LEARNING AND PRODUCTIVITY PERFORMANCE IN SINGAPORE MANUFACTURING INDUSTRIES

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INTRODUCTION

In the need to respond to global competition and remain competitive, companies have made concerted efforts to capitalize on the intellectual properties and core competence available within the enterprises. In particular, it is reckoned that an enterprise 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. This short paper develops a simple model to investigate the phenomenon of learning and productive performance of workers in Singapore's manufacturing industries, which have continuously restructured to meet international challenges.

The results of the paper suggest that (a) there are substantial learning and productivity improvements in Singapore manufacturing industries, (b) the learning and productivity improvements varies across the different manufacturing clusters and (c) industries that are more open (higher export ratio) and have greater foreign ownership tend to experience higher learning effects.

LEARNING CURVE

The learning curve is one of the most important concepts in evaluating the dynamic efficiency and competitiveness of companies and industries in the economy. When employees in an industry learn and gain experience by producing more of the same product, the value created per employee (productive performance of the worker) will increase; and the cost per unit of output will accordingly decline.

[1] The authors would like to thank Ms Elizabeth Quah, the former director of the Manpower Planning and Policy Division in the Ministry of Manpower, for her helpful comments.

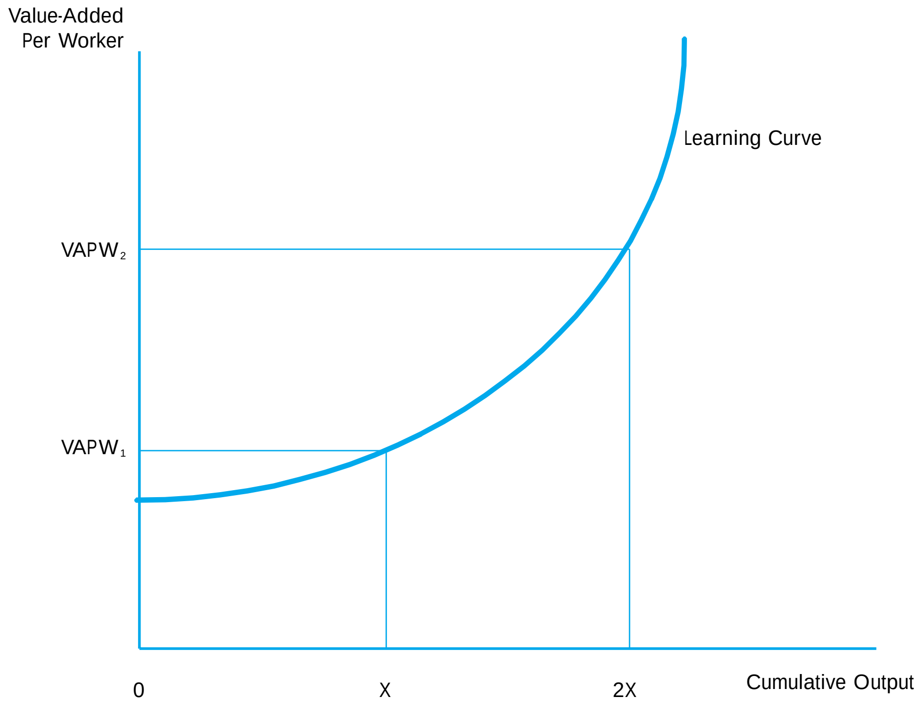
Hence, it is natural to specify that the unit cost of production to be dependent on the cumulative output since the start of production; or that the value-added per worker is expressed as a function of the cumulative production. In logarithmic form, the learning curve can be written as[2]:

$$\log VAPW = \mathbf{a} + \mathbf{b} \log QCUM$$

where VAPW is the value-added per worker, QCUM is the cumulative output since the start of production. **a** and **b** are parameters to be estimated.

Based on the estimated learning curve, we could derive the learning index, LIV, which indicates the percentage increase in value-added per worker (labour productivity) when the cumulative output is doubled (the derivation of LIV is given in the *Appendix*).

