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**Learning by Exporting and High-tech Capital  
Deepening in Singapore Manufacturing  
Industries, 1974-2006**

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# Learning by Exporting and High-tech Capital Deepening in Singapore Manufacturing Industries, 1974-2006.

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## Abstract

A number of fundamental factors enhance the growth of industries' productivity. Among others, the export-led and high-tech capital deepening strategies are widely adopted by developing economies. This paper attempts to empirically investigate the extent to which both industrial development policies affect the total factor productivity growth (TFPG) in Singapore manufacturing industries from 1974 to 2006. Using the panel data estimations, I find that both development strategies bring about TFPG via non-neutral technological growth, and the former more largely explains TFPG than does the latter. The present study captures the measure of learning by exporting by the lagged export intensity and therefore contributes to the literature, in which only whether or not firms are active in export markets is conventionally employed. Methodologically, my main contributions are a more detailed treatment of (non-neutral) technological changes, and an improved measure of export intensity.

*Keywords:* Learning by exporting; High-tech Capital Deepening; Total Factor Productivity Growth; Neutral and Factor-biased Technological Progress.

*J.E.L. Classification:* F13 ; F14; L6

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## 1. Introduction

Productivity growth stems from a combination of fundamental factors, such as trade liberalization, high-tech capital deepening, expansion and improvement of educational facilities and development of new technologies. Among these factors, the export-led growth and high-tech capital formation are the most prevalent strategies adopted by developing economies (Stiglitz, 1996; and Bruton, 1998).

In the last three decades, the Singapore economy has experienced a considerable increase in the degree of openness as a result of the export-oriented industrialization strategy. To ensure that Singapore achieves a high growth path, a number of policy initiatives have also been implemented to move the manufacturing industries toward higher-technology, higher value added production by promoting high-tech capital deepening at the establishment level. In this paper, I examine the Singapore experiences with the export-led development and high-tech capital formation to reveal how these two strategies contribute to total factor productivity growth (TFPG) in Singapore manufacturing industries.

The mechanism through which exporting activities generate externalities vis-à-vis technological and informational spillovers and lead to productivity growth is the learning-by-exporting hypothesis (Evenson and Westphal, 1995).<sup>1</sup> Exporting activities enable firms to improve their efficiency since they obtain the access to new technology and technical assistance.<sup>2</sup> However, the empirical evidence regarding the causality running from export-market participation to productivity improvement is rather mixed and less clear-cut. Clerides, Lach, and Tybout (1998) employ the establishment-level data of manufacturing sectors in Colombia, Mexico, and Morocco and find little evidence that export-market participation results in higher productivity performance. Weak evidence of the learning effect is subsequently confirmed by Bernard and Jensen (1999) for the US; Aw, Chung, and Roberts (2000) for South Korea; and Greenaway and Kneller (2004) for the UK, among others. In contrast, a number of recent studies, such as Aw, Chung, and Roberts (2000) for Taiwan; Baldwin and Gu (2003) for Canada; Van Biesebroeck (2005)

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<sup>1</sup> It should be highlighted that the learning-by-exporting hypothesis is in contrast with the self-selection hypothesis (Bernard and Jensen, 1995; Bernard, et al., 2003; and Melitz, 2003) under which more productive firms become exporters.

<sup>2</sup> The way in which exporting activities bring about new knowledge works through international contacts with foreign markets.

for sub-Saharan Africa; and De Loecker (2007) for Slovenia, assert that exporters increase their productivity performance following the entry to export markets. It should be highlighted that the notion of the learning effect in all of these studies focuses on subsequent productivity improvements following export-market participation. To me, this conventional notion of learning by exporting fails to capture the role of export intensity which may shed light on the success in reaping benefits from technological and informational spillovers, which are the crucial mechanism through which the exposure to international markets leads to subsequent productivity growth.

High-tech capital deepening has been a source of debate as it has diffused into manufacturing sectors in various economies. One may expect that a high-tech capital accumulation results in higher productivity performance, thereby enhancing productivity growth and profitability. As is the learning effect, the impacts of high-tech capital formation on the productivity growth are unclear because the existing studies have yielded conflicting results.<sup>3</sup> Whereas Morrison and Berndt (1991) and Oliner and Sichel (1994) among others using the US data find that the contribution of high-tech capital investments to productivity improvements is small, Siegel and Griliches (1992) and Siegel (1997) show that high-tech capital formation is a crucial source of productivity growth. Furthermore, the later study by Oliner and Sichel (2000) updates their earlier work by showing that information technology, rather than computers, has contributed to productivity growth.

In this paper, I employ the data of two-digit SIC Singapore manufacturing industries from 1974 to 2006. My empirical strategies are based on the TFPG decomposition as in Feenstra and Hanson (1997). Using the panel data estimations, I find the following interesting results. Firstly, the learning effect and high-tech capital deepening affect TFPG via non-neutral (factor-biased) technological progress. Secondly, the former is labor- and capital-augmenting, but materials-saving, whereas the latter is materials- and energy-augmenting, but capital-saving. Lastly, although both development strategies contribute to TFPG in Singapore manufacturing industries, my empirical model

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<sup>3</sup> The contradictory results in the existing literature may be explained by the methodologies used for the calculation of productivity growth, data characteristics and sources, etc. See Siegel (1997) for more detailed discussions.

reveals that the learning effect can explain TFPG more largely than a high-tech capital accumulation.

The present paper contributes to the literature on the productivity impacts of learning by exporting and high-tech capital deepening in a number of ways. Firstly, this paper is the first to examine both industrial development policies in the Singapore manufacturing sector. Secondly, I employ lagged export intensity, instead of export-market participation, as a key variable representing the learning by exporting. This notion of the learning effect may better capture the extent to which an industry can obtain subsequent productivity improvements from engaging in exporting activities. Hence, the results may be complementary to the existing literature on export-led growth. Lastly, my TFPG decomposition aims to capture the neutral and factor-biased productivity effects. To the best of my knowledge, the present paper is the first attempt to answer not only whether the learning effect and the high-tech capital accumulation entail the performance improvement, but also how they affect the productivity growth.

The remainder of this paper is organized as follows: Section 2 depicts my data sources and the overview of the Singapore manufacturing sector. Section 3 discusses the empirical methodology and the estimation techniques. Section 4 presents the empirical results and evaluates the contributions of the learning effect and high-tech capital formation to TFPG. Section 5 concludes.

## **2. Data Sources and Overview of the Singapore Manufacturing Sector**

### *2.1 Data Sources*

The primary source of the dataset is retrieved from the *Census of Manufacturing Activities* (CMA) from 1974 to 2006 published by Singapore Economic Development Board (EDB), which collected comprehensive data on the establishments engaged in manufacturing activities, such as output, workers, value added, sales, exports, net fixed assets, and capital expenditure, classified according to the Standard Industrial Classification (SIC) and reported at the two-digit aggregation level.<sup>4</sup> Since the CMA database reports all variables in current-value terms, various price deflators are also used

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<sup>4</sup> I exclude the recycling of metal/non-metal waste and scrap from the dataset since it is absent from the reports from 2004 onwards.

and gathered from *Monthly Digest of Statistics Singapore* (MDSS) provided by Singapore Department of Statistics.<sup>5</sup>

As discussed in next section, the measurement of total factor productivity growth (TFPG) requires information on real value added, factor shares, and real factors of production. Real value added ( $V_t$ ) is calculated by value added deflated by Singapore Manufactured Products Price Index.<sup>6</sup> A factor share ( $s_{xt}$ ) is defined as the ratio of the payment to a particular input to total expenditure on all inputs. The number of workers ( $L_t$ ) can be directly retrieved from CMA. Capital ( $K_t$ ) is calculated by the value of estates (land, building, and structure) and machinery deflated by Commercial Property Rental Index and Machinery Price Index, respectively. Raw materials ( $M_t$ ) are measured by the value of raw materials deflated by Domestic Supply Price Index.<sup>7</sup> Energy ( $E_t$ ) is calculated from the cost of utilities and fuel deflated by Fuel Price Index.

