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Article

Efficiency analysis of manufacturing industries in Singapore using the DEA-Malmquist productivity index

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Abstract: This study evaluated the efficiency and productivity of the manufacturing industries of Singapore. Singapore is one of the world's most competitive countries and manufacturing giants. All 21 manufacturing industries as classified by Singapore's Department of Statistics were included in the study as decision-making units (DMUs). Using the Malmquist DEA on data spanning 2015–2021, we found that excerpt for the Paper and Paper product industry, all industries recorded positive total factor productivity (TFP). TFP ranged from 0.977 to 1.481. In terms of technical efficiency, 14 out of 21 industries showed positive efficiency change. The highest TFP was recorded in 2020 and the lowest in 2016. By measuring and improving efficiency, industries in Singapore can achieve cost savings, increase output, and enhance their competitiveness in the global marketplace. In addition, efficiency measurement can help policymakers identify potential areas for improvement and develop targeted policies to promote sustainable economic growth. Given these benefits, performance measurement is inevitable for industries and policymakers in Singapore to achieve economic objectives. Manufacturing industries need to find ways to manage the size and scale of operations as we flag this as an area for improvement.

Keywords: data envelopment analysis; total factor productivity; Singapore; manufacturing industry; Malmquist index

1. Introduction

As a small highly developed country, Singapore faces intense global competition exacerbated by its stock of limited natural resources. To remain competitive, Singapore has focused on promoting productivity growth and innovation across industrial sectors. Accordingly, the ability of these industrial sectors to make valuable contributions to growth depends on how efficient resources can be deployed and how performance management is monitored and enhanced. Hence, the subject of efficiency and total factor productivity become critical, especially in good-producing sectors such as the manufacturing industries. Economic development in Singapore during the 1970s and 1980s was achieved through the growth of its manufacturing sector (**Figure 1**) which contributed more than 30 percent of its GDP. However, following a recession in 1984, the share of manufacturing to GDP suffered a downward trend. Thereafter, the Strategic Economic Plan was formulated in 1991 which outlined a long-term vision to develop Singapore's manufacturing sector by enhancing productivity and innovation to maintain their economic growth, international competitiveness, and efficiency.

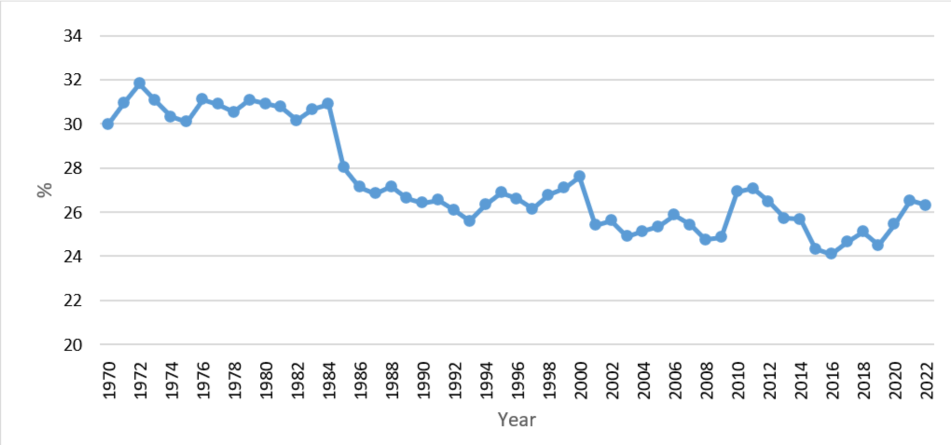

Figure 1. Contribution of manufacturing to the GDP of Singapore (%).
Source: World Bank, 2022.

Today, Singapore stands as one of the leading economies in terms of competitiveness. The IMD World Competitiveness Rankings has consistently scored Singapore among the top 5 countries since 2019. This underscores how effectively the country has managed its competencies to create long-term value. Notably, innovation has been fundamental to Singapore's identity, fostering advancements in manufacturing technologies like robotics, additive manufacturing, predictive analytics, and artificial intelligence (Economic Development Board, 2018). This entrepreneurial spirit has attracted multinational firms to collaborate on cutting-edge technology trials. As a result, Singapore has built a robust and diverse manufacturing base, leading in sectors such as aerospace, electronics, biomedical sciences, and precision engineering.

For historical reasons, we note that since 2000, the macroeconomic trends in Singapore have suffered severe fluctuations witnessing a recession in 2001, a sharp decline in its electronic industries in 2002 followed by the SARS pandemic in 2003, and the global financial crisis in 2008–2009. Despite these economic upheavals, the manufacturing sector in Singapore has played a key role in maintaining the steady growth of the nation, contributing between 24 to 26 percent of the GDP in the last two decades (**Figure 1**). The successful development experience and the stability of the Singapore economy can be traced to its robust manufacturing sector, where the key clusters include electronics, chemicals, biomedical sciences, logistics, and transport engineering.

