apparel, except footwear	9.0
Morocco	322	Wearing apparel, except footwear	5.8

N.B. In Korea, Rubber products cluster is able to achieve 64.7% increase in productivity when cumulative output is doubled.

Source: Author's calculations.

As shown in Table 1, the magnitude of learning effects for the best and worst performers differs from one industry to another. The best and worst performers differ also from one country to another. Moreover, between the worst performers in terms of learning effects, industries are found that have been actively promoted. Traditional industries, like textiles and clothing, rubber and plastic products, non-metal mineral products, fabricated metal products, food and beverage were observed to have relatively lower *LIV* scores either because these activities are often dependent on unskilled labor or because of low value added and lack of product innovation.

All these heterogeneities in industrial technological learning level may be attributed to different macro, industrial, and/or micro level factors such as government policies, level of stock of knowledge, financial, human and physical capital and demand structure. They could broadly be investigated in further studies .

Conclusion

This paper indicates that the five considered Arab countries – Egypt, Jordan, Morocco, Oman and Tunisia – have a relatively inexperienced and less capable manufacturing workforce compared to the two reference countries, i.e. Korea and Turkey, as illustrated by the weak learning and productivity improvements in Arab manufacturing industries.

To empower the productivity growth with the learning potentials, it is highly recommended that cluster of industries with relatively good learning potential be given more encouragement and intensively emphasized compared to other clusters of industries with poor learning potential to enable sustainable growth.

Three factors, not necessarily independent of each other, could be identified as potential explanation for the variation of learning performance: (a) Export orientation; (b) Level of human capital; and (c) Availability of physical assets per worker. Unfortunately, the lack of disaggregated data at this stage of the analysis did not enable the testing of the contribution of these factors and to empirically determine the sources of the learning effects.

This study may be extended in several directions. An important caveat is that the learning effects are invariant over time. Like many economic activities, the technological learning level would vary over time, depending on the special given circumstances. Various extended non-linear models have been derived suggesting that the learning elasticities and the learning rates are dynamic over time (Badiru, 1992; Carlsson,1996; Kim, 2001; Karaoz and Albeni, 2005). The nonlinear or dynamic approach to the experience curve would be a useful tool both for estimating the long-term annual technological progress ratios of the past periods and for predicting its future path (Karaoz and Albeni, 2005).

Another shortcoming of the approach adopted in this study when analyzing experience curves is the difficulty to separate different dynamic cost elements such as input price and scale effects from that of technological knowledge (Nye, 1996; Kim, 1998; Karaoz and Albeni, 2005). While economies of scale represent a movement along the unit cost curve, technological knowledge represents a shift in the same. A common approach is to incorporate an experience variable in the traditional Cobb–Douglas production function to distinguish between experience and scale effects. However, this approach omits the input price effect leaving doubts whether the experience effects are due to experience or simple input price reductions. A production function is not suitable to handle price information (Lundmark, 2008).

Appendix 1. Econometric Methodology

The estimation of Equation 7 is used which belongs to the following more general class of models that may be estimated using pool procedures:

$$y_{it} = \alpha_{it} + x'_{it}\beta_i + \varepsilon_{it}$$

where y_{it} is the dependent variable, and x_{it} and β_ι are vectors of non-constant regressors and parameters for i = 1, ..., N cross-sectional units (Isic code). Each cross-section unit is observed for dated periods t = 1, ..., T (sample from 1993 to 2003 for Tunisia as an example).

These data may be viewed as a set of cross-section specific regressions for *N* cross-sectional equations:

$$y_i = \alpha_i + x'_i\beta + \varepsilon_i$$

each with *T* observations, stacked on top of one another. For purposes of discussion, the stacked representation is referred to as:

$$Y = \alpha + X\beta + \varepsilon$$

where α, β and X are set up to include any restrictions on the parameters between cross-sectional units.

The residual covariance matrix for this set of equations is given by:

$$\Omega = E(\varepsilon\varepsilon') = E\begin{pmatrix} \varepsilon_1\varepsilon_1' & \varepsilon_2\varepsilon_1' & \cdots & \varepsilon_N\varepsilon_1' \\ \varepsilon_2\varepsilon_1' & \varepsilon_2\varepsilon_2' & \cdots & \varepsilon_N\varepsilon_2' \\ \vdots & \vdots & \ddots & \vdots \\ \varepsilon_N\varepsilon_1' & \varepsilon_2\varepsilon_N' & \cdots & \varepsilon_N\varepsilon_N' \end{pmatrix}$$

The basic specification treats the pool specification as a system of equations and estimates the model using system Ordinary Least Squares (OLS). This specification is appropriate when the residuals are contemporaneously uncorrelated, and time-period and cross-section homoskedastic:

$$\Omega = \sigma^2 I_N \otimes I_T$$

The **fixed effects** estimator allows α_i differing across cross-section units by estimating different constants for each cross-section (industry). The fixed effects are generally computed by subtracting the “within” mean from each variable and estimating OLS using the transformed data. The coefficient covariance matrix estimates are given by the usual OLS covariance formula applied to the mean differenced model.