Central to our analyses are the structural variables of learning by exporting and high-tech capital deepening. The export-market participation is commonly used as a proxy of learning by exporting in the literature. However, this measure may be inappropriate to capture the technological and informational spillovers of learning by exporting since the learning effect is more likely to depend on how intensive the exporting activities are, rather than only on whether a producer remains active in the export markets. In other words, export-market participation will not result significantly in the learning effect if the industries' export status is not improved. For example, the hike of productivity growth in the Singapore electronics industry may be explained more by its long-term expansion of exporting activities, which resulted in heightened adoption of new technology, acquiring new knowledge and technical assistance from international contact and exposure, and changes in managerial and organizational structures. Consequently, it may be more appealing to employ the ratio of exports to total sales, export intensity henceforth, lagged one period ( $XI_{t-1}$ ) as a proxy of learning by exporting.

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<sup>5</sup> The updated MDSS is available on-line at <http://www.singstat.gov.sg/pubn/reference/mdsjan.pdf>. All price indices are adjusted to have 1974 as the base year.

<sup>6</sup> Singapore Manufactured Products Price Index represents the production price of the commodity items.

<sup>7</sup> Domestic Supply Price Index measures the prices of imported and locally manufactured products retained for the use in the economy.

The index of high-tech capital deepening ( $T_t$ ) is measured by the ratio of high-tech machinery, such as computer machinery and office equipment, to total assets as in Amiti and Wei (2006).<sup>8</sup> Each type of assets is obtained from their net values at the end of year deflated by their appropriate price indices.<sup>9</sup> The general statistics and the correlation matrix of TFPG and structural variables are portrayed in Tables 1 and 2, respectively.

**[Insert Tables 1 and 2 here]**

## *2.2 Structural Characteristics in the Singapore Manufacturing Sector*

**[Insert Table 3 here]**

In the past three decades, Singapore has materialized exceptional rates of economic growth together with substantially low rates of unemployment. The development of manufacturing sectors played a pivotal role in the persistent economic growth, characterized by an expansion of manufactured exports and an accumulation of high-tech capital. With the average growth rate of 7.7 percent per annum, the Singapore manufacturing sector contributed 26 percent to Singapore's GDP and employed 32.2 percent of the total employed labor force on average during 1974-2006.

**[Insert Figures 1 here]**

Despite the lack of natural resources, Singapore's small size, strategic location, excellent port, well-established infrastructure, and well-endowed human capital made the manufacturing sectors as well as industrialization strategies to be highly outward-oriented. The volume of manufactured exports exhibited a dramatically increasing trend throughout the period of 1974-2006.<sup>10</sup> Under the Singapore's export-oriented path of industrial development, the learning by exporting hypothesis implies the subsequent indigenous learning process via the transfer of technological, administrative, marketing, organizational knowledge.

A series of policy initiatives directed toward a higher-technology capital accumulation in order to generate more value added manufactures also characterizes

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<sup>8</sup> In my dataset, capital stock is reported as market values at the end of the year and therefore has taken into account market prices and depreciation. In this sense, deflating the values of capital by the present price indices is justified.

<sup>9</sup> The deflators of asset values are retrieved from Singapore Manufactured Product Price Index.

<sup>10</sup> Singapore switched from the import-substitution policies to the outward-looking strategies in the late 1960s after the separation of Singapore from the Federation of Malaysia.

Singapore manufacturing industries during 1974-2006.<sup>11</sup> This is achievable with the strikingly high rates of investment, including FDI. The rationale why Singapore government tried to pave the way toward higher technology is that the shortage of labor resources will make an increase in the productivity growth in Singapore manufacturing industries infeasible otherwise. To ensure long-term productivity growth, Singapore government encouraged establishments in manufacturing sectors to upgrade their production efficiency by restructuring, automation, and computerization.

**[Insert Figure 2 and 3 here]**

Figure 2 reveals the time trends of the export intensity ( $XI$ ) and high-tech capital deepening ( $T$ ) in the Singapore manufacturing industries during 1974-2006. One may observe that the proportion of exports are roughly 50 percent of total sales and slightly increases over time despite a decline during early 1990s. In contrast, the high-tech capital intensity dramatically increases after the late 1980s from approximately 60 percent of total capital before 1990 to 80 percent after 2000. This may suggest the policy shifts or structural changes from the export orientation to the high-tech capital accumulation during early 1990s.

Figure 3 portrays the scattered plot of  $XI$  and  $T$  averaged across the time horizon. Although Figure 2 portrays that the export intensity ( $XI$ ) in Singapore manufacturing industries are relatively unchanged over time, Figure 3 shows that there is a cross-industry variation in the intensity of export activities. It reveals that electronic products, optical instruments, wearing apparel, pharmaceutical, and machinery are highly export-oriented ( $XI$ s are higher than 60 percent), whereas printing, basic metal, fabricated metal, rubber, and paper are not ( $XI$ s are lower than 40 percent). Figures 2 and 3 may imply that learning by exporting may be associated with industry-specific characteristics.<sup>12</sup> Furthermore, Figure 3 also unveils that Singapore manufacturing industries intensively employ high-tech capital since the index of  $T$  are ranging from 60-90 percent on average (except wearing apparel with  $T$  equal to 45 percent).

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<sup>11</sup> These policy initiatives were introduced in the early 1980s.

<sup>12</sup> The standard deviation of  $XI$  in each industry overtime ranges from a low of 3.3-3.5 percent (Printing and Reproduction of Recorded Media) to a high of 16.5-17 percent (Leather Product & Footwear and Refined Petroleum Product).

### 3. Empirical Methodology

The empirical approach to analyzing the roles of learning by exporting and high-tech capital deepening in explaining the productivity growth in Singapore manufacturing industries follows Feenstra and Hanson's (1997) methodology under which the discrete-time version of a total factor productivity growth (TFPG) index and the econometric model can be constructed. This methodology uncovers the channels through which these two factors affect TFPG and the extent to which they could explain TFPG. In so doing, I first discuss the measure of TFPG and then elaborate the econometric specifications and their estimation strategies.

#### 3.1 TFPG Measurement

The conventional approach to estimating the total factor productivity growth (TFPG) is to totally differentiate the production function to obtain the primal measure of TFPG, the growth rate of real output after deducted by the share-weighted growth of real production factors.<sup>13</sup> Although this measurement theoretically sounds, it is unclear how its infinitesimal changes in output and production factors could be applied for the real-world manufacturing data, which are in general reported either yearly or quarterly. To me, it may be more preferable to employ the TFPG measurement that can capture the discrete changes of those variables.

Consider a manufacturing sector comprised of  $N$  industries in which the production of real value added in an industry  $i$  ( $V_i$ ), where  $i = 1, \dots, N$ , requires four production factors: labor ( $L_i$ ), capital ( $K_i$ ), raw materials ( $M_i$ ), and energy ( $E_i$ ). To pursue further analyses, I assume the translog real value added function and temporarily drop the industry subscript.<sup>14</sup>

$$\ln V_t = a_{0t} + (\boldsymbol{\alpha} + \mathbf{a}_t)' \ln \mathbf{x}_t + \frac{1}{2} \ln \mathbf{x}_t' \mathbf{B} \ln \mathbf{x}_t, \quad (1)$$

where  $\mathbf{x}_t' = [L_t \quad K_t \quad M_t \quad E_t]$ , and  $\mathbf{B}$  is a  $4 \times 4$  matrix of parameters. The time-varying scalar  $a_{0t}$  and  $4 \times 1$  vector  $\boldsymbol{\alpha} + \mathbf{a}_t$  represent the neutral and factor-biased technological

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<sup>13</sup> Hsieh (2002) shows that, based on the national account identity, national income is equal to the payments to all factors of production, and hence the primal estimate of TFPG is equivalent to the dual one.