Yue (2014) explains that in the 1990s, Singapore recruited foreign manpower to augment its weakened and less skillful workforce. In its quest to transition into a knowledge-based economy (KBE), the Strategic Economic Plan (SEP) was designed. The SEP affirmed the role of value-added manufacturing as the driver of economic growth through the Manufacturing 2000 Program (M 2000). The M 2000 program aimed to contribute to the KBE by improving the innovative capabilities of enterprises, an idea that was carried through all phases of economic development. Unfortunately, from 2012 to 2015, the relevance of the manufacturing sector to Singapore's economy was minimal and declined faster (**Figure 1**). Consequently, most manufacturing SMEs were supported by the government to go abroad and learn industry best practices to increase productivity (AHK Singapur, 2016).

Since 2015, Singapore focused on its science and technology capabilities to strengthen industrial output and to grow its innovative talent. This followed a government policy intervention called the Industry Transformation Programme which sought to invest in smart manufacturing from 2016 onwards (AHK Singapur, 2016). This substantive move by the government was also accompanied by regulations through tightening the job market to prevent the influx of foreign workers who a decade before had been active participants in the industrial development of Singapore (Yue, 2014). The result of the various interventions began to fruition in 2016 when the manufacturing contribution to GDP increased from 24.32% to 26.5% in 2021.

By 2021, Singapore established its position as a technology node not only in the Asia Pacific but also as one of the most innovative and advanced economies in the world. According to the Global Innovation Index (GII), Singapore's output index which was ranked 20th in 2015 had improved to 13th in 2021, however, the input index remained the same at 1st position (WIPO, 2015, 2021). To this end, Singapore's manufacturing sector is well poised as a powerhouse to move up the value chain by transitioning to the Fourth Industrial Revolution.

To provide a comprehensive, step-by-step approach for companies to gain a deeper understanding of Industry 4.0 concepts, assess the current condition of their facilities, and develop a thorough transformation roadmap, the Singapore Economic Development Board (EDB) designed the world's first diagnostic tool for the manufacturing industries called the Singapore Smart Industry Readiness Index (SIRI). Later, the SIRI became a global tool for monitoring manufacturing successes (World Economic Forum, 2022). This represents a milestone that reflects the extent of the revolution the manufacturing sector has gone through. Accordingly, the above discussion calls for an investigation into the analysis of the efficiency and total factor productivity of the manufacturing sector of Singapore.

Yet, given the trajectory of the manufacturing sector of Singapore between 2015 and 2021, no current studies have tried to explore the efficiency of and the total factor productivity of manufacturing industries. The closest however different study was conducted by Lee (2014) who focused only on the top ten industries classifying the whole manufacturing industry as one sector and comparing it against other non-manufacturing sectors.

Our study offers fresh evidence and dives deep into the manufacturing industries by considering 21 key sectors driving trade, employment, and entrepreneurship in Singapore. Maintaining the relevance of the manufacturing sector requires ensuring sustainable and efficient use of limited resources (Huang, 2023). This is important to drive innovation (Hwang et al., 2023; Song et al., 2015) to foster the competitiveness of firms. Having noted a dearth in the literature on the topic, particularly regarding Singapore, we consider this study as theoretically and practically worthwhile for policy-making and knowledge contribution. The results and recommendations would help Singapore identify the 'best practice' sector as well as the laggards. Additionally, limited studies are found on industry-wise efficiency and total factor productivity comparison. However, there are sufficient studies on inter-firm efficiency comparisons. Our study, therefore, becomes one of the leading discussions on inter-industry comparison of total factor productivity and efficiency.

We employed the Data Envelopment Analysis (DEA) technique which is a non-parametric method for measuring the relative efficiency of economic entities or decision-making units (DMUs) based on their input and output data. DEA evaluates the efficiency of each DMU and identifies the most efficient DMUs that lie on the production frontier. Farrell (1957) introduced the concept of input-output efficiency which was extended by Charnes et al. (1978) to become a powerful method for measuring productivity. The measure became more comprehensive when Lovell and Grosskopf (1980) developed the dynamic case of the DEA framework, based on the initial quantity-index and distance functions proposed by Malmquist (1953). The resulting Malmquist Productivity Index (MPI) is particularly useful for recognizing potential sources of inefficiency amongst the DMUs and has been widely used in empirical studies (Banjerdpaiboon and Limleamthong, 2023; Habib and Mourad, 2023; Lin et al., 2023; Habib and Mourad, 2022; Rella et al., 2024) to identify factors that contribute to productivity change over time.

The DEA has several advantages so it has been preferred to many parametric approaches such as stochastic frontier analysis. A few of its advantages include: DEA envelops the observed input-output data without necessitating the prior specification of functional forms. It also focuses on observable "best-practices frontier" and not the descriptive features of the frontiers.

The primary aim of this paper is to employ Data Envelopment Analysis (DEA) as an alternative method for assessing Total Factor Productivity (TFP) growth. Additionally, we decompose this growth into technological change and technical efficiency. Technical efficiency is further decomposed into pure technical efficiency and scale efficiency. This decomposition is intended to elucidate the sources of productivity growth, thereby informing policy development within the Singaporean manufacturing sector.

The format of the paper is as follows. Section 2 presents a brief discussion of theoretical background. Section 3 shows the literature review of relevant studies on manufacturing sector productivity measurement in Singapore and other countries. The classical DEA model and its extension into the Malmquist productivity index are explained in Section 4. Section 5 elaborates on the results and discussions. Section 6 presents the conclusions and recommendations.