The **random effects** model assumes that the term α_{it} is the sum of a common constant α and a time-invariant cross-section specific random variable that is uncorrelated with the residual ε_{it}. The random effects model can be estimated using the Generalized Least Squares (GLS) procedure.

Cross-section weighted regression is appropriate when the residuals are cross-section heteroskedastic and contemporaneously uncorrelated:

$$\Omega = E(\varepsilon\varepsilon') = E\begin{pmatrix} \sigma_1^2 I_T & 0 & \cdots & 0 \\ 0 & \sigma_2^2 I_T & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_N^2 I_T \end{pmatrix}$$

It may be estimated by performing feasible GLS where σ^2_i are estimated from a first-stage pooled OLS regression.

Seemingly Unrelated Regression (SUR) weighted least squares, or Parks estimator, is the feasible GLS estimator when the residuals are both cross-section heteroskedastic and contemporaneously correlated:

$$\Omega = E(\varepsilon\varepsilon') = E\begin{pmatrix} \sigma_{11} I_T & \sigma_{12} I_T & \cdots & \sigma_{1N} I_T \\ \sigma_{21} I_T & \sigma_{22} I_T & \cdots & \sigma_{2N} I_T \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{N1} I_T & \sigma_{N2} I_T & \cdots & \sigma_{NN} I_T \end{pmatrix} = \Sigma \otimes I_T$$

where Σ is the symmetric matrix of contemporaneous correlations.

The parameter estimates and the covariance matrix of the parameters of the model are computed using the standard GLS formulae.

Appendix 2. Tables

Table A1. Sectors and Period Covered by Country

ISIC Code	ISIC Description	Countries			
		Egypt 1980 to 1996	Jordan 1980 to 2000	Morocco 1988 to 2000	Oman 1994 to 2003
311	Food products	YES	YES	YES	YES
313	Beverages	YES	YES	YES	YES
321	Textiles	YES	YES	YES	YES
322	Wearing appare Wearing apparel, except footwear	YES	YES	YES	YES
323	Leather products	YES	YES	YES	**NO**
324	Footwear, except rubber or plastic	YES	YES	**NO**	YES
331	Wood products, except furniture	YES	YES	YES	YES
332	Furniture, except metal	YES	YES	**NO**	YES
341	Paper and products	YES	YES	YES	YES
342	Printing and publishing	YES	YES	**NO**	YES
351	Industrial chemicals	YES	YES	YES	YES
352	Other chemicals	YES	YES	**NO**	YES
353	Petroleum refineries	YES	YES	**NO**	YES
354	Misc. petroleum and coal products	YES	**NO**	**NO**	**NO**
355	Rubber products	YES	YES	YES	YES
356	Plastic products	YES	YES	**NO**	YES
361	Pottery, china, earthenware	YES	YES	**NO**	**NO**
362	Glass and products	YES	YES	**NO**	YES
369	Other non-metallic mineral products	YES	YES	**NO**	YES
371	Iron and steel	YES	YES	YES	**NO**
372	Non-ferrous metals	YES	YES	**NO**	YES
381	Fabricated metal products	YES	YES	YES	YES
382	Machinery, except electrical	YES	YES	**NO**	YES
383	Machinery, electric	YES	YES	YES	YES
384	Transport equipment	YES	YES	YES	YES
385	Professional & scientific equipment	YES	**NO**	YES	**NO**
390	Other manufactured products	YES	YES	YES	YES

Table A2. Learning Index for the Egyptian Manufacturing Clusters

ISIC Code	ISIC Description	Estimated β	*LIV (%)*
353	Petroleum refineries	0.4246	34.2
354	Misc. petroleum and coal products	0.3967	31.6
390	Other manufactured products	0.3918	31.2
361	Pottery, china, earthenware	0.3884	30.9
385	Professional & scientific equipment	0.3723	29.4
313	Beverages	0.3713	29.4
355	Rubber products	0.3679	29.0
383	Machinery, electric	0.3663	28.9
323	Leather products	0.3632	28.6
342	Printing and publishing	0.3624	28.6
372	Non-ferrous metals	0.3614	28.5
356	Plastic products	0.3602	28.4
332	Furniture, except metal	0.3597	28.3
362	Glass and products	0.3588	28.2
341	Paper and products	0.3585	28.2
369	Other non-metallic mineral products	0.3574	28.1
352	Other chemicals	0.3566	28.0
351	Industrial chemicals	0.3511	27.5
382	Machinery, except electrical	0.3499	27.4
381	Fabricated metal products	0.3491	27.4
322	Wearing apparel, except footwear	0.3490	27.4
324	Footwear, except rubber or plastic	0.3490	27.4
331	Wood products, except furniture	0.3486	27.3
384	Transport equipment	0.3428	26.8
371	Iron and steel	0.3340	26.1
311	Food products	0.3204	24.9
321	Textiles	0.3038	23.4