<sup>14</sup> Value added is defined as the difference between total output and the total operating cost incurred in the production of goods and services or ancillary activities. Therefore, it accounts for the uses of intermediate inputs and can be interpreted as the return to factors of production.

change, respectively. Furthermore, I also assume that the industry's technology (1) is symmetric and exhibits constant returns to scale. Therefore, the parameters in (1) pertain to the following constraints: 1)  $\mathbf{B}' = \mathbf{B}$ , 2)  $t'\boldsymbol{\alpha} = 1$ , 3)  $t'\mathbf{a}_t = \mathbf{0}$ , and 4)  $t'\mathbf{B} = \mathbf{B}'t = \mathbf{0}$ , where  $t$  is a vector whose elements are all unity. With the assumption of symmetry and homogeneity of degree one and from Shepard's Lemma, a revenue share ( $s_{xt}$ ) of a factor  $x$ , where  $x = L, K, M$ , and  $E$ , can be obtained by logarithmically differentiating (1) with respect to  $\ln \mathbf{x}_t$ .

$$\mathbf{s}_{xt} = \frac{\partial \ln V_t}{\partial \ln \mathbf{x}_t} = \boldsymbol{\alpha} + \mathbf{a}_t + \mathbf{B} \ln \mathbf{x}_t, \quad (2)$$

where  $\mathbf{s}_{xt} = [s_{Lt} \quad s_{Kt} \quad s_{Mt} \quad s_{Et}]$ .

By taking the first-difference operator into (1), it is straightforward to show that

$$\Delta \ln V_t = \Delta a_{0t} + \Delta \mathbf{a}_t' \overline{\ln \mathbf{x}_t} + (\boldsymbol{\alpha} + \overline{\mathbf{a}_t})' \Delta \ln \mathbf{x}_t + \frac{1}{2} \Delta (\ln \mathbf{x}_t' \mathbf{B} \ln \mathbf{x}_t), \quad (3)$$

where  $\overline{\ln \mathbf{x}_t} = \frac{1}{2} (\ln \mathbf{x}_{t-1} + \ln \mathbf{x}_t)$  and  $\overline{\mathbf{a}_t} = \frac{1}{2} (\mathbf{a}_{t-1} + \mathbf{a}_t)$ .<sup>15</sup>

The first two terms represent the total productivity changes, which can be further decomposed into the neutral ( $\Delta a_{0t}$ ) and factor-biased ( $\Delta \mathbf{a}_t' \overline{\ln \mathbf{x}_t}$ ) technological changes. The former captures the effect of technological progress on the overall productivity level, whereas the latter accounts for the changes in the efficiency of each production factor, which in turn affects relative factor demands and total industry productivity. Therefore, total factor productivity growth (TFPG) can be defined as

$$TFPG_t \equiv \Delta a_{0t} + \Delta \mathbf{a}_t' \overline{\ln \mathbf{x}_t}. \quad (4)$$

However, neither  $\Delta a_{0t}$  nor  $\Delta \mathbf{a}_t' \overline{\ln \mathbf{x}_t}$  is observable. To measure total factor productivity growth (TFPG), I have to make use of (2) to show that

$$\overline{\mathbf{s}}_{xt}' \Delta \ln \mathbf{x}_t = (\boldsymbol{\alpha} + \overline{\mathbf{a}_t})' \Delta \ln \mathbf{x}_t + \frac{1}{2} \Delta (\ln \mathbf{x}_t' \mathbf{B} \ln \mathbf{x}_t), \quad (5)$$

<sup>15</sup> To obtain (3), I make use of the fact that

$$\ln \mathbf{x}_t = \overline{\ln \mathbf{x}_t} + \frac{1}{2} \Delta \ln \mathbf{x}_t \quad \text{and} \quad \ln \mathbf{x}_{t-1} = \overline{\ln \mathbf{x}_t} - \frac{1}{2} \Delta \ln \mathbf{x}_t.$$

where  $\bar{\mathbf{s}}_{xt} = \frac{1}{2}(\mathbf{s}_{xt-1} + \mathbf{s}_{xt})$ . By substituting (4) and (5) into (3), we have a measure of total factor productivity growth as

$$TFPG_t = \Delta \ln V_t - \bar{\mathbf{s}}_{xt}' \Delta \ln \mathbf{x}_t. \quad (6)$$

The measure of total factor productivity growth (6) states that it is the growth rate of real value added after subtracting the averaged-share-weighted growth rates of production factors. This discrete measurement is analogous to the standard TFP Divisia index and applicable for the manufacturing dataset directly.<sup>16</sup>

### 3.2 Econometric Model and Estimations

Since my objective is to empirically investigate the impacts of learning by exporting and high-tech capital formation on Singapore's industry productivity, I introduce the lagged export intensity ( $XI_{t-1}$ ) and the high-tech capital deepening ( $T_t$ ) as crucial control variables.<sup>17</sup> Recall that the export intensity ( $XI$ ) is measured by the ratio of direct exports to total sales, and the high-tech capital deepening ( $T$ ) is calculated by the real value of high-tech capital to total capital.

Specifically, I assume that these structural variables affect both neutral and non-neutral technological levels of an industry  $i$  according to the following specifications:

$$a_{0it} = \gamma' \mathbf{J}_{it} + u_{it} \quad (7)$$

$$\mathbf{a}_{it} = \mathbf{C} \mathbf{J}_{it} + \mathbf{v}_{it}, \quad (8)$$

where  $\mathbf{J}_{it}$  is a vector of structural variables;  $\gamma$  and  $\mathbf{C}$  are a  $2 \times 1$  vector and a  $4 \times 2$  matrix of parameters; and  $u_{it}$  and  $\mathbf{v}_{it}$  are the error terms. By taking first differences and substituting (7) and (8) into (4), I obtain the econometric model of total factor productivity growth as follows

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<sup>16</sup> A TFP Divisia index captures the continuous growth rate of output out of the share-weighted growth rates of inputs and in general takes the following form

$$TFP_t = \hat{V}_t - \mathbf{s}_x' \hat{\mathbf{x}}_t,$$

where  $\hat{V} = \dot{V}/V$  and  $\hat{x} = \dot{x}/x$ . See Bartelsman and Gray (1996) for the detailed discussion.

<sup>17</sup> As explained in Amiti and Wei (2006), the high-tech capital deepening ( $T_t$ ) represents the industry-specific technological level. Therefore, it may be more reasonable to employ its current value  $T_t$ , rather than its lagged value  $T_{t-1}$ , as a determinant of productivity.

$$TFPG_{it} = \gamma' \Delta \mathbf{J}_{it} + \Delta \mathbf{J}_{it}' \mathbf{C}' \overline{\ln \mathbf{x}_{it}} + \varepsilon_{it} \quad (9)$$

where  $\varepsilon_{it} = \Delta \mathbf{v}_{it}' \overline{\ln \mathbf{x}_{it}} + \Delta u_{it}$  and  $E[\varepsilon_{it} | \Delta \mathbf{J}_{it}, \overline{\ln \mathbf{x}_{it}}] = 0$ . The natural interpretations of  $\gamma$  and  $\mathbf{C}$  are neutral and factor-biased productivity shifts, respectively. The former captures the direct impact of learning by exporting and high-tech capital deepening on TFPG and therefore can be interpreted as the neutral technological progress. In contrast, the latter represents their factor-augmenting effects or the indirect impacts on TFPG via changes in the relative demands for production factors.

Before discussing the econometric techniques employed for estimating the parameters in (9), it is worthwhile to discuss the specifications of the vector of structural variables  $\Delta \mathbf{J}_{it}$ . Firstly, one could expect that the industries which intensively engaged in exporting activities in the past can enjoy high productivity growth in the present. In this sense, learning by exporting affects the productivity growth. To capture this idea, it may be reasonable to utilize the level of lagged export intensity ( $XI_{t-1}$ ). I also employ the first-differenced, lagged export intensity ( $\Delta XI_{t-1}$ ) for a robustness check (see Baldwin and Gu, 2003).<sup>18</sup> Secondly, as conventionally employed in the literature, such as Feenstra and Hansen (1997) among others, the first-differenced high-tech capital deepening ( $\Delta T_t$ ) enters the equation (9) since high-tech capital intensity is related to the industry-specific levels of technology. Lastly, I implicitly control for the industry size since the ratios, rather than the levels, of exports to total sales ( $XI$ ) and high-tech capital to total capital ( $T$ ) are employed in the estimations. Accordingly, I define  $\Delta \mathbf{J}_{it}' \equiv [XI_{t-1} \quad \Delta T_t]$  and  $\Delta \mathbf{J}_{it}' \equiv [\Delta XI_{t-1} \quad \Delta T_t]$  in Specification I and II, respectively.