Overview of the manufacturing sector in Singapore

Table 1 provides a brief overview of the manufacturing sector in Singapore, highlighting the changes in the sector since 2015. Manufacturing output, value-added, and net operating surplus grew by an impressive 67 percent, 40 percent, and 113 percent respectively. Importantly, this was achieved with only a modest increase of 8.68 percent in the number of establishments. Another striking feature was the addition of fixed assets in the manufacturing sector of Singapore despite its increase in costs in terms of remunerations, materials, and operating costs. Productivity, in terms of output per worker went up by 61 percent during this period, which makes it imperative to delve into the performance measure of the manufacturing sector of Singapore, to identify the factors that have led to their sustained growth, in the backdrop of readiness towards the transition to the Fourth Industrial Revolution.

Table 1. Growth of manufacturing industry in Singapore (2015 and 2021).

Data Series	2021	2015	Change (%)
Establishments (number)	9540	8778	8.68
Value Added (million $)	115,341	69,002	67.16
Output (million $)	380,225	271,120	40.24
Remuneration (million $)	23,030	21,678	6.24
Materials (million $)	192,573	145,057	32.76
Other Operating Costs (million $)	86,586	70,632	21.25
Net Operating Surplus (million $)	81,284	38,212	112.72
Sales (million $)	377,472	271,842	38.86
Direct Exports (million $)	278,208	183,295	51.78
Net Fixed Assets at End of Year (million $)	81,213	66,538	22.06
Gross Fixed Assets at End of Year (million $)	225,700	172,563	30.79
Output per Worker ($)	1,085,151	672,277	61.40

Source: Singapore Department of Statistics (2022).

Some of the indicators and indices, however, reveal that Singapore ranked very low on its innovative outputs. The Global Innovation Index 2019 declared that investments in Singapore were far higher than the innovation outputs. In terms of the Creative Productivity Index 2014, Singapore showed the highest government investments in terms of innovation inputs but fell to 10th place in innovation outputs indicating that the investments were not translated efficiently into the corresponding outputs. Therefore, it becomes relevant to investigate the productivity structure of the manufacturing sector of Singapore, using an input-output matrix that would capture the productivity and efficiency of each sector.

2. Theoretical background

The subject of efficiency and productivity has been an age-old discussion in both academic and industrial scope. Debreu (1951) introduced the initial measure of efficiency following which Koopmans (1951) conceptualized the term technical efficiency (TE). Building on TE, various models were developed, aimed at either minimizing inputs while maintaining at least a given level of output (input-oriented model) or maximizing outputs without exceeding the observed input levels (output-oriented model) (Amirteimoori et al., 2023). Arguing that efficiency is important to maximize output, Isaksson (2007) submits that total factor productivity (TFP) measures the efficiency at which all factors of production (such as labor and capital) are utilized to produce output. It reflects technological progress, innovation, and managerial efficiency that cannot be attributed to individual inputs. TFP growth leads to increased output without a corresponding increase in inputs, contributing to overall economic growth and welfare.

Following the neoclassical growth models led by Solow's seminal works in 1956 and 1957 prominent for their argument that technological progress is exogenous to the production model, proponents of modern growth models such as Romer (1986, 1990) recognized that a complete production model includes technological progress. Romer stresses that rational profit-maximizing decision-making units make a deliberate effort to invest in technology which is, all things being equal, catalytic to growth. As a result, estimating TFP for DMUs represents the product of their technical changes and efficiency (Hasanov and Mikayilov, 2021), and this is easily calculated using the Malmquist DEA approach which has been utilized in this study.

Efficiency and productivity are only important because of resource allocation. Habib and Mourad (2022) contend that resources are limited and so businesses strive to make the best use. This is consistent with the view of the Resource Allocation Theory from which Bower (2019) conjectures that within its chosen ventures, an organization undertakes a resource allocation analysis to identify the most effective way to distribute its production inputs. Li and Cui (2008) add that the analysis should result in the selection of the most cost-effective distribution to reap an efficient functioning of the DMU. From a manufacturing and production perspective, the theory rightly situates the efficient combination of labour and capital by a manufacturer to obtain the optimum levels of output.

Thus far, the discussion on efficiency and productivity has received enormous attention across economic sectors: in the service sector (Drake et al., 2009; Patra et al., 2023; Sharma et al., 2013), the banking and insurance sectors (Biener et al., 2016; Jarraya et al., 2023; Phung et al., 2024; Phung and Dao, 2024), the hospitality sector (Flegl et al., 2023; Pérez-Granja and Inchausti-Sintes, 2023); education and defense (Solana Ibáñez et al., 2020; Witte and López-Torres, 2017) the agriculture sector (Priyadarshini and Abhilash, 2023), and manufacturing sector (Ngo and Tran, 2014; Wang et al., 2020). The importance of the subject matter stems from the assumption that every rational decision-maker aims to maximize output or minimize the use of input to save cost and time or generate more revenue and maximize profit during the value-creation process.

3. Literature review

Although several scholars have studied the efficiency of the manufacturing sector in Singapore, there are two important aspects. Firstly, most of these studies cover the period before the turn of the century and secondly, conclusions about TFP growth in Singapore's manufacturing sector remain ambiguous. Since the 1970s, the manufacturing sector of Singapore grew at almost 10 percent per annum, especially in the electric and machinery clusters. However, researchers remain ambiguous in terms of the Total Factor Productivity (TFP) of Singapore's manufacturing sector and their results vary extensively.