LEARNING CURVE AND LEARNING INDEX* [Exhibit 1]



* Learning Index = LIV = 100 x [$VAPW_2$ / $VAPW_1$ – 1]

APPLICATION TO THE MANUFACTURING INDUSTRIES

The learning curve is estimated for 6 clusters of manufacturing industries using data from 1980 to 2002. The clusters include precision instruments and machinery, electronics, refined petroleum products, transport equipment, chemical and chemical products as well as general manufacturing. The methodology used in estimating the learning curve is detailed in the *Appendix*.

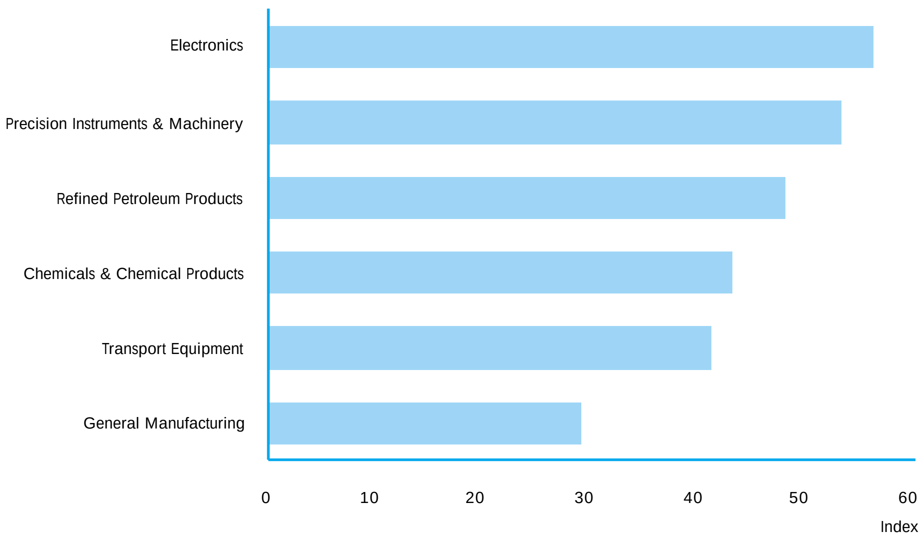
[2] The learning curve has been formulated in a variety of ways. A common version is that the logarithm of the average cost of production as a linear function of the logarithm of the cumulative output. In this paper we have opted for value creation per worker instead of unit cost as the dependent variable. For an alternative specification and estimation, see Toh M.H. & L.Low (1995) where comparison of learning across 3 Asian economies is made.

The estimated values of ‘**b**’ and the learning index, LIV is presented in *Exhibit 2*. A graphical presentation of the learning index, LIV, for the manufacturing clusters ranked in descending order is shown in *Exhibit 3*.

LEARNING INDEX FOR MANUFACTURING CLUSTERS [Exhibit 2]

	Industry Clusters	B	LIV
1	Electronics	0.6405	55.9
2	Precision Instruments & Machinery	0.6156	53.2
3	Refined Petroleum Products	0.5646	47.9
4	Chemicals & Chemical Products	0.5158	43.0
5	Transport Equipment	0.5003	41.5
6	General Manufacturing	0.3699	29.2

LEARNING INDEX FOR MANUFACTURING CLUSTERS [Exhibit 3]



In general, industries which are often classified as ‘high tech’ such as electronics, precision instruments & machinery, petroleum products as well as chemical products do have relatively good learning scores (i.e. LIV above 40). These are also industries that have been actively promoted. Traditional industries, like rubber and plastic products, non-metal mineral products, fabricated metal products, basic metals, and food, beverage and tobacco, which are included in general manufacturing cluster, were observed to have relatively lower LIV scores.

The electronics industry, which accounted for more than 40 per cent of manufacturing output in recent years, shows a strong LIV index of 56 per cent. Following closely is the precision instruments and machinery cluster which is able to achieve a 53 per cent increase in productivity when cumulative output is doubled.