N.B. Method of estimation pooled GLS with Cross-section specific regressors and in presence of period specific effects. Panel Corrected Standard Error (PCSE) methodology is used to obtain covariance estimators which are robust to heteroskedasticity across periods. Source: Author's calculations.

Table A3. Learning Index for the Jordanian Manufacturing Clusters

ISIC Code	ISIC Description	Estimated β	*LIV (%)*
372	Non-ferrous metals	0.3142	24.3
313	Beverages	0.3122	24.2
361	Pottery, china, earthenware	0.3030	23.4
355	Rubber products	0.2967	22.8
371	Iron and steel	0.2963	22.8
351	Industrial chemicals	0.2945	22.7
383	Machinery, electric	0.2904	22.3
323	Leather products	0.2876	22.1
384	Transport equipment	0.2815	21.5
353	Petroleum refineries	0.2755	21.0
382	Machinery, except electrical	0.2667	20.3
352	Other chemicals	0.2656	20.2
369	Other non-metallic mineral products	0.2647	20.1
321	Textiles	0.2640	20.1
341	Paper and products	0.2636	20.0
342	Printing and publishing	0.2629	20.0
324	Footwear, except rubber or plastic	0.2576	19.5
362	Glass and products	0.2558	19.4
356	Plastic products	0.2503	18.9
331	Wood products, except furniture	0.2503	18.9
390	Other manufactured products	0.2428	18.3
332	Furniture, except metal	0.2400	18.1
381	Fabricated metal products	0.2352	17.7
322	Wearing apparel, except footwear	0.2299	17.3
311	Food products	0.2298	17.3

N.B. Method of estimation pooled GLS with Cross-section specific regressors and in presence of period specific effects. White diagonal methodology is used to obtain covariance estimators which are robust to heteroskedasticity across periods.

Source: Author’s calculations.

Table A4. Learning Index for the Moroccan Manufacturing Clusters

ISIC Code	ISIC Description	Estimated β	*LIV (%)*
371	Iron and steel	0.1992	14.8
313	Beverages	0.1726	12.7
351	Industrial chemicals	0.1628	11.9
355	Rubber products	0.1549	11.3
341	Paper and products	0.1397	10.2
384	Transport equipment	0.1372	10.0
390	Other manufactured products	0.1337	9.7
383	Machinery, electric	0.1328	9.6
385	Professional & scientific equipment	0.1276	9.2
381	Fabricated metal products	0.1188	8.6
331	Wood products, except furniture	0.1156	8.3
311	Food products	0.1127	8.1
321	Textiles	0.1003	7.2
323	Leather products	0.0940	6.7
322	Wearing apparel, except footwear	0.0807	5.8

N.B. Method of estimation pooled GLS with Cross-section specific regressors and in presence of period specific effects. Panel Corrected Standard Error (PCSE) methodology is used to obtain covariance estimators which are robust to heteroskedasticity across periods.

Source: Author’s calculations.

Table A5. Learning Index for the Omani Manufacturing Clusters

ISIC Code	ISIC Description	Estimated β	*LIV (%)*
353	Petroleum refineries	0.3083	23.8
351	Industrial chemicals	0.2316	17.4
352	Other chemicals	0.2205	16.5
372	Non-ferrous metals	0.2172	16.2
355	Rubber products	0.2076	15.5
383	Machinery, electric	0.2059	15.3
382	Machinery, except electrical	0.2038	15.2
321	Textiles	0.1958	14.5
341	Paper and products	0.1919	14.2
362	Glass and products	0.1906	14.1
390	Other manufactured products	0.1878	13.9
356	Plastic products	0.1876	13.9
324	Footwear, except rubber or plastic	0.1842	13.6
369	Other non-metallic mineral products	0.1833	13.6
313	Beverages	0.1783	13.2
342	Printing and publishing	0.1778	13.1
332	Furniture, except metal	0.1770	13.1
311	Food products	0.1761	13.0
384	Transport equipment	0.1713	12.6
331	Wood products, except furniture	0.1644	12.1
381	Fabricated metal products	0.1583	11.6
322	Wearing apparel, except footwear	0.1244	9.0

N.B. Method of estimation pooled GLS with Cross-section specific regressors and in presence of period specific effects. Panel Corrected Standard Error (PCSE) methodology is used to obtain covariance estimators which are robust to heteroskedasticity across periods.