3.1. Singapore-related review

Tsao (1985) found that despite Singapore's impressive manufacturing growth in the 1970s, TFP growth was as low as 0.08 percent per annum which was corroborated by many researchers later at different periods (Kim and Lau, 1994; Mahadevan and Kalirajan, 2000; Young, 1995). Leung (1997) elaborated that the rapid transformation of Singapore's manufacturing was mainly due to input growth rather than increasing productivity since cumulative output had a negative influence on TFP growth in his sample covering 30 sectors from 1983 to 1993. In the same line, Sun (2007) examined 25 of Singapore's manufacturing industries and found a negative TFP growth rate of

−0.8 percent per year during 1970–1997 despite the impressive increase in output.

On the other hand, Rao and Lee (1995) found a 3.2 percent TFP growth in manufacturing during 1987–1994. Similarly, Wong and Gan (1994) studied 27 manufacturing industries and confirmed a significant contribution to TFP growth particularly between the first and second halves of the 1980s. Lucas (1993) and Lee (2014) confirmed that the positive output growth in manufacturing was entirely attributable to its capital and labor inputs, suggesting a lack of innovation and a lack of diffusion of new technologies. In contrast, Leung (2008) opined that Singapore's growth trajectory was not attributable to learning by doing. Kong and Tongzon (2006) also estimated the TFP for 10 industrial sectors of Singapore and found that the manufacturing sector has demonstrated the most significant advancements in technical change, as anticipated. Over the past 16 years, the adoption of more advanced technologies has accelerated. For instance, numerous manufacturing companies are now utilizing high-end computers and sophisticated machinery in their production processes.

Bloch and Tang (2007) focused on Singapore's electronics production for the period 1972–1997 and found the surprising result that despite being one of the most important sectors in Singapore, the TFP growth had been only 0.02% per annum. They showed that the sector depended on export-led increasing returns to scale with the adoption of new technology but declined in overall performance due to the increasing price competition. Other studies linked Singapore's TFP growth to international trade where volatility in export and import growth had varied impacts (Mahadevan and Suardi, 2011); and globalization (Joel et al., 2018). Cheang (2022) attributed the high growth in employment to the "accumulation of factor inputs, rather than the intelligent use of resources". The main focus of the education system in Singapore was on scientific subjects (Tan et al., 2016) with the clear objective of securing elite jobs that ensured lucrative remuneration packages either in the Government (Quah, 2010) or in a multinational company (Randstad, 2017) which resulted in a lack of creativity and dearth of entrepreneurial talent.

This ambiguity and anomaly between the impressive output growth in Singapore's industries and its productivity growth has been a topic of debate throughout the past decades. This study adds to the literature by estimating the Malmquist Productivity Index for the Singapore manufacturing industry and providing a detailed sector-wise breakup of its technological advancement, technical efficiency, and scale efficiency during the 2015–2021 period.

3.2. Review related to countries other than Singapore

Research on efficiency and total factor productivity of the manufacturing sector or across the manufacturing industries reveals varying results across countries (**Table 2**). Al-Refaie et al. (2016) found that inefficiencies in energy production among industrial sectors in Jordan are attributed to both input and managerial factors, emphasizing the need for better resource utilization and management. Introducing new technology is crucial for achieving productivity growth in the industrial sector, as indicated by the Malmquist index results.

Table 2. Summary of literature review.

Authors	Methods	Context	Findings
Bloch and Tang (2007)	Non-linear three-stage least square	Singapore electronics industry	The TFP growth had been only 0.02% per annum
Kong and Tongzon (2006)	Malmquist-DEA	Singapore's Top 10 Industrial Sectors	The manufacturing sector showed the highest technical change
Lee (2014)	Malmquist Productivity and Truncated regression	Singapore's manufacturing sector	Growth in TFP was attributed to efficiency change with no technical progress.
Al-Refaie et al. (2016)	Malmquist-DEA	Jordan's manufacturing sector	Inefficiencies in production emerge from resource utilization and management
Suntherasegarun and Devadason (2023)	Stochastic Frontier Analysis	Malaysia's manufacturing industries	Petroleum was the most efficient industry
Mahadevan and Kalirajan (2000)	Malmquist-DEA	Malaysia's manufacturing industries	Overall TFP was around 0.8%, technical change, and efficiency had both changed positively
Wang et al. (2020)	Malmquist-DEA	World Automobile manufacturers	Varying efficiencies were obtained. 4 obtained the highest and 2 were worst performing
Aneja and Arjun (2021)	Malmquist-DEA	Technology industries	TFP is increasing over time
Al-Refaie et al. (2019	DEA	Jordan's pharmaceutical industry	Low efficiencies were reported due to poor input utilization
Gascón et al. (2017)	DEA	Global large pharmaceutical companies	Efficiency was relatively high
Wong and Gan (1994)	Logarithmic production function	Singapore	TFP performance improved between the first and second halves of the 1980s, with structural change being a key factor in manufacturing TFP growth.
Sun (2007)	Varying Coefficient Frontier Model	Singapore's manufacturing industries	A negative TFP of 0.8% was found between the period