#### Specification I:

$$TFPG_{it} = \gamma_X XI_{it-1} + \gamma_T \Delta T_{it} + c_{LX} XI_{it-1} \overline{\ln L_{it}} + c_{LT} \Delta T_{it} \overline{\ln L_{it}} + c_{KX} XI_{it-1} \overline{\ln K_{it}} + c_{KT} \Delta T_{it} \overline{\ln K_{it}} + c_{MX} XI_{it-1} \overline{\ln M_{it}} + c_{MT} \Delta T_{it} \overline{\ln M_{it}} + c_{EX} XI_{it-1} \overline{\ln E_{it}} + c_{ET} \Delta T_{it} \overline{\ln E_{it}} + \varepsilon_{it} \quad (10)$$

#### Specification II:

$$TFPG_{it} = \gamma_X \Delta XI_{it-1} + \gamma_T \Delta T_{it} + c_{LX} \Delta XI_{it-1} \overline{\ln L_{it}} + c_{LT} \Delta T_{it} \overline{\ln L_{it}} + c_{KX} \Delta XI_{it-1} \overline{\ln K_{it}} + c_{KT} \Delta T_{it} \overline{\ln K_{it}} +$$

<sup>18</sup> Note that Baldwin and Gu (2003) proxy the industry performance by labor productivity, but we focus on TFPG.

$$c_{MX}\Delta XI_{it-1}\overline{\ln M}_{it} + c_{MT}\Delta T_{it}\overline{\ln M}_{it} + c_{EX}\Delta XI_{it-1}\overline{\ln E}_{it} + c_{ET}\Delta T_{it}\overline{\ln E}_{it} + \varepsilon_{it} \quad (11)$$

To control for unobservable industry heterogeneity, the parameter estimates in (10) and (11) will be obtained based on the Random Effects model estimated by the Generalized Least Squares (GLS).<sup>19</sup> As is well known, if the industries are heterogeneous, the Ordinary Least Squares (OLS) estimation will convey the biased estimators. I will employ the Breusch-Pagan test to investigate whether the industry-specific effects exist.

In addition to the industry heterogeneity, there are two potential econometric problems needed to be taken into considerations. First, it is possible that the unobservable industry-invariant effects are correlated with the structural variables included on the right-hand side of the equations (10) and (11). In this case, the assumption that  $E[\varepsilon_{it}|\Delta \mathbf{J}_{it}, \overline{\mathbf{lnx}}_{it}] = 0$  is violated, thereby resulting in the biased GLS estimates. To tackle with this problem, I will employ the Within and Between transformation together with the Hausman's specification test to reveal whether the GLS estimates are consistent and asymptotically efficient. It should be noted that the GLS estimates are tested based on the null that  $E[\varepsilon_{it}|\Delta \mathbf{J}_{it}, \overline{\mathbf{lnx}}_{it}] = 0$ , using two pairs of estimates: GLS estimates versus Within estimates and GLS estimates versus Between estimates. As shown by Hausman and Taylor (1981), these tests are numerically exactly identical.<sup>20</sup>

My empirical framework is based on the assumption that the translog value added function (1) is linearly homogenous. From (8), it is straightforward to see that it satisfies the homogeneity of degree one only when  $\iota' \mathbf{C} = \mathbf{0}$ . This assumption also implies that some of the coefficients representing the non-neutral technological changes have to be negative if others are positive. The negative factor-augmenting effects are said to be 'very factor-saving' according to Fei and Ranis' (1965) terminology.

Although the simplest way to handle this issue is to impose the parameter restrictions of  $\iota' \mathbf{C} = \mathbf{0}$  on (10) and (11) at priori, it impedes ones to empirically test whether this assumption does hold statistically. Therefore, rather than imposing the parameter restrictions of  $\iota' \mathbf{C} = \mathbf{0}$ , I first obtain the unrestricted estimates and then perform

<sup>19</sup> Under the random effects model, the GLS estimates are the Swamy-Arora estimators.

<sup>20</sup> Baltagi (2005), p. 70 provides a cautionary note that one should not utilize the pair of Within and Between estimators with the Hausman command in the Stata package.

the test whether the null hypothesis of  $t'C = \mathbf{0}$  can be rejected. In so doing, I test the null hypotheses of  $\sum_j c_{jX} = 0$  and  $\sum_j c_{jT} = 0$ , where  $j = L, K, M, E$ , jointly.

Moreover, due to the cross-industry variation in size, my parameter estimates may suffer from the problem of heteroskedasticity. Although ones may still obtain the consistent estimates under the homoskedastic disturbances when heteroskedasticity is present, the estimates will not be efficient. To correct this problem, I will employ the heteroskedasticity-robust estimators.

I then account for the extent to which learning by exporting ( $\Delta TFPG_X$ ) and high-tech capital deepening ( $\Delta TFPG_T$ ) may explain TFPG in Singapore manufacturing industries by evaluating the following equations at the mean values.

$$\Delta TFPG_{Xit} = \hat{\gamma}_X X_{it-1} + \hat{c}_{LX} X_{it-1} \overline{\ln L_{it}} + \hat{c}_{KX} X_{it-1} \overline{\ln K_{it}} + \hat{c}_{MX} X_{it-1} \overline{\ln M_{it}} + \hat{c}_{EX} X_{it-1} \overline{\ln E_{it}} \quad (12)$$

$$\Delta TFPG_{Tii} = \hat{\gamma}_T \Delta T_{it} + \hat{c}_{LT} \Delta T_{it} \overline{\ln L_{it}} + \hat{c}_{KT} \Delta T_{it} \overline{\ln K_{it}} + \hat{c}_{MT} \Delta T_{it} \overline{\ln M_{it}} + \hat{c}_{ET} \Delta T_{it} \overline{\ln E_{it}} \quad (13)$$

All in all, the empirical methodology for empirically investigating the impacts of learning by exporting and high-tech capital deepening on TFPG in Singapore manufacturing industries can be summarized as follows. Firstly, I measure the index of TFPG according to (6). Secondly, I perform the estimation techniques for testing the model specifications in (10) and (11) and obtaining the parameter estimates. Lastly, I make use of the estimates together with (12) and (13) to measure the contributions of both factors to TFPG in Singapore manufacturing industries.

#### 4. Empirical Results

In this section, the parameter estimates based on the methodology depicted in the previous section will be reported and analyzed. Moreover, I divide the dataset into two sub-periods, 1974-1994 and 1995-2006 to see whether the learning effect and high-tech capital deepening may be time-variant. Then, I utilize the estimates to evaluate the extent to which the learning-by-exporting effect and high-tech capital deepening may account for total factor productivity growth (TFPG) in the Singapore manufacturing sector.

##### 4.1 Neutral and Factor-augmenting Productivity Effects of Learning by Exporting and High-tech Capital Deepening

**[Insert Tables 4 here]**

Tables 4 reports the parameter estimates of the Specification I and II, respectively. The first column represents the empirical results based on the Random Effects model estimated by the Generalized Least Squares (GLS) with Swamy-Arora and heteroskedasticity-robust estimators. The second column portrays the Within (Fixed Effects) estimates obtained by the standard Ordinary Least Squares (OLS) with the heteroskedasticity-robust procedure. I also compute the Between estimates by utilizing the Weighted Least Squares (WLS) estimation reported in the third column. For the sake of presentation simplicity, I portray the estimates in the vector  $\gamma$  as the neutral technological progress (Neutral TP) and the matrix  $\mathbf{C}$  appearing in both (10) and (11) into the factor-augmenting technological progress (factor-augmenting TP).

Before analyzing the parameter estimates, the Breusch-Pagan LM statistic is statistically significant at 5 percent, and therefore the null hypothesis that there are no random effects can be rejected. This implies that controlling for industry-specificity under the Random Effects model is appropriate. As mentioned in the previous section, the crucial assumption of the panel regression model is  $E[\varepsilon_{it} | \Delta \mathbf{J}_{it}, \overline{\ln \mathbf{x}_{it}}] = 0$ . However, this assumption may not hold if the unobserved disturbances containing the industry-specific effects are correlated with  $\Delta \mathbf{J}_{it}$  and  $\overline{\ln \mathbf{x}_{it}}$ . If  $E[\varepsilon_{it} | \Delta \mathbf{J}_{it}, \overline{\ln \mathbf{x}_{it}}] \neq 0$ , the GLS estimates under the Random Effects model, as is well known, will be neither unbiased nor consistent. To account for this issue, I perform a Hausman's specification test. The Hausman test statistic yields a Chi-squared statistic of 4.42, and the null hypothesis that the GLS estimates under the Random Effects model are consistent cannot be rejected. In this sense, the GLS estimates reported in the first column may dominate those under the Within and Between Effects models.