FACTORS EXPLAINING THE VARIATION IN LEARNING PERFORMANCE

Four factors, not necessarily independent of each other, are identified as possible explanation for the variation of learning performance. They are (a) export orientation, (b) foreign equity participation, (c) level of human capital, and (d) availability of physical assets per worker.

Industries which are dependent on exports are likely to face higher level of competitive pressure which in turn will bring about faster rate of learning and productivity improvement (see Holger and Greenaway, 2002). Industries with more pervasive foreign ownership of companies will experience higher learning effects, since foreign companies tends to bring along new management techniques, methods of production and technological know-how.

Four factors are believed to underpin learning effects in industries.

The availability of more capital per employee in an industry is believed to accelerate learning and development of skill among workers, since new technology embodied in new capital stock tends to enhance learning and human capital. Thus we could expect skilled workers to learn and accumulate their human capital (technology specific skills) much faster than unskilled workers. The complementary effects of the skilled workers with new capital stock can be a contributory factor to accumulation of human capital. In this case, the higher level of human capital involved in production can be expected to engender a corresponding higher level of learning and productivity gains. However, a contrarian view is that over-reliance on capital may stifle learning when there is over-accumulation of capital and rapid structural changes. In this case, we could expect stagnant learning effects, where workers might be simply shifting from one learning curve to another.

To empirically determine the sources of the learning effects, we examined export intensity, share of foreign ownership (XOQ), share of foreign equities in industry (FS), proportion of employed workforce classified as professionals, associate professionals and technicians (HP), and net fixed assets per employee (KOL) in a simple linear correlation analysis with LIV. The correlation between LIV and each of the factors is shown in *Exhibit 4*[3].

CORRELATION COEFFICIENT OF LIV AND FACTORS [Exhibit 4]

	Correlation coefficient of LIV and factor	T statistics of Correlation Coefficients	Probability Value
Export to Output Ratio (XOQ)	0.5767	2.8235	0.0055
Share of Foreign Ownership (FS)	0.4493	2.0117	0.0462
Human Capital (HP)	0.3209	1.3553	0.1776
Capital Intensity (KOL)	0.0558	0.2237	0.8233

[3] The correlation results are based on the estimation of LIV for 20 different industries of the manufacturing sector from 1980 to 2002.

The correlation of export-output ratio (XOQ) and Share of Foreign Ownership (FS) to LIV is relatively high and statistically significant, which suggests that openness and foreign ownership structures tend to have positive impact on the productive performance of workers in Singapore. Human capital has a positive correlation with LIV but is only significant at the 18 per cent level. Similarly, capital intensity (KOL) does not seem to have any linear correlation with LIV.

The overall and interactive effects of the above variables were examined using a regression analysis. The results are given in the Appendix. The four factors together, are able to explain 80 per cent of the variation in Learning index, LIV. Export-output ratio (XOQ) maintains its significance as the main explanatory variable. Foreign ownership (FS) has a positive effect on productivity improvement, and the coefficient of XOQ is statistically significant at 10 per cent level.

The four factors are able to explain 80 per cent of the variation in the Learning Index.

Human capital has the expected positive sign, but is only marginally significant at the 12 per cent level. Somewhat contrary to expectation, capital intensity has a negative impact on learning. Though the magnitude is relatively small, it is statistically different from zero. While the notion that high capital asset per worker stifles learning cannot be ruled out, the influence of capital intensity on learning could be non-linear and indirect.

CONCLUSION

This paper indicates that Singapore has an experienced and capable manufacturing workforce, as illustrated by the substantial learning and productivity improvements in Singapore manufacturing industries. The effects of international competition also force learning across the industries. Empirical analysis shows that industries which have relatively higher export ratio and higher foreign ownership are able to attain better learning effects.

Learning effects found to correlate positively with the degree of international competition and foreign ownership.

The above study could be extended in several directions. An important caveat is that the learning effects of different age groups are not examined in the paper and these might be critical components of productive performance in an aging labour force. Similarly, the impact of training could be incorporated in the study. The study could also be extended to the services sector where the learning effects from “learning-by-doing” might be very important to maintain high service standards.