Across Malaysian manufacturing industries, Suntherasegarun and Devadason (2023) employed stochastic frontier analysis to assess technical efficiency using data from 2014 to 2019 spanning 19 industries. Petroleum emerged as the most efficient industry followed by machinery and equipment (M&E) and chemicals since Malaysia focused policies on becoming a hub for oil and gas through its Economic Transformation Programme (ETP). Industries like M&E and chemicals were reported as "catalytic industries" owing to their high presence in the 11th Malaysian Plan. Previously, Mahadevan and Kalirajan (2000) used Malmquist DEA to estimate the productivity growth of the Malaysian manufacturing sector. It was discovered that the annual total factor productivity (TFP) growth in the Malaysian manufacturing sector was modest at 0.8%. This growth was attributed to minor improvements in both technical change and technical efficiency, with industries functioning near their optimal scale.

Wang et al. (2020) investigated the productivity trajectory of top global automobile manufacturers. They used the Malmquist-DEA approach and data spanning 2015–2018. Their findings revealed that 4 of the 20 automakers were very productive and two were extremely unproductive. In India, Aneja and Arjun (2021) found that between 2008 and 2018, the productivity of high and medium-high-technology manufacturing industries increased over time. Technical change accounted for the changes in high-technology industries than in medium-high-technology industries.

In the pharmaceutical industry, Al-Refaie et al. (2019) analyzed the efficiency of three blistering machines of a Jordanian manufacturer of medicines using DEA for the year 2014 and found that the machines were operating at low efficient levels due to poor input utilization and failure to operate at the most productive scale size. However, on a global scale, Gascón et al. (2017) also used the DEA approach and found that global large pharmaceutical companies were relatively efficient in their laboratory operations. This was largely due to a well-curated R&D investment into production.

4. Methodology

Although a natural starting point of DEA is Farrell's seminal 1957 paper on concepts of efficiency and its computation, it is widely accepted that Charnes et al. (1978) introduced DEA as a tool for evaluating the efficiency of DMUs. Farrell (1957) considered the elementary problem with two inputs and one output, while Charnes et al. (1978) extended the concept to an unlimited number of inputs and outputs. As a powerful method for measuring efficiency and productivity, DEA has gained widespread acceptance in both academia and industry and has been widely used in a variety of fields, including economics, finance, operations research, and management science. The present study adds to the literature by applying MPI, based on DEA, to the Singapore manufacturing industry. The efficiency of 21 sectors within the manufacturing industry in Singapore has been studied based on the data from the Singapore Department of Statistics.

4.1. Data envelopment analysis (DEA)

DEA is rooted in the concept of production frontier analysis, which seeks to identify the best-practice production function that represents the highest level of output that can be produced for a given level of inputs. DEA extends this concept to identify the relative efficiency of DMUs, which can be firms, organizations, industrial sectors, or other decision-making units. DEA evaluates the efficiency of each DMU by comparing its input-output ratios with those of the other DMUs in the sample and identifying the most efficient DMUs that lie on the production frontier (Benchmarking). DEA can also be used to identify the factors that contribute to inefficiency and to determine how much input or output should be adjusted to achieve maximum efficiency. Overall, DEA is a powerful method for measuring efficiency and productivity that has gained widespread acceptance in both academia and industry.

DEA is a two-step process where initially the problem is formulated as a fractional programming model, which is then simplified to a linear programming model. Generally speaking, efficiency is defined as the ratio of the output to the input as in Equation (1).

$$\text{Efficiency} = \text{Output}/\text{Input} \tag{1}$$

which will change to the following form when there is a vector of inputs and a vector of outputs:

$$\text{Efficiency} = \text{Weighted sum of outputs}/\text{Weighted sum of inputs} \tag{2}$$

As the model in **Figure 2** shows, given an input vector X (x_1, x_2, …, x_i), each DMU (DMU_1, DMU_2, …, DMU_n) produces a Y (y_1, y_2, …, y_r) vector of outputs. DMU*j* consumes x_{ij} of input i and produces y_{rj} of output r.

Figure 2. A schematic presentation of a DMU with *i* inputs and *r* outputs.

Therefore, we can define the objective function as a maximizing function:

$$\text{Max } h_0 = \sum_{r=1}^{s} u_r y_{r_0} \Big/ \sum_{i=1}^{m} v_i x_{i_0} \tag{3}$$

where the y_{ro}'s and x_{io}'s are the observed output and input values, respectively, of DMU*o* which is the DMU to be evaluated.

Adding non-negativity constraints and a set of normalizing constraints, we will have a complete mathematical programming model as follows:

$$\text{Max } h_0 = \sum_{r=1}^{s} u_r y_{r_0} \Big/ \sum_{i=1}^{m} v_i x_{i_0} \tag{4}$$

subject to

$$\sum_{r=1}^{s} u_r y_{r_i} \Big/ \sum_{i=1}^{m} v_i x_{i_i} \leq 1 \qquad j = 1, \ldots . n$$

$$v_r, u_i \geq 0\ ;\ r = 1, \ldots s, i = 1, .. m,$$

4.2. Malmquist productivity index (MPI)

The Malmquist Productivity Index (MPI) is a nonparametric method for measuring total factor productivity (TFP) changes over time or across different DMUs. It compares the efficiency of a DMU in one period to its efficiency in another period, or to the efficiency of other units in the same period. It is based on the concept of DEA which measures relative efficiency by comparing the inputs and outputs of a DMU to a set of benchmark DMUs, called the efficient frontier. The index is calculated as the geometric mean of two separate DEA efficiency scores, one for the current period and one for the benchmark period. Caves et al. (1982) defined Total Factor Productivity (TFP) using Malmquist's distance functions by defining the input-output vectors for two time periods. Fare et al. (1992) decomposed the MPI into two components - technological change to incorporate innovation and technical efficiency change as a proxy for learning-by-doing.