Source: Author's calculations.

Table A6: Learning Index for the Tunisian Manufacturing Clusters

ISIC Code	**ISIC Description**	**Estimated β**	***LIV (%)***
390	Other manufactured products	0.3918	31.2
361	Pottery, china, earthenware	0.3884	30.9
313	Beverages	0.3713	29.4
355	Rubber products	0.3679	29.0
323	Leather products	0.3632	28.6
372	Non-ferrous metals	0.3614	28.5
356	Plastic products	0.3602	28.4
341	Paper and products	0.3585	28.2
369	Other non-metallic mineral products	0.3574	28.1
351	Industrial chemicals	0.3511	27.5
382	Machinery, except electrical	0.3499	27.4
322	Wearing apparel, except footwear	0.3490	27.4
384	Transport equipment	0.3428	26.8
311	Food products	0.3204	24.9

N.B. Method of estimation pooled GLS with Cross-section specific regressors. Panel Corrected Standard Error (PCSE) methodology is used to obtain covariance estimators which are robust to heteroskedasticity across periods.

Source: Author’s calculations.

Table A7. Learning Index for the Korean Manufacturing Clusters

ISIC Code	ISIC Description	Estimated β	*LIV (%)*
355	Rubber products	0.7198	64.7
362	Glass and products	0.7072	63.3
324	Footwear, except rubber or plastic	0.6767	59.8
313	Beverages	0.6724	59.4
314	Tobacco	0.6170	53.4
369	Other non-metallic mineral products	0.6072	52.3
385	Professional & scientific equipment	0.5565	47.1
352	Other chemicals	0.5551	46.9
356	Plastic products	0.5530	46.7
321	Textiles	0.5360	45.0
311	Food products	0.5334	44.7
332	Furniture, except metal	0.5159	43.0
372	Non-ferrous metals	0.5104	42.4
383	Machinery, electric	0.5042	41.8
322	Wearing apparel, except footwear	0.4623	37.8
384	Transport equipment	0.4531	36.9
341	Paper and products	0.4483	36.4
361	Pottery, china, earthenware	0.4427	35.9
342	Printing and publishing	0.4393	35.6
351	Industrial chemicals	0.4345	35.1
331	Wood products, except furniture	0.4302	34.7
354	Misc. petroleum and coal products	0.4288	34.6
323	Leather products	0.4233	34.1
382	Machinery, except electrical	0.3927	31.3
371	Iron and steel	0.3683	29.1
381	Fabricated metal products	0.2578	19.6

N.B. Method of estimation pooled GLS with Cross-section specific regressors and in presence of cross sections specific effects. Panel Corrected Standard Error (PCSE) methodology is used to obtain covariance estimators which are robust to heteroskedasticity across periods.

Source: Author’s calculations.

Table A8. Learning Index for the Turkish Manufacturing Clusters

ISIC Code	ISIC Description	Estimated β	*LIV (%)*
372	Non-ferrous metals	0.5630	47.7
352	Other chemicals	0.5600	47.4
355	Rubber products	0.5009	41.5
361	Pottery, china, earthenware	0.4939	40.8
351	Industrial chemicals	0.4721	38.7
385	Professional and scientific equipment	0.4550	37.1
382	Machinery, except electrical	0.4418	35.8
356	Plastic products	0.4261	34.4
371	Iron and steel	0.4235	34.1
369	Other non-metallic mineral products	0.4173	33.5
311	Food products	0.4069	32.6
384	Transport equipment	0.4023	32.2
331	Wood products, except furniture	0.4009	32.0
381	Fabricated metal products	0.3911	31.1
341	Paper and products	0.3773	29.9
362	Glass and products	0.3664	28.9
324	Footwear, except rubber or plastic	0.3526	27.7
342	Printing and publishing	0.3516	27.6
383	Machinery, electric	0.3430	26.8
321	Textiles	0.3103	24.0
313	Beverages	0.2912	22.4
390	Other manufactured products	0.2729	20.8
332	Furniture, except metal	0.2262	17.0
353	Petroleum refineries	0.2194	16.4
323	Leather products	0.1859	13.7
322	Wearing apparel, except footwear	0.1306	9.5
314	Tobacco	0.0940	6.7
354	Misc. petroleum and coal products	0.0938	6.7

N.B. Method of estimation pooled GLS with Cross-section specific regressors and in presence of cross sections specific effects. Panel Corrected Standard Error (PCSE) methodology is used to obtain covariance estimators which are robust to heteroskedasticity across periods.

Source: Author’s calculations.

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