In addition, my empirical framework, as discussed earlier, requires that the parameter estimates must satisfy  $t' \mathbf{C} = \mathbf{0}$ . The joint hypotheses testing on the GLS estimates reveal that the null of  $t' \mathbf{C} = \mathbf{0}$  cannot be rejected at the 5 percent level of

significance (the Chi-squared statistic is 4.9).<sup>21</sup> Hence, the GLS estimates well behave. Accordingly, the following analyses of empirical results will be elaborated based on the GLS estimates under the Random Effects model.

According to Table 4, I find the following interesting results. Firstly, the factor-biased effects of learning by exporting and a high-tech capital accumulation are both indispensable since the factor-biased effects seem to characterize the impacts of these two factors on TFPG, and the parameter estimates of neutral technological progress, resulting from the learning effect and the high-tech capital deepening are not statistically significant. Given the importance of factor-biased effects, the present paper attempting to segregate the productivity effects may yield clearer insights into these two paths of industrial development and shed further light on the literature on the learning effect and the high-tech capital deepening.

Secondly, the learning effect contributes to TFPG in Singapore manufacturing industries via the labor- and capital-augmenting technological progress (with coefficients of .035 and .049 and statistically significant at 5 and 10 percent, respectively). The export-led technological progress may be explained by the gains stemming from exporting activities (Evenson and Westphal, 1995). Exporters may obtain technical assistance, new product design, quality improvement, and product standardization, when dealing with foreign buyers. My results show that these benefits entail efficiency gains for labor and capital employed in the industries. To me, these findings are plausible given the knowledge that Singapore economy has long become export-oriented and its most important trading partners are the United States and Japan where production technology is highly advanced.

Thirdly, my TFPG decomposition reveals that the learning effect is not always beneficial for all factors of production. The results show that the learning effect brings about the materials-saving technological progress, thereby reducing intra-industry relative demands for raw materials. The negative learning effect on the relative demands for raw materials may be explained by the fact that the industries by engaging in exporting activities can obtain the access to the larger pool of intermediate materials. The

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<sup>21</sup> I also perform the test on the null hypotheses of  $\sum_j c_{jX} = 0$  and  $\sum_j c_{jT} = 0$  individually. Both cannot be rejected at 5 percent with the Chi-squared statistics equal to .24 and 3.52, respectively.

ability to source the production of intermediate materials, as opposed to employing raw materials and producing them in-house, will have negative impacts on the relative demands for raw materials employed domestically.

Fourthly, the high-tech capital deepening is capital-saving as the negative capital-augmenting technological progress (with a coefficient of -1.903 and statistically significant at 5 percent) prevails in the estimation results. This result is not surprising, however. It seems logical since the index of the high-tech capital deepening is measured by the ratio of high-tech capital to total capital. When the industries become high-tech capital-intensive, the existing capital is replaced. Hence, the capital-saving technological progress resulting from high-tech capital deepening should be observed.

Lastly, the high-tech capital accumulation is materials- and energy-augmenting (with coefficients of 1.274 and .802 and statistically significant at 5 and 10 percent, respectively). When the production technology becomes machinery- and computer-intensive, the efficiency of existing raw materials and energy inputs is augmented. In this sense, the high-tech capital deepening is complements to raw materials and energy relative utilization.

#### *4.2 A Robustness Check*

##### **[Insert Tables 5 here]**

In this sub-section, I attempt to perform a robustness check of the aforementioned empirical results under Specification I. In so doing, I re-estimate the parameters based on Specification II in which  $XI_{t-1}$  is replaced by  $\Delta XI_{t-1}$ . The interpretation of this specification is that the intensity of exporting activities affects the level, rather than the growth, of industry's technology.

Based on Table 5, the Breusch-Pagan LM statistic (with a Chi-squared statistic of 2.91 and statistically significant at 10 percent) rejects the null hypothesis of no Random Effects. Therefore, the GLS estimates under the Random Effects model are justified. Furthermore, the Hausman's specification test (with a statistic of 0.65 and statistically insignificant) cannot reject the null of  $E[\varepsilon_{it} | \Delta \mathbf{J}_{it}, \overline{\mathbf{lnx}}_{it}] = 0$ , and the joint hypotheses of

$t'C = 0$  cannot be rejected.<sup>22</sup> This implies that the GLS estimates are both unbiased and consistent and support the assumption of linear homogeneity. As before, the discussions in this sub-section will be based on the GLS estimates reported in the first column of Table 5.

The results can be summarized as follows. First, the absence of neutral technological progress resulting from the learning effect and the high-tech capital deepening is robust with respect to the model specifications. That is, both factors affect TFPG mainly through the non-neutral technological progress. Secondly, although the signs of parameter estimates for the learning effect are unchanged, the labor-augmenting and materials-saving technological progress turn out to be statistically insignificant, whereas the strong, energy-saving technological progress (with the coefficient of -.4736 and statistically significant at 5 percent) is observed. Therefore, the learning effect is energy-saving as it reduces the relative demand for energy utilization. Lastly, the results that a high-tech capital accumulation is capital-saving and materials- and energy-augmenting are robust across two specifications.

Although the productivity impacts of the learning effects are susceptible to the econometric model specifications,<sup>23</sup> my empirical exercise yields the clearer insights into the channel through which the learning effect accounts for TFPG in Singapore manufacturing industries. When the industries intensively engage in exporting activities, the existing labor and capital employed are likely to reap benefits from the productivity improvements, whereas the export-led strategy may result in a decline in the domestic relative demands for raw materials and energy consumption. To me, Specification I may be more preferable due to the fact that the labor-augmenting and materials-saving technological progress turn out to be statistically insignificant in Specification II. Furthermore, Specification I yields the slightly higher degree of model fitness in terms of Chi-squared.

#### *4.3 Time-specific Effects of Learning by Exporting and High-tech Capital Deepening*

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<sup>22</sup> The Chi-squared statistic for the joint hypotheses of  $t'C = 0$  is .202 and not statistically significant at 5 percent. The results are qualitatively unchanged for the individual hypotheses testing.

<sup>23</sup> It should be highlighted that Specifications I and II have different interpretations. The former implies that the export intensity affects the industry's technological growth, and the latter shows that the export intensity affects the level of technology.

In this sub-section, I divide the dataset of Singapore manufacturing industries into two sub-periods, 1974-1994 and 1995-2006. As discussed in Section 2, the trends portrayed in Figure 2 seem to suggest that there were structural shifts or policy changes from the export-led development to the high-tech capital accumulation. It may be interesting to see whether the learning effect and high-tech capital deepening may play different roles in explaining TFPG in the Singapore manufacturing sector.

**[Insert Table 6 here]**

Table 6 shows the GLS estimates of Specification I under the Random Effects model. The Chow test indicates that there are structural changes in these two sub-periods (with the Chi-squared statistic equal to 17.91 and statistically significant at 10 percent). The results reveal that the materials-saving technological progress of learning by exporting prevails in both 1974-1994 and 1995-2006. Interestingly, the factor-biased productivity gains from the learning effect are evolved over time. For the period of 1974-1994, the learning effect is capital-augmenting (with the coefficient of .081 and statistically significant at 10 percent) and therefore shifts the relative demand for capital. In the period of 1995-2006, the productivity improvements from exporting activities are labor-augmenting (with the coefficient of .092 and statistically significant at 5 percent). That is, the existing labor can reap benefits from the non-neutral technological growth resulting from the learning effect.

High-tech capital deepening also plays different roles in explaining TFPG in these two sub-periods. It contributes to TFPG via the materials-augmenting technological growth (with the coefficient of 1.487 and statistically significant at 5 percent) during 1974-1994 but is capital-saving and energy-augmenting (with the coefficients of -3.525 and 2.341 and statistically significant at 5 and 10 percent, respectively) during 1995-2006.