Technical efficiency change was further disaggregated into pure technical efficiency change and changes in scale efficiency (Fare, 1995). The ratio of the two efficiency scores provides a measure of productivity change over time, with a value greater than 1 indicating an increase in productivity, and a value less than 1 indicating a decrease in productivity. The Malmquist index is decomposed into two separate components, one measuring technological change, as a proxy of innovation, and the other measuring technical efficiency change, as a concept of learning-by-doing.

The MPI framework can be illustrated in **Figure 3**, following Hjalmarsson and Veiderpass (1992), Price and Weyman-Jones (1996), Mazumdar and Rajeev (2009), Majumdar and Asgari (2017) amongst others. There are two observations on the input-output domain, at time '*t*' and '*t* + 1', which capture the growth in productivity from *z*(*t*) to *z* (*t* + 1). The potential production frontier represents the efficient levels of output that can be produced, given a particular level of input. The production at time 't' would become technically efficient if the bundle *z*(*t*) is reduced by the horizontal distance ratio (ON/OS). Similarly, production in time '*t* + 1' will be technically efficient if *z*(*t* + 1) is reduced by the horizontal distance ratio (OP/OQ), as depicted in **Figure 3**. Therefore, Malmquist indices of TFP calculate changes in total outputs relative to inputs without assuming any underlying functional form for the production function or the technology. DEA-based MPI can be applied to panel data to measure the productivity changes between two time periods for a given set of DMUs.

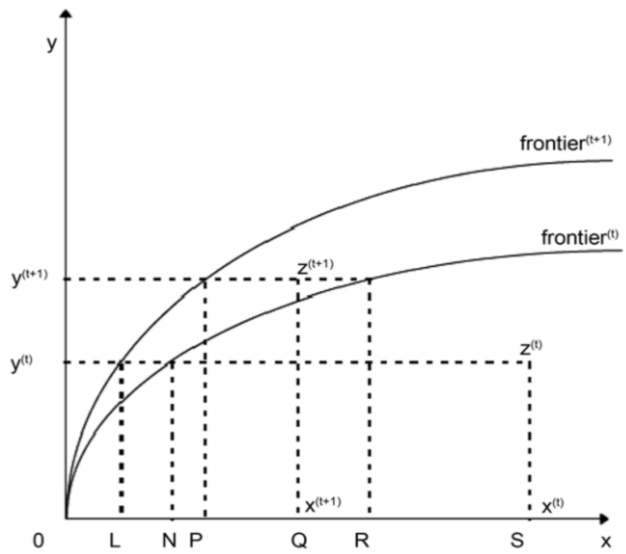

Figure 3. Decomposition of Total Factor Productivity TFP growth.

The MPI-based TFP growth between the time period *t* and *t* + 1 is calculated as the geometric mean of the efficiency change and the technical change components. Equation (5) shows the MPI calculation formula, where '*m*' represents the productivity of production points x_{t+1}, y_{t+1} relative to x_t, y_t.

$$m_o(y_{t+1}, x_{t+1}, x_t, y_t) = \left[\frac{d_o^t(x_{t+1,}y_{t+1})}{d_o^t(x_{t,}y_t)} \times \frac{d_o^{t+1}(x_{t+1}, y_{t+1})}{d_o^{t+1}(x_t, y_t)}\right]^{\frac{1}{2}} \quad (5)$$

If this index exceeds 1, it implies that there has been an improvement in productivity between periods *t* and *t* + 1. Conversely, values less than 1 suggest a decline in productivity.

- For Constant Returns to Scale:

MPI or TFP growth = Technological Change × Technical Efficiency Change

Technological Change depicts innovation between the time periods. It measures the change in the production frontier over time or across units and is calculated as the ratio of the distance between the efficient frontier in the second period and the efficient frontier in the first period to the distance between the frontier in the first period and a reference period frontier.

Technical Efficiency over the two periods indicates whether the DMU is getting closer to its efficiency frontier over time due to learning by doing. It is calculated as the ratio of the distance between the current unit and the efficient frontier in the second period to the distance between the same unit and the frontier in the first period.

- For Variable Returns to Scale:

MPI = Technological Change × Pure Technical Efficiency Change × Scale Efficiency Change

Scale Efficiency Change measures how close a DMU moves to the frontier due to changes in its scale or size of production.