REFERENCES

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APPENDIX

A. The learning index, LIV is defined as:

$$LIV = (2^b - 1) \times 100$$

It indicates the percentage increase in value-added per worker (labor productivity) when the cumulative output is doubled. The larger is LIV, the greater is the productivity gain. Graphically as shown in *Exhibit 1*, when cumulative output doubles from X to 2X, LIV is equal $100 \times (VAPW_2 - VAPW_1)/VAPW_1$.

B. <u>Specification</u>

$$\mathrm{Log}(VAPW)_t = a + b.\log(QCUM^*)_t \quad (1)$$

Where VAPW = Value-added per worker
QCUM* = a latent variable measured by the weighted average of past $QCUM_t$.

$$\log QCUM^*_t = \lambda.\log QCUM_t + \lambda_1 \log QCUM_{t-1} + \lambda_2 \log QCUM_{t-2} + \ldots.$$

Suppose the weights follow a geometric series which gives larger weight to recent observation than those in the past:

That is $\lambda_1 = \lambda(1 - \lambda)$; $\lambda_2 = \lambda(1 - \lambda)^2$; $\lambda_3 = \lambda(1 - \lambda)^3$; …
Note that $\lambda + \lambda_1 + \lambda_2 + \lambda_3 + \ldots = 1$

$$\mathrm{Log}(VAPW)_t = a + b.[\lambda.\log QCUM_t + \lambda_1 \log QCUM_{t-1} + \lambda_2 \log QCUM_{t-2} + \ldots.] \quad (2)$$

$$\mathrm{Log}(VAPW)_t = a + b.[\lambda.\log QCUM_t + \lambda(1 - \lambda)\log QCUM_{t-1} + \lambda(1 - \lambda)^2 \log QCUM_{t-2} + \ldots.] \quad (3)$$

Lagging (3) by one period, multiply both sides of the resulting equation by $(1 - \lambda)$, and subtracting from (3) gives the estimable function as:

$$\mathrm{Log}(VAPW)_t = a\lambda + b\lambda.\log(QCUM)_t + (1 - \lambda)\log(VAPW)_{t-1} \quad (4)$$

Equation (4) can also be derived if QCUM* is assumed to be generated by the adaptive expectation process:

$$\log QCUM^*_t - \log QCUM^*_{t-1} = \lambda[\log QCUM_t - \log QCUM^*_{t-1}]$$

More compactly, equation (4) is written as:

$$\mathrm{Log}(VAPW)_t = \alpha + \beta.\log(QCUM)_t + \gamma.\log(VAPW)_{t-1} \quad (5)$$

When equation (5) is estimated, an estimate of the parameter, b can be obtained as $\beta/(1 - \gamma)$

C. Data Sources and Preparation

The main source of the data used in this exercise is the Annual Census of Industrial Production published by the Economic Development Board. The span of our data is from 1980 to 2003. In deriving the data series on the cumulative output for each industry, we assumed the initial cumulative stock of output in the starting year 1980 is 3 times that of the output in that year. The values of cumulative output for the other years are obtained by the recurrent formula:

$$QCUM_t = QCUM_{t-1} + Q_{t-1}$$

where Q_{t-1} is the output in year t – 1

Output and value added are accordingly deflated by the price indices (Domestic Supply Price Index used) available in the Yearbook of Statistics published by the Singapore Department of Statistics, to obtain variables in real terms.

D. Regression Results on Sources of the Learning Effects

The four factors are likely to exert their influence on learning simultaneously. Regression analysis can be used to discern the impact of individual factor while holding the other factors constant. The regression result is shown below:

Regression Results

$$LIV = \mathbf{15.357} + \mathbf{35.305}*XOQ + \mathbf{0.815}*FS + \mathbf{62.089}*HP - \mathbf{0.0727}*KOL$$

	C	XOQ	FS	HP	KOL
t-stat	1.602	1.963	1.934	1.693	-2.199
p-value	0.133	0.071	0.075	0.114	0.047

R-squared = 0.801 Adjusted R-squared = 0.709
F-statistic = 8.714 Prob value of F-stat = 0.0006