To summarize, my empirical exercises in this sub-section are complementary to the discussions in Sub-sections 4.1 and 4.2. I show that the factor-biased technological progress resulting from the export-led development and the high-tech capital accumulation is period-specific since the productivity improvements depend on how the industrial development policies and endogenous economic transformation are directed toward factors of production. My empirical exercise taking into account the structural changes in this sub-section complements my preliminary results based on the pooled

dataset discussed in previous sub-sections. Nevertheless, the results reveal only some small differences.

#### *4.4 The Impacts of the Learning Effect and High-tech Capital Deepening on the TFPG*

In this sub-section, I aim to analyze the extent to which the learning effect and high-tech capital deepening may explain the total factor productivity growth (TFPG) in Singapore manufacturing industries during 1974-2006. In so doing, I employ the consistent GLS estimates based on the Random Effects model (in Table 4) and evaluate (12) and (13) at mean values.<sup>24</sup>

#### **[Insert Table 7 here]**

Table 7 reports  $\Delta TFPG_x$  and  $\Delta TFPG_T$  in contrast with the actual  $TFPG$ . It yields the following interesting results. First and most importantly, the learning effect can largely explain the TFPG in the Singapore manufacturing sector during 1974-2006 ( $\Delta TFPG_x = .0142$  compared with the actual  $TFPG = .0178$ ). My results may be in contrast with most previous studies which find little evidence that participating in the export markets can improve productivity performance, i.e. Clerides, Lach, and Tybout (1998) for Columbia, Mexico, and Morocco; Bernard and Jensen (1999) for the US; and Greenaway and Kneller (2004) for the UK, among others.<sup>25</sup> However, as is highlighted earlier, their notion of learning by exporting is captured by the export market participation whereas that in the present paper is captured by how intensive the exporting activities are. In this sense, this paper may contribute to the literature on learning by exporting in a way that the productivity growth from the learning effect relies crucially on the export intensity. In addition, my results may shed further light on the importance of outward-oriented strategies which substantiate learning and knowledge accumulations as a primary source of productivity growth.

Secondly, my TFPG decomposition reveals the mechanism through which the learning effect entails productivity growth. Specifically, the positive net effect on TFPG stems from the fact that the labor- and capital-augmenting effects of learning by

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<sup>24</sup> Recall that a Hausman test cannot reject the null hypothesis that the GLS estimates under the Random Effects model are consistent.

<sup>25</sup> Nonetheless, Baldwin and Gu (2003) for Canadian manufacturing and De Loecker (2007) for Slovenian manufacturing show that export-market participation can more or less account for the subsequent TFP growth.

exporting dominate the materials- and energy-saving ones (see Table 4). It should be noted that the positive net effect on TFPG from learning by exporting characterize most of the manufacturing industries, except food, beverage, and tobacco; refined petroleum products; petrochemical products; and basic metal products. Interestingly, these industries have relatively low values of the export intensity index (less than 50 percent).<sup>26</sup> This may implies that the industries successfully reaping benefits from the learning effect are those intensively engaged in exporting activities.

Thirdly, high-tech capital deepening also contributes to TFPG in the manufacturing sector ( $\Delta TFPG_T = .0079$  compared with the actual  $TFPG = .0178$ ).<sup>27</sup> Therefore, my empirical results have shown that the Singapore's industrialization path with high-tech capital formation at the establishment levels is rather successful in sustaining productivity growth. Nevertheless, its contribution seems to be smaller than the learning effect. Therefore, the learning effect may be a better explanatory factor for TFPG in Singapore manufacturing industries during 1974-2006.

Last but not least, the productivity growth from high-tech capital formation may not always hold at the industry-specific level. Specifically, its positive net effect prevails in most of the industries, except food, beverage, and tobacco; leather products and footwear; paper products; printing; petrochemical products; pharmaceutical products; non-metallic mineral products; and transportation equipment.

## 5. Concluding Remarks

The present paper employs the Feenstra and Hanson's (1997) approach to decomposing total factor productivity growth (TFPG) to empirically investigate the extent to which the learning-by-exporting and high-tech capital deepening may account for the TFPG in Singapore manufacturing industries during 1974-2006. Unlike the existing literature on export-led growth, the notion of learning by exporting is captured by the lagged intensity of exports, instead of export-market participation. The index of high-tech capital deepening is measured by the ratio of high-tech capital to total capital.

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<sup>26</sup> See Figure 3 in Sub-section 2.2.

<sup>27</sup> Ones may observe that the total effect of learning effect and high-tech capital deepening is greater than the actual TFPG. This is possible since the actual TFPG also incorporates other unobserved factors.

The decomposition of TFPG may contribute to the literatures on export-led growth and high-tech capital formation since it reveals how both factors affect TFPG and relative factor demands. The empirical results show that Singapore manufacturing industries may benefit from non-neutral technological progress by engaging in exporting activities. The productivity improvements from having been an exporter may be attainable by the transfer of technology, administrative and organizational knowledge, automation, and standardization. My results, though sensitive to model specifications, show that the learning effect results in the labor- and capital-augmenting technological progress. However, it also entails the materials- and energy-saving technological progress. In contrast to the learning effect, the high-tech capital formation is capital-saving and materials- and energy-augmenting. This is not surprising in that, as the industries become more computerized, the relative demands for other complementary inputs, i.e. materials and energy inputs, will increase whereas that of the existing capital will decline.

By using the parameter estimates, I evaluate the contributions of the learning effect and high-tech capital deepening to the actual TFPG. In contrast with most previous studies (Clerides, Lach, and Tybout, 1998; Bernard and Jensen, 1999, among others), the learning effect can largely explain TFPG in the Singapore manufacturing sector. Like the learning effect, a high-tech capital accumulation has positive, though smaller, impacts on TFPG. Therefore, the learning effect better explains TFPG in Singapore manufacturing industries than high-tech capital deepening during 1974-2006.

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## Appendix

Table 1: Summary of Statistics, Singapore Manufacturing Industries 1974-2006.

Variables	Obs.	Mean	S.D.	Min	Max
<i>TFPG</i>	608	0.0105	0.1712	-1.0322	0.9765
$s_L$	627	0.1388	0.0623	0.0074	0.4879
$s_K$	627	0.3098	0.1020	0.0693	0.6481
$s_M$	627	0.5268	0.1242	0.2149	0.9111
$s_E$	627	0.0247	0.0226	0.0032	0.1844
Labor (number)	627	15957.25	24274.79	577	144942
Capital (thousand \$)	627	872031.5	1940262	2733	$1.71 \times 10^7$
Materials (thousand \$)	627	2200057	6458614	17957.22	$5.30 \times 10^7$
Energy (thousand \$)	627	34471.82	52668.57	169.4972	360839.7
<i>XI</i>	627	0.4907	0.2227	0.0346	0.9486
<i>T</i>	627	0.6911	0.1756	0.2907	0.9857

Note: 1) The values of production factors and exports are deflated by appropriate price indices. 2)  $s_x$  is the cost share of a factor  $x$ . 3) *XI* is the ratio of real exports to total real sales. 4) *T* is the ratio of high-tech to total capital after adjusted by appropriate capital price indices.

Table 2: A Correlations Matrix of Total Factor Productivity Growth and Structural Variables.

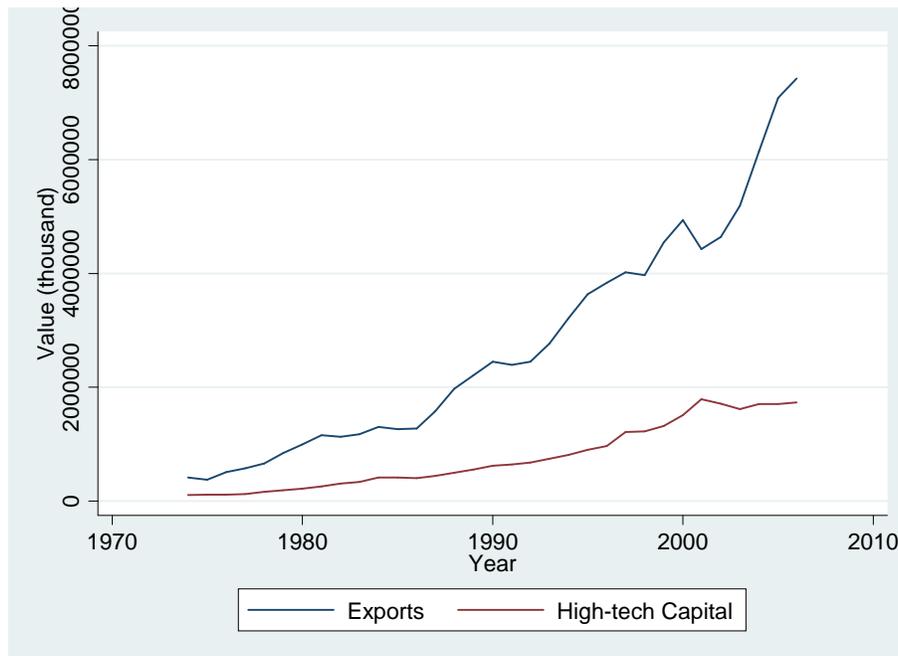
	<i>TFPG</i>	$XI_{t-1}$	$\Delta XI_{t-1}$	$\Delta T_t$
<i>TFPG</i>	1			
$XI_{t-1}$	0.0173	1		
$\Delta XI_{t-1}$	-0.02	0.0913	1	
$\Delta T_t$	-0.0905	0.0204	-0.048	1

Table 3: Selected Key Indicators in Singapore Manufacturing Sectors, 1974-2006.

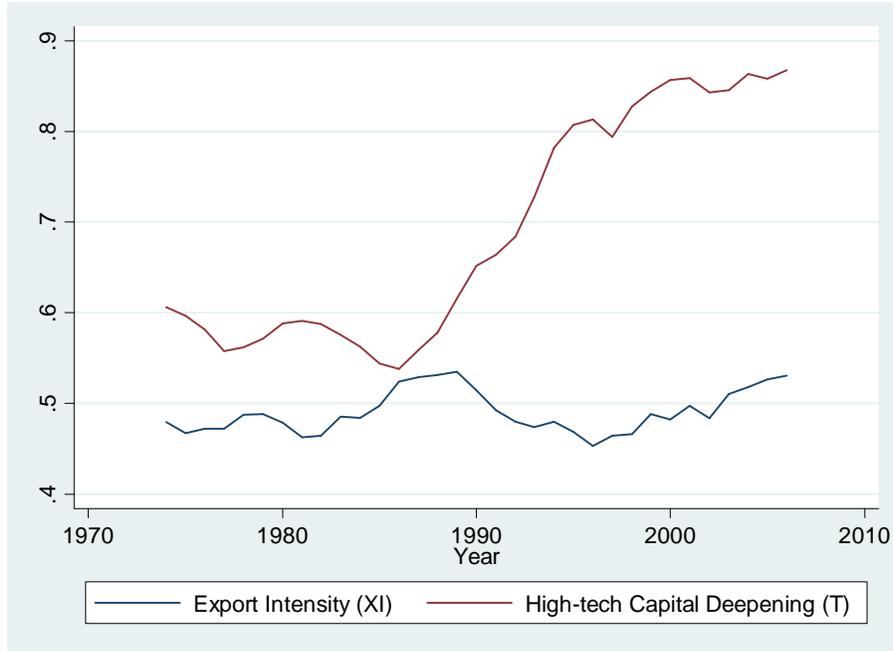
Indicators	Percentage
Manufacturing Value Added (% of GDP)	26.05
Annual Growth Rate of Manufacturing Sectors	7.68
Gross Saving Rate (% of GDP)	41.82
Employment in Manufacturing Sectors (% of Total Employment)	32.24
Unemployment Rate	3.46
Manufacturing Exports (% of Total Manufacturing)	49.07
High-tech Capital (% of Total Capital)	69.11

Sources: World Development Indicators (WDI) database, *The World Bank Group* and Census of Manufacturing Activities (CMA), *Singapore Economic Development Board*.

Figure 1: Exports and High-tech Capital Formation in Singapore Manufacturing Industries, 1974-2006.

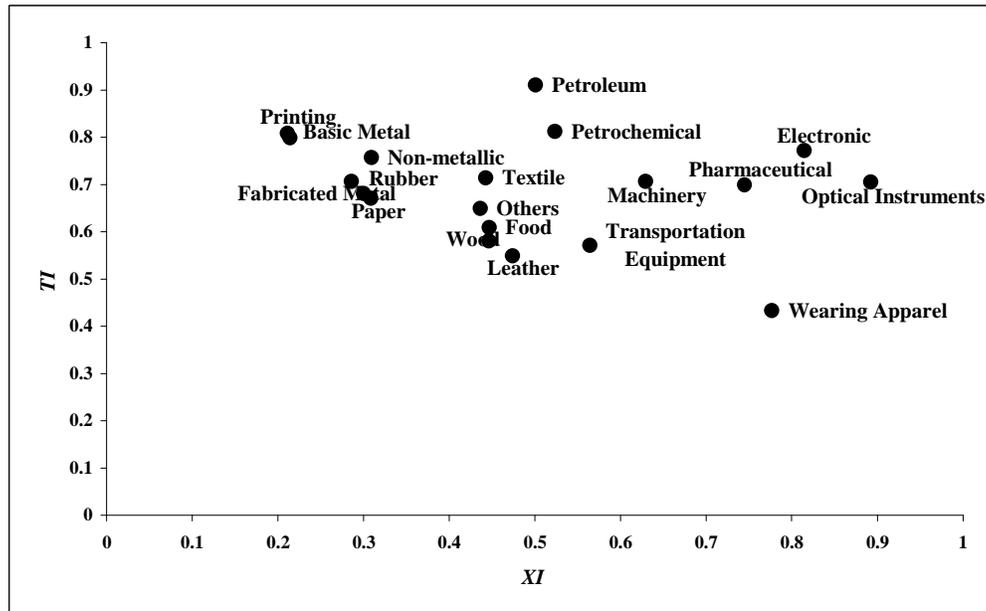


**Figure 2:** The Ratios of Export Intensity ( $XI$ ) and High-tech Capital Deepening ( $T$ ) in Singapore Manufacturing Industries, 1974-2006.



**Note:**  $XI$  is measured by the ratio of exports to total sales.  $T$  is measured by the ratio of high-tech assets, such as machinery, computers, and office equipment, to total assets.

**Figure 3:** Scatter Plot of the Ratios of Export Intensity ( $XI$ ) and High-tech Capital Deepening ( $T$ ) across Singapore Manufacturing Industries.



**Note:**  $XI$  is measured by the ratio of exports to total sales.  $T$  is measured by the ratio of high-tech assets, such as machinery, computers, and office equipment, to total assets.

Table 4: Panel Data Estimations of Specification I, Singapore Manufacturing Industries, 1974-2006.

$$\text{Specification I: } TFP_{it} = \gamma_X XI_{it-1} + \gamma_T \Delta T_{it} + c_{LX} XI_{it-1} \overline{\ln L_{it}} + c_{LT} \Delta T_{it} \overline{\ln L_{it}} + c_{KX} XI_{it-1} \overline{\ln K_{it}} + c_{KT} \Delta T_{it} \overline{\ln K_{it}} + c_{MX} XI_{it-1} \overline{\ln M_{it}} + c_{MT} \Delta T_{it} \overline{\ln M_{it}} + c_{EX} XI_{it-1} \overline{\ln E_{it}} + c_{ET} \Delta T_{it} \overline{\ln E_{it}} + \varepsilon_{it}$$

	Random Effects		Within (Fixed Effects)		Between	
	$XI_{t-1}$	$\Delta T_t$	$XI_{t-1}$	$\Delta T_t$	$XI_{t-1}$	$\Delta T_t$
Neutral TP	.0095(.130)	-2.7000(2.452)	.2471(.273)	-2.7611(2.466)	.1215(.211)	-2.711(11.102)
L-augmenting TP	.0350(.018)**	.1629(.333)	-.0508(.045)	.1692(.333)	-.0044(.018)	3.3632(1.425)**
K-augmenting TP	.0492(.028)*	-1.9026(.79)**	.0579(.042)	-1.8967(.78)**	.1048(.043)**	-6.1492(2.14)**
M-augmenting TP	-.0461(.025)*	1.2740(.502)**	-.0548(.037)	1.260(.513)**	-.0605(.019)**	2.8679(1.452)*
E-augmenting TP	-.0330(.024)	.8024(.440)*	.0113(.039)	.8103(.430)*	-.0591(.036)	1.2122(1.095)
No. of Obs.	608		608		608	
Chi-squared	28.73**		-----		-----	
F Statistic	-----		2.03**		10.09**	
Breusch-Pagan	7.42**		-----		-----	
Hausman Test	4.42					
$H_0 : \iota' C = \mathbf{0}$	Accepted					

Note: 1) Robust standard errors in parentheses. 2) \* statistically significant at 10 percent; 3) \*\* statistically significant at 5 percent. 4) The Generalized Least Squares (GLS) estimation using the Swamy-Arora and heteroskedasticity-robust estimators is employed in the Random Effects model. 5) The Ordinary Least Squares (OLS) estimation with heteroskedasticity-robust estimators is employed in the Fixed Effects model. 6) The Weighted Least Squares (WLS) estimation is employed in the Between model. 7) The Breusch-Pagan test is based on the Lagrange Multiplier (LM) test under the null hypothesis that there are no random effects. 8) The Hausman test is under the null hypothesis that Random Effects estimates are unbiased and consistent and is calculated by using the pair of Random Effects and Fixed Effects estimates. 9)  $H_0 : \iota' C = \mathbf{0}$  is jointly tested against GLS estimates at the 5 percent level of significance.

Table 5: Panel Data Estimations of Specification II, Singapore Manufacturing Industries, 1974-2006.

**Specification II:**  $TFPG_{it} = \gamma_X \Delta XI_{it-1} + \gamma_T \Delta T_{it} + c_{LX} \Delta XI_{it-1} \overline{\ln L_{it}} + c_{LT} \Delta T_{it} \overline{\ln L_{it}} + c_{KX} \Delta XI_{it-1} \overline{\ln K_{it}} + c_{KT} \Delta T_{it} \overline{\ln K_{it}} + c_{MX} \Delta XI_{it-1} \overline{\ln M_{it}} + c_{MT} \Delta T_{it} \overline{\ln M_{it}} + c_{EX} \Delta XI_{it-1} \overline{\ln E_{it}} + c_{ET} \Delta T_{it} \overline{\ln E_{it}} + \varepsilon_{it}$

	Random Effects		Within (Fixed Effects)		Between	
	$\Delta XI_{t-1}$	$\Delta T_t$	$\Delta XI_{t-1}$	$\Delta T_t$	$\Delta XI_{t-1}$	$\Delta T_t$
Neutral TP	-1.6027(.982)	-.6877(2.091)	-1.3544(.996)	-.6601(2.164)	-3.5684(8.044)	2.7201(9.034)
L-augmenting TP	.0477(.1251)	.3917(.383)	.0494(.123)	.2383(.409)	-.6010(.930)	1.8911(.794)*
K-augmenting TP	.6109(.264)**	-1.9905(.80)**	.6327(.269)**	-2.024(.814)**	.1353(1.197)	-1.1628(1.379)
M-augmenting TP	-.1480(.210)	.9195(.500)*	-.1902(.213)	1.0158(.527)*	.6663(1.091)	-.5428(1.189)
E-augmenting TP	-.4736(.20)**	.9803(.418)**	-.4736(.203)**	1.0323(.406)**	-.1681(1.239)	.2119(1.189)
No. of Obs.	589		589		589	
Chi-squared	24.17**		-----		-----	
F Statistic	-----		2.19**		2.31	
Breusch-Pagan	2.91*		-----		-----	
Hausman Test	0.65					
$H_0 : \iota' C = \mathbf{0}$	Accepted					

Note: 1) Robust standard errors in parentheses. 2) \* statistically significant at 10 percent; 3) \*\* statistically significant at 5 percent. 4) The Generalized Least Squares (GLS) estimation using the Swamy-Arora and heteroskedasticity-robust estimators is employed in the Random Effects model. 5) The Ordinary Least Squares (OLS) estimation with heteroskedasticity-robust estimators is employed in the Fixed Effects model. 6) The Weighted Least Squares (WLS) estimation is employed in the Between model. 7) The Breusch-Pagan test is based on the Lagrange Multiplier (LM) test under the null hypothesis that there are no random effects. 8) The Hausman test is under the null hypothesis that Random Effects estimates are unbiased and consistent and is calculated by using the pair of Random Effects and Fixed Effects estimates. 9)  $H_0 : \iota' C = \mathbf{0}$  is jointly tested against GLS estimates at the 5 percent level of significance.

**Table 6:** Generalized Least Squares (GLS) Estimations of Specification I, Singapore Manufacturing Industries, 1974-1994 and 1994-2006.

$$\text{Specification I: } TFP G_{it} = \gamma_X XI_{it-1} + \gamma_T \Delta T_{it} + c_{LX} XI_{it-1} \overline{\ln L_{it}} + c_{LT} \Delta T_{it} \overline{\ln L_{it}} + c_{KX} XI_{it-1} \overline{\ln K_{it}} + c_{KT} \Delta T_{it} \overline{\ln K_{it}} + c_{MX} XI_{it-1} \overline{\ln M_{it}} + c_{MT} \Delta T_{it} \overline{\ln M_{it}} + c_{EX} XI_{it-1} \overline{\ln E_{it}} + c_{ET} \Delta T_{it} \overline{\ln E_{it}} + \varepsilon_{it}$$

	1974-1994		1995-2006	
	$XI_{t-1}$	$\Delta T_t$	$XI_{t-1}$	$\Delta T_t$
Neutral TP	.0208(.220)	-3.875(3.039)	.0537(.224)	-6.3038(6.0263)
L-augmenting TP	.0180(.018)	-.0435(.385)	.0915(.043)**	.2444(.706)
K-augmenting TP	.0812(.045)*	-1.3785(.932)	.0309(.047)	-3.525(1.798)**
M-augmenting TP	-.0661(.036)*	1.4869(.570)**	-.0766(.041)*	2.3413(1.744)
E-augmenting TP	-.0317(.040)	.1652(.579)	-.0245(.056)	1.7146(.971)*
No. of Obs.	380		228	
Chi-squared	23.02**		39.82**	
Chow Test	17.91*			

**Note:** 1) Robust standard errors in parentheses. 2) \* statistically significant at 10 percent; 3) \*\* statistically significant at 5 percent. 4) The Chow test is under the null hypothesis that there are no structural changes.

Table 7: The TFPG Contributions of the Learning Effect ( $\Delta TFPG_x$ ) and the High-tech Capital Deepening ( $\Delta TFPG_T$ ), Singapore Manufacturing Industries, 1974-2006.

Industry	Actual <i>TFPG</i>	$\Delta TFPG_x$	$\Delta TFPG_T$
Food, Beverage & Tobacco	.0160	-.0002	-.0012
Textile & Textile Manufacture	.0138	.0016	.0056
Wearing Apparel Except Footwear	.0283	.0272	.0062
Leather, Leather Product & Footwear	.0178	.0012	-.0058
Wood & Wood Products Except Furniture	.0069	.0017	.0009
Paper & Paper Product	.0066	.0059	-.0050
Printing and Reproduction of Recorded Media	.0071	.0167	-.0114
Refined Petroleum Products	-.0421	-.0495	.0020
Petrochemical & Petrochemical Products	-.0454	-.0121	-.0095
Pharmaceutical Products and Other Chemical Products	.0131	.0178	-.0114
Rubber and Plastic Products	.0170	.0066	.0034
Non-metallic Mineral Products	-.0086	.0029	-.0075
Basic Metal	-.0147	-.0129	.0066
Fabricated Metal Products	.0076	.0078	.0021
Machinery and Equipment	.0301	.0216	.0012
Electronic Products, Machinery & Components	.0312	.0010	.0185
Medical, Precision & Optical Instruments, Watches & Clocks	.0565	.0413	.0002
Transportation Equipment	.0437	.0373	-.0145
Other Manufacturing Industries	.0151	.0074	.0012
<b>Total Manufacturing</b>	<b>.0178</b>	<b>.0142</b>	<b>.0079</b>

Note:  $\Delta TFPG_x$  and  $\Delta TFPG_T$  are calculated by using the parameter estimates from the GLS estimation in Table 4 and evaluated at mean values.