5. Result and discussion

The Malmquist Productivity Index based on DEA has been calculated, in order to evaluate the efficiency of 21 sectors within the manufacturing industry of Singapore. Data was collected from the Singapore Department of Statistics for the period 2015 to 2021 (21 industries × 7 years = 147 observations). The matrix for DEA was formed with capital and labor as input variables, and with sales as the output variable. Net fixed asset at the end of the year was used as a proxy for capital while remuneration was included to capture the cost of labor, for each year. GDP deflator was used to calculate real values for the input and output variables. The descriptive statistics are presented in **Table 3**.

Table 3. Descriptive statistics of inputs and output (in thousand dollars).

YEAR	Sales	Remuneration	Net Fixed Assets
Mean	311,762,539	22,027,988	74,895,145
Median	305,132,093	21,827,870	73,106,607
SD	40,934,970	630,684	6,162,595
Minimum	259,132,522	21,188,974	66,538,383
Maximum	377,472,257	23,030,172	81,213,492

The MPI was calculated by adopting the variable return to scale (VRS) model in light of the ongoing structural change in Singapore's manufacturing sector. **Table 4** provides the overall MPI scores over the years where if the value of the Malmquist index or any of its components is less than 1, this denotes regression or deterioration in performance, and values greater than one denote improvement in performance relative to the best practice in the sample.

Table 4. Malmquist productivity index summary of annual means.

Year	MPI	Technological Change	Technical Efficiency	Pure Efficiency Change	Scale Efficiency Change
2016	0.999	0.933	1.071	1.091	0.981
2017	1.094	1.232	0.888	0.914	0.971
2018	1.073	1.102	0.975	0.961	1.014
2019	1.043	0.922	1.132	1.201	0.943
2020	1.264	1.222	1.034	1.149	0.900
2021	1.254	1.239	1.012	1.059	0.956
OVERALL	**1.131**	**1.108**	**1.021**	**1.062**	**0.961**

The MPI for the entire sector was 1.131 indicating that the Total Factor Productivity of the manufacturing industry in Singapore improved over the years from 2015 to 2021. The improvement was mainly driven by technological change with an index of 1.108 rather than technical efficiency which had a lower index of 1.021. Further decomposition of the technical efficiency change into its components indicates that the enterprises have suffered in terms of their scale efficiency (index = 0.961) since firms have not been able to achieve their optimal scale of operation over time.

The spurts in MPI in 2017 were due to the technological advancements in the country in its drive towards transforming Singapore into a smart city. In 2017, the Singapore Government rolled out Industry Transformation Maps (ITMs) along with Industry Digital Plans to facilitate digitalization in every industry. Digital platforms such as e-invoicing were being introduced to help small and medium enterprises save costs, speed up transactions, and reduce mistakes in accounting.

Table 5. Malmquist productivity index according to industry sub-sector.

DMU	Industry/Products	MPI	Technological Change	Technical Efficiency	Pure Efficiency Change	Scale Efficiency Change
6	Wearing Apparel	1.481	1.331	1.113	1.110	1.003
4	Wood & Wood Products	1.460	1.270	1.150	1.202	0.957
7	Leather Products, Footwear	1.269	1.177	1.078	1.272	0.848
9	Printing	1.231	1.190	1.034	1.170	0.884
5	Textile & Textile Manufacture	1.183	1.151	1.027	1.200	0.856
17	Machinery & Equipment	1.177	1.074	1.096	1.190	0.921
16	Electrical Equipment	1.129	1.077	1.049	1.127	0.931
14	Basic Metals	1.122	1.064	1.055	1.082	0.975
20	Other Transport Equipment	1.120	1.090	1.028	1.097	0.937
21	Other manufacturing Industries	1.118	1.063	1.051	1.110	0.947
15	Fabricated Metal products	1.117	1.083	1.032	1.110	0.929
11	Chemicals	1.098	1.113	0.986	0.978	1.009
10	Refined Petroleum Products	1.063	1.063	1	1	1
12	Rubber & Plastic products	1.042	1.084	0.961	1.005	0.956
18	Motor Vehicles, Trailers	1.023	1.116	0.917	0.932	0.984
1	Food, Beverage, Tobacco	1.022	1.013	1.009	1.017	0.992
3	Computer, Electronic, Optical	1.022	1.011	1.011	0.964	1.049
2	Pharmaceutical, Biological	1.021	1.020	1.000	0.998	1.003
19	Furniture	1.020	1.183	0.863	0.863	1.000
13	Non-metallic mineral products	1.001	1.065	0.940	0.943	0.996
8	Paper and Paper Products	0.977	1.036	0.943	0.943	1.000

The wearing apparel industry in Singapore has undergone a significant technological change, recording an overall productivity index of 1.48 (**Table 5**). The Textile and Fashion Federation of Singapore has encouraged new businesses to introduce innovative technology in their entire supply chain. Advancement of computer graphics has resulted in virtual garment simulations from design to production in a virtual environment before creating the actual output. As a result, trials and errors requiring time and costs are being avoided through computer-aided garment simulations. Clothing is also being created from Lyocell, which utilizes nanotechnology to convert wood pulp and cotton waste into a synthetic fiber that is stronger and silkier than cotton. Apparel researchers in Singapore have introduced 'smart clothing' which helps to enhance the life of wireless devices like smartwatches and headphones through its 'Metamaterial'. The T-shirt helps to enhance the wireless connectivity of devices with the laced strips of metamaterial textile. Therefore, the wearing apparel industry secured the first position in the total factor productivity measure in the Singapore manufacturing industry during the 2015–2021 period.

The second-highest productivity index was secured by the Wood and Wood Products sector (**Table 5**). The innovation in wood technology is being seen as a game changer for Singapore in view of the high energy consumption and carbon emissions produced by concrete high-rises. One example of a material as a substitute for concrete is mass-engineered timber. Over the last decade, a leap of technology in the wood products sector has been mass-engineered timber which gained immense popularity due to lower costs and faster construction. However, the main challenge has been its inflammability and there have been innovative technological breakthroughs to combat this. Nanyang Technological University (NTU) developed an invisible coating that provides a flame barrier and has been amalgamated with the mass-engineered timber elements, proving to be a boon to the construction industry. The new coating developed by NTU becomes active when exposed to high heat to insulate the wood underneath making it a revolutionary step forward for the timber construction industry. Another path-breaking innovation has been the Cross Laminated Timber (CLT) which has a load-bearing capacity similar to that of concrete, but is 80 percent lighter, fire resistant is also claimed to help reduce the energy needed for cooling buildings in tropical Singapore. CLT is being promoted by Singapore's Economic Development Board to enable the construction industry to build high rise apartments since the technology allows faster construction with fewer on-site staff, reducing waste, noise, and dust pollution in the surrounding community.

Singapore is heavily reliant on imports of animal-derived products, which contributes to a large carbon footprint. To address this issue, the Singapore Green Plan invested in the research and development of sustainable materials and technologies for sectors like the leather industry which, apart from the slaughter of animals, adversely affects the environment due to the use of water, toxic chemicals, and the release of greenhouse gases. With cellular engineering, cultured skin cells are now being transformed into leather. Also, Mycotech Singapore has developed cultivates agri-waste based materials bound by mushroom mycelium to form bio-fabrication leather, a material that resembles animal leather. Mycelium leather has been considered the next best alternative leather. Some of the world's biggest fashion brands are now incorporating innovative leather alternatives into their manufacturing processes for bags and footwear following the mushroom-derived leather that include Hermes, Gucci, and Saint Laurent, to name a few.

Printing has scored high on both technological change (1.19) as well as pure technical change (1.17) with an overall productivity index of 1.231 (**Table 5**), which highlights the importance of this sector in Singapore's growth model. In order to unlock the opportunities of technology the Government of Singapore announced

InfoComm and Media (ICM) as a core sector as a value-added industry to create new jobs and bring in multiplier effects across the economy. 3D printing or additive manufacturing has been introduced to simplify production processes, particularly for product assembly and ‘intelligent production’. Moving towards Industry 4.0, the application of 3D printing reduces waste products and, therefore, the overall production costs by producing prototypes with advanced features. Companies like Airbus have adopted this technology to design lighter and more efficient aircraft components; Adidas and Nike are producing high-performance shoes; doctors are designing high-tech diagnostic and surgical tools. The printing industry has been acknowledged as a vital enabler for Singapore to strengthen its overall manufacturing industry.

6. Conclusion

The significant transformation in Singapore’s manufacturing sector has fueled discussions on the origins of the growth of the sector. The persistent claims by extant studies suggest that the growth in the sector is mainly caused by the accumulation of inputs and volatility in the exports and imports. This paper makes two main contributions: First, we show the year-on-year productivity growth for the entire manufacturing sector, and second, we use industry-level data to offer fresh evidence on how each industry in the manufacturing sector has performed over the study period. Calculating the Malmquist Productivity Index (MPI), we show that since 2017, productivity growth for Singapore has remained positive, and this growth, rather than a mere accumulation of inputs, results from progress in technological change and efficient utilization of inputs for most industries. An impressive 20 out of 21 sectors showing positive technological changes and 14 showing positive efficiency change marks great improvements in the manufacturing sector. The findings lay sufficient evidence of the success of Singapore’s aggressive but cautiously designed frameworks that have targeted innovation and automation in the manufacturing sector. The SIRI system explained earlier has been a big push aligning most manufacturing industries to the national agenda of smart and innovative manufacturing. The results also corroborate the Singaporean government’s dedication to collaborating with industry stakeholders and higher education institutions to provide individuals with the skills needed for advanced manufacturing through national initiatives like the “SkillsFuture Series in Advanced Manufacturing”. On the front of the manufacturing sector’s technological adoption progress, Singapore can be recognized as a blueprint for many emerging economies aiming to boost industrialization through technological smart manufacturing.

The findings show technical efficiency change, especially scale efficiency, as an area of improvement for 7 manufacturing industries which scored less than 1. Manufacturing industries need a thorough analysis of their operations regarding unit economics from a labor and machinery perspective. This will pave the way for optimizing performance, reducing cost, and removing less productive factors of production. Also, readjusting production capacity to fit the scale to enjoy economies of scale is possible under the findings reported. We limited our study to identifying the TFP growth and decomposing the growth into technical efficiency change and technological change. Further research identifying the determinants of efficiency in the manufacturing industries will augment policy implications. Accordingly, we recommend the same for further studies. Also, from the findings, we suggest for further research a deep dive landscape analysis of the wearing apparel industry of Singapore which has distinguished itself as the most efficient and productive manufacturing industry. This is important for leveraging best practices for use in other industries